

Article

# Influence of Contextual Variables on Educational Performance: A Study Using Hierarchical Segmentation Trees

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**Abstract:** The general objective of this study is to explore the relationship between students' contextual characteristics and their performance in mathematical reasoning (MR) and linguistic comprehension (LC) skills. The census data from the ESCALA (E**S**critura, **C**Alculo y **L**ectura en Andalucía) tests developed by Agencia Andaluza de Evaluación Educativa (AGAEVE) in 2017 were used. These tests are carried out in the second year of primary school in the Autonomous Community of Andalusia (Spain). These data have been analysed through the data mining technique known as segmentation trees, using the CRT (Classification and regression trees) algorithm for each of the skills. This has allowed the detection of the high influence of social and cultural status (ESCS) and familial expectations regarding academic performance in both tests. In addition, it allows us to point out that there are different interactions between contextual characteristics and their relationship to performance in MR and LC. These results have made it possible to establish groups of students who may be at risk of not reaching the minimum required levels. Some characteristics of at-risk students are low ESCS, low family expectations or being born in the last six months of the year. The detection of at-risk profiles could contribute to the optimisation of the performance of these groups by creating specific plans.

**Keywords:** educational efficiency; educational evaluation; educational quality; academic achievement; student evaluation

## 1. Introduction

Large-scale educational evaluations allow us to thoroughly understand educational reality [1], improve educational systems [2,3] and optimise the education received by students [3,4]. Their results are often used to establish changes in educational policies [3,5] or as an empirical basis on which to justify established educational reforms [6]. They also make it possible to establish reference standards for current educational trends [3].

In the particular area of school effectiveness, large-scale evaluations have made it possible to detect variables that influence student performance [7]. Economic, social and cultural status (ESCS), gender, migrant status or ethnic minority status have been topics of interest in numerous research studies on school effectiveness and educational performance.

Numerous studies indicate that the ESCS [2,7–15], the location of the centre [13,16], the parents' attendance at university [11] and the number of books at home [17] have a decisive influence on the level of performance achieved by students in large-scale assessments. It is likely that the cultural level of the families influences the value of the education and educational opportunities offered [14,18,19]. Preschool education attendance seems to benefit the low ESCS student body more [20], which could indicate that it provides compensatory educational opportunities for the most disadvantaged families.

In addition, the influence of the ESCS interacts with variables such as the gender of the student, girls being the most sensitive to its influence [21]. Therefore, the ESCS would influence student performance mediated by its interaction with other educational and contextual variables.

Some studies [14,22] present results that show that immigrant students achieve worse academic results and that the greater the presence of ethnic minorities in the school, the lower the performance [14]. Again, the cultural level of the families may be the variable that is truly driving these results, in addition to other cultural mechanisms that could limit access to resources by these families [23].

Although in primary education, there seems to be no difference between boys' and girls' results [24], in secondary education, girls tend to perform worse in mathematics and better in reading and writing [13,25]. This could be explained by the influence of gender stereotypes still present in today's society [26].

Students repeating a year [16] and a high level of religiosity in the school [27] seem to negatively influence educational performance. On the other hand, attendance, high levels of motivation [7] and discipline [28] have a positive effect.

#### Data Mining in Educational Research

Data mining (DM) is part of exploratory research techniques. DM allows the exploration of patterns that explain the educational phenomenon in order to improve it [29,30]. In other words, these predictive analyses help to detect characteristics that put academic achievement at risk. This valuable information should be used by educational institutions to prevent low levels of achievement [31–33]. In the achievement of this objective, as stated by Anwar and Ahmed [29], appropriate modifications of the curriculum and performance assessment systems can have a very positive impact.

In the educational field, DM is mainly used in distance education [34,35] because e-learning platforms generate a large amount of data that can be analysed using the big data technique. The qualification of the students is used as a dependent variable, while the characteristics of the students [30], their context [36] and the interaction with the teaching platform in the case of e-learning are usually used as independent variables.

Some studies on school effectiveness that use these techniques indicate that adolescents who are in a relationship achieve worse educational performance, although this may be due to a lower level of dedication to study [37]. By contrast, higher levels of achievement are associated with students who are more aware of the seriousness of drug use and have parents with low rates of alcohol consumption and higher levels of education [30,37].

Within hierarchical segmentation, segmentation trees is a technique that provides results that are simple to interpret and allows non-linear effects and higher-order interactions to be automatically found [38,39]. Segmentation trees are appropriate for the study of large amounts of data and the detection of patterns. They allow the classification of independent variables to forecast values of a dependent variable, reduce the number of independent variables and facilitate the explanation of a phenomenon [40]. In this sense, this study has the following objectives:

- To explore the influence of contextual variables and their interaction on academic achievement obtained in mathematical reasoning (MR) and linguistic communication (LC) skills;
- To detect profiles of students at risk of school failure.

## 2. Materials and Methods

### 2.1. Research Sample

To carry out the study, census data from the ESCALA (diagnostic test **E**scritura, **C**álculo y **L**ectura en Andalucía [Writing, Calculating and Reading in Andalusia]) tests, administered by the Agencia Andaluza de Evaluación Educativa (AGAEVE), during the academic year 2016–2017 in Spain, were used. Once the sample was refined, the results of 75,820 students were used (50.9% male and 49.1% female). The purpose of these tests is to objectively and rigorously evaluate the competencies in LC and MR of students in the 2nd grade of primary education (7–8-year-old students). In addition, it is

complemented with a context questionnaire, administered to families, which provides information on contextual and cultural factors. Andalusia is one of the areas with the least social and educational development in Europe [41], so it is necessary to know what factors could be influencing it from an educational point of view. This region is located in the south of Spain and is the autonomous community with the largest population in the country (8,427,000). The results in mathematics of the last Programme for International Student Assessment (PISA) (2018) placed the region almost 30 points below the OECD (Organisation for Economic Cooperation and Development) average [42] The region's proximity to Morocco means that there is an immigrant population of around 20% in some provinces such as Málaga and Almería, and the foreign population accounts for 7.77% in Andalusia (see <http://www.juntadeandalucia.es/justiciaeinterior/opam/es/node/90>).

Table 1 shows a description of the contextual variables extracted from the context questionnaire [43], as well as the debugging treatment used and the categorisation made.

**Table 1.** Description of the Contextual Factors Used.

Variable Name	Description	Treatment	Categories
Gender	Unique dichotomous choice (boy or girl)		0 = boy 1 = girl
ESCS	Amount of resources available in the house, work and studies of both parents, attendance of cultural activities and number of books.	Factorial analysis	
Hora_acuesta (Bedtime)	Unique polytomous choice of the time students go to bed during the week with 4 options (before 21:00, 09:00–21:30, 9:30–22:00 and after 22:00).	It is grouped into 3 categories, instead of 4, by recoding on the same variables.	1 = before 9 pm 2 = between 9 pm and 10 pm 3 = after 10 pm
Cantidad_tareas (Amount of homework)	Unique polytomous choice in which they have to evaluate the number of tasks (4 options).		1 = few 2 = justified 3 = less 4 = none
Tiempo_tareas (Time spent on homework)	Unique polytomous choice in which they have to evaluate the time that the student dedicates to the accomplishment of school tasks (5 options).	It is grouped into 3 categories.	1 = up to 15 min 2 = 15 to 60 min 3 = more than one hour
Compromiso_lector (Commitment to reading)	Nominal scale (nothing, little, enough and a lot) for 5 questions (I read with the student, we usually read at home, shared reading or commenting on the reading) that evaluate the commitment to reading.	Average of the scores assigned by the parents and dichotomisation of the variable.	1 = nothing–little 2 = very much–enough
N_extracurriculares (Number of extracurriculars)	Unique dichotomous choice (yes or no) for 4 types of extracurricular activities (sports, musical, language or other)	Summary of the scores obtained.	1 = none 2 = from 1 to 2 3 = 3 or more
Horas_pantallas (Screen consumption hours)	Nominal scale (no time, up to one hour, 1 to 2 h or more than two hours) for two different questions (watching TV or playing on a console)	Average of the scores reached in both questions and dichotomisation of the variable	1 = up to 1 h 2 = 1–2 h 3 = more than two hours

Table 1. Cont.

Variable Name	Description	Treatment	Categories
Expectativas_FAM (Family expectations)	Unique polytomous choice in which they have to evaluate the degree of studies they think the student will finish from 5 options. Both parents answer.	Average of the scores assigned by the parents and dichotomisation of the variable.	1 = obligatory education or middle studies 2 = higher education
ImpliFAM_estudiante (Family involvement with the student)	Nominal scale (never, some days, almost every day, every day) of 5 questions (encourage to study, ask for homework, check homework, ask how the class went and help with homework) that assess their involvement with the student.	Average of the scores reached in the questions and dichotomisation of the variable.	1 = never–some days 2 = almost every day
ImpliFAM_colegio (Involvement of families with the school)	Nominal scale (nothing, little, quite and a lot) for 5 questions (attendance at tutorials, participation in school activities, relationship with the school's parents' association, relationship with the parent delegates and relationship with the school council) that assess their involvement with the school.	Average of the scores reached in the questions and dichotomisation of the variable.	1 = nothing–little 2 = very much–enough
MES_nacimiento (Month of birth)	Open question about the month of birth.	Grouping in two categories.	1 = first six months 2 = last six months

## 2.2. Analysis

The analysis was carried out using the Statistical Package for the Social Sciences (SPSS) [44]. The independent variable was LC or MR, while the dependent variables were the contextual factors of the students. The analysis was initially carried out with the CHAID (Chi-square automatic interaction detector) and CRT (Classification and regression trees) algorithms. The CHAID algorithm was finally discarded, because it generated a high number of nodes that made interpretation difficult.

Therefore, the algorithm ultimately used was CRT, which is suitable for weighing the importance of contextual factors in the explanation of school performance [45] and facilitates the interpretation of the data by dividing the variables in a binary way. For this same reason, pruning has been used, using SPSS commands, which avoids over-adjustments and simplifies the results.

## 3. Results

As can be seen in Table 2, according to the means (M) and standard deviations (SD), the results in MR and LC do not present large differences, although it is noteworthy that the minimum score in MR reaches lower values than in LC. On the other hand, the variable family involvement with the student presents a low SD, which could be interpreted as a small intra-group difference. This has led us to discard it for the segmentation technique. The independent variable with the greatest intra-group variance seems to be the ESCS, if we consider the difference between the mean, the maximum and the minimum. In this case, as it is a standardised variable, SD is close to 1.

**Table 2.** Descriptive Statistics of the Dependent and Independent Variables.

	Variables	Minimum	Maximum	M	SD
Dependent	LCN1	129.568	613.459	507.632	94.817
	MRN1	77.0237	600.067	506.376	94.733
Independent	ESCS	−2.86954	3.06001	0.0836802	0.9875545
	Hora_acuesta (Bedtime)	1	3	2.17	0.452
	Cantidad_tareas (Amount of homework)	1	4	2.13	0.635
	Tiempo_tareas (Time spent on homework)	1	3	2.03	0.503
	Compromiso_lector (Commitment to reading)	1.00	2.00	1.4172	0.49310
	Número_extraescolares (Number of extracurriculares)	1.00	3.00	1.9802	0.48646
	Horas_pantallas (Screen consumption hours)	1.00	3.00	1.3561	0.54900
	Expectativas_familiares (Family expectations)	1.00	2.00	1.6857	0.46425
	ImplicacionFAM_estudiante (Family involvement with the student)	1.00	2.00	1.9918	0.09042
	ImplicacionFAM_colegio (Involvement of families with the school)	1.00	2.00	1.6926	0.46143
	MES_nacimiento (Month of birth)	1.00	2.00	1.5046	0.49998

The annex [46] presents the results of the CRT algorithm for MR. The tree contains 63 nodes (32 of them terminals) distributed over 5 levels. The dependent variables selected by the algorithm for the construction of the segmentation tree were ESCS, Expectativas\_familiares, Tiempo\_tareas, MES\_nacimiento, Cantidad\_tareas and gender.

The variable that best predicts achievement in MR is the ESCS (nodes 1 and 2), as already pointed out in the scientific literature. It is remarkable that the two different groups that are constituted based on the ESCS interact in different ways with the contextual variables. While students with low ESCS are influenced by the expectations that the family places on them (nodes 3 and 4), those with high ESCS are affected by the time they spend on tasks (nodes 5 and 6). Students from families who expect higher education obtain the highest scores. It could be understood, therefore, that family expectations act as a protective factor in the face of unfavourable socioeconomic situations, probably because they are associated with a more positive evaluation of education and its importance.

It seems that students are negatively affected when they spend more than one hour on schoolwork (see nodes 6 and 10), while spending up to one hour seems to be beneficial (see nodes 5 and 9). This may be because students with higher needs and lower academic achievement generally need more time to complete assignments. On the other hand, being born in the last six months of the year seems to decrease MR performance (see nodes 15 and 16). The amount of homework, when families believe that they should have less (see nodes 55 and 56), is positive for performance.

The segmentation tree for the case of LC is shown in the annex [47]. It is composed of 61 nodes, 31 of them terminals, distributed over 5 levels. The variables included by the algorithm were ESCS, Expectativas\_familiares, Tiempo\_tareas, gender and MES\_nacimiento.

In the case of LC, the variables mentioned above act in the same way as in MR. However, in this case, gender does seem to influence students negatively and positively (see nodes 7 to 14). Regarding the number of tasks in the case of LC, their absence may be worse for performance than their presence (nodes 59 and 60). It is noteworthy that commitment to reading is not among the variables selected

by the algorithm, which could be due to the fact that the ESCS would catalyse, in some way, cultural commitment in general.

Taking as a reference the results presented to respond to the second objective of the research, both in LC (see node 31) and MR (see node 32), the student body that presents one or more of the following characteristics could be catalogued as an at-risk group: low ESCS, low family expectations, born in the last six months of the year. In the case of LC, we can also add being a male student. By contrast, having high family expectations seems to protect students with low ESCS, in both tests.

#### 4. Discussion

The findings are consistent with the existing scientific literature in the field of school effectiveness and educational performance, as they confirm that the ESCS is the variable that best predicts academic success. The influence of ESCS has been confirmed in studies carried out with large-scale evaluations, such as PISA, both in a national context [10,16] and at the international level [2,7,9,11–15,19]. However, this contribution to the existing body of knowledge has demonstrated that high expectations of families may be a protective factor for students with low ESCS. This could be explained by the fact that these same students are also likely to have greater social capital and support from their families [18,48]. However, it could also be due to the reciprocity of expectations, i.e., higher expectations for students who perform well.

On the other hand, spending too much time on homework does not seem to be beneficial for elementary school students. This is probably because, as Valle et al. [49] stated, it is the students with the greatest difficulties who spend the most time on homework. However, at the secondary school level, it is the students who spend more time on homework that perform better [12,50]. This could be a consequence, once again, of ESCS, since students with a more comfortable socioeconomic position are also the ones who generally receive more support from their parents and more learning opportunities [19].

The issue of gender also deserves to be highlighted. While no interaction was found in mathematical reasoning, it was recorded in linguistic understanding, with male students being disadvantaged. This partially confirms the evidence provided by the scientific literature of the better performance of female students in communication skills and higher performance of male students in MR [13,19,24,51]. Educational systems should undertake appropriate changes in educational programmes to overcome this shortcoming and achieve, at early ages, gender equity in these two basic competencies.

As some of the previous studies have shown [6,52], the results derived from educational research are not usually used to promote educational changes at the centre or teaching methodology level, even in countries with a long tradition of educational evaluation [9]. They are usually used more for political than educational purposes [6]. Even so, taking as a reference the profiles detected for students at risk of academic failure, we consider that it could be beneficial to develop workshops in schools, aimed at raising awareness among families about the importance of family expectations in student achievement. It would also be helpful for schools to offer extracurricular activities of a cultural nature for low-ESCS students. Book-lending services could also help to narrow the gap between students, as families with fewer resources have more difficulty acquiring books [53].

Educational systems must guarantee equality of opportunity, overcoming the segregation of students by contextual characteristics [54] that may have been aggravated by the coronavirus crisis [55,56]. The results of this study managed to explain about 10% of the variance in performance in LC and MR among 7- and 8-year-old schoolchildren according to their contextual factors, which is close to the results of previous studies [57]. This makes us reconsider the moment at which the influence of the ESCS begins to determine results in school effectiveness [2,7–15]. Performance at these ages could be explained more by individual characteristics, such as differences in executive functions [57–62] than by context. Although these results could be evaluated as positive, since it is not contextual factors that determine performance at early ages of schooling, they do invite reflection on the factors that could affect performance at these ages and when contextual factors begin to gain importance. Some



studies suggest that students from families with lower ESCS may have lesser development of certain cognitive skills [62]. However, early interventions aimed at stimulating these skills could mitigate these inequalities [63,64]. Therefore, it is necessary to detect vulnerable students and promote actions that allow for equitable and sustainable educational systems within today's society. This also raises questions for future research. For example, at what point are the ESCS and other contextual factors decisive for school effectiveness? Could the ESCS effects be avoided with early stimulation of variables associated with executive function? What role do teachers and teaching–learning methodologies play in this effectiveness? Would the effectiveness of the educational centre have an influence in the early years of schooling? To do this, progress must be made on the early detection of students at risk, using large-scale evaluations for educational purposes and integrating them into the daily work of educational centres. This progress should also aim to connect the information coming from the large-scale evaluation with the dialogue between different paradigms and more everyday realities [65]. Only the synergy between the different perspectives on educational research will allow progress in the identification of at-risk student profiles. According to the results of the study, in the early ages of schooling, contextual factors still do not explain to a great extent the variance in student performance.

As for the limitations of the study, variables that could be relevant to the explanation of academic performance have been left out of the research. Specifically, we are referring to immigrant status, pre-school attendance and bilingualism. These types of variables were not included in the context questionnaire administered by AGAEVE, so it was impossible to access this information. Resolving this situation would require collaboration between institutions and researchers, which, given the complex bureaucratic framework, is not always easy to achieve. In this sense, for educational science to advance, research must open its doors to both institutions and schools themselves.

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## References

1. Johansson, S. International large-scale assessments: What uses, what consequences? *Educ. Res.* **2016**, *58*, 139–148. [[CrossRef](#)]
2. Ferrão, M.E. School effectiveness research findings in the Portuguese speaking countries: Brazil and Portugal. *Educ. Res. Policy Pract.* **2014**, *13*, 3–24. [[CrossRef](#)]
3. OECD. *Synergies for Better Learning: An International Perspective on Evaluation and Assessment*; OECD Publishing: Paris, France, 2013. [[CrossRef](#)]
4. Means, B.; Haugan, B.; Harris, J. How the science of learning is changing science assessment. In *Developing Minds in the Digital Age: Towards a Science of Learning for 21st Century Education*, Educational Research and Innovation; OECD Publishing: Paris, France, 2019; pp. 197–210. [[CrossRef](#)]
5. Childs, J.; Russell, J.L. Improving Low-Achieving Schools. *Urban Educ.* **2017**, *52*, 236–266. [[CrossRef](#)]
6. Fischman, G.E.; Topper, A.M.; Silova, I.; Goebel, J.; Holloway, J.L. Examining the influence of international large-scale assessments on national education policies. *J. Educ. Policy* **2019**, *34*, 470–499. [[CrossRef](#)]

7. Martnez-Abad, F.; Lizasoain, L.; Castro, M.; Joaristi, L.M. Selección de escuelas de alta y baja eficacia en Baja California (México). *Rev. Electron. Investig. Educ.* **2017**, *19*, 38–53. [[CrossRef](#)]
8. Banerjee, P.A. A systematic review of factors linked to poor academic performance of disadvantaged students in science and maths in schools. *Cogent Educ.* **2016**, *3*. [[CrossRef](#)]
9. Damiani, V. Large-scale assessments and educational policies in Italy. *Res. Pap. Educ.* **2016**, *31*, 529–541. [[CrossRef](#)]
10. Gamazo, A.; Martínez-Abad, F.; Olmos-Migueláñez, S.; Rodríguez-Conde, M.J. Evaluación de factores relacionados con la eficacia escolar en PISA 2015. Un análisis multinivel. *Rev. Educ.* **2017**, 56–78. [[CrossRef](#)]
11. Jennings, J.L.; Deming, D.; Jencks, C.; Lopuch, M.; Schueler, B.E. Do Differences in school quality matter more than we thought? New evidence on educational opportunity in the Twenty-First century. *Sociol. Educ.* **2015**, *88*, 56–82. [[CrossRef](#)]
12. OECD. *Low-Performing Students: Why They Fall behind and How to Help Them Succeed*; OECD: Paris, France, 2016; pp. 1–212. [[CrossRef](#)]
13. Özdemir, C. Equity in the Turkish education system: A multilevel analysis of social background influences on the mathematics performance of 15-year-old students. *Eur. Educ. Res. J.* **2016**, *15*, 193–217. [[CrossRef](#)]
14. Strand, S. Ethnicity, gender, social class and achievement gaps at age 16: Intersectionality and ‘getting it’ for the white working class. *Res. Pap. Educ.* **2014**, *29*, 131–171. [[CrossRef](#)]
15. Valenzuela, J.P.; Bellei, C.; Allende, C. Measuring systematic long-term trajectories of school effectiveness improvement. *Sch. Eff. Sch. Improv.* **2016**, *27*, 473–491. [[CrossRef](#)]
16. Cordero, J.M.; Manchón, C. Factores explicativos del rendimiento en educación primaria: Un análisis a partir de TIMSS 2011. *Estud. Sobre Educ.* **2014**, *27*, 9–35. [[CrossRef](#)]
17. Evans, M.D.; Kelley, J.; Sikora, J. Scholarly Culture and Academic Performance in 42 Nations. *Soc. Forces* **2014**, *92*, 1573–1605. [[CrossRef](#)]
18. Li, H. The ‘secrets’ of Chinese students’ academic success: Academic resilience among students from highly competitive academic environments. *Educ. Psychol.* **2017**, *37*, 1001–1014. [[CrossRef](#)]
19. Schmidt, W.H.; Burroughs, N.A.; Zoido, P.; Houang, R.T. The Role of Schooling in Perpetuating Educational Inequality: An International Perspective. *Educ. Res.* **2015**, *44*, 371–386. [[CrossRef](#)]
20. OECD. *Education at a Glance 2018*; OECD Publishing: Paris, France, 2018. [[CrossRef](#)]
21. Van Hek, M.; Kraaykamp, G.; Pelzer, B. Do schools affect girls’ and boys’ reading performance differently? A multilevel study on the gendered effects of school resources and school practices. *Sch. Eff. Sch. Improv.* **2018**, *29*, 1–21. [[CrossRef](#)]
22. Williams-Klotz, D.N.; Gansemer-Topf, A. Examining Factors Related to Academic Success of Military-Connected Students at Community Colleges. *Community Coll. J. Res. Pract.* **2018**, *42*, 422–438. [[CrossRef](#)]
23. Assari, S.; Boyce, S.; Bazargan, M.; Caldwell, C. Mathematical Performance of American Youth: Diminished Returns of Educational Attainment of Asian-American Parents. *Educ. Sci.* **2020**, *32*. [[CrossRef](#)]
24. Muñoz-Chereau, B.; Thomas, S.M. Educational effectiveness in Chilean secondary education: Comparing different ‘value added’ approaches to evaluate schools. *Assess. Educ.* **2016**, *23*, 26–52. [[CrossRef](#)]
25. Troncoso, P.; Pampaka, M.; Olsen, W. Beyond traditional school value-added models: A multilevel analysis of complex school effects in Chile. *Sch. Eff. Sch. Improv.* **2016**, *27*, 293–314. [[CrossRef](#)]
26. Wach, F.S.; Spengler, M.; Gottschling, J.; Spinath, F.M. Sex differences in secondary school achievement—The contribution of self-perceived abilities and fear of failure. *Learn. Instr.* **2015**, *36*, 104–112. [[CrossRef](#)]
27. Stoet, G.; Geary, D.C. Students in countries with higher levels of religiosity perform lower in science and mathematics. *Intelligence* **2017**, *62*, 71–78. [[CrossRef](#)]
28. Ning, B.; Van Damme, J.; Van Den Noortgate, W.; Yang, X.; Gielen, S. The influence of classroom disciplinary climate of schools on reading achievement: A cross-country comparative study. *Sch. Eff. Sch. Improv.* **2015**, *26*, 586–611. [[CrossRef](#)]
29. Anwar, M.A.; Ahmed, N. Analyzing Undergraduate Students’ Performance in Various Perspectives using Data Mining Approach. *Inf. Knowl. Manag.* **2013**, *3*, 59–65. [[CrossRef](#)]
30. Martínez, F.; Chaparro, A.A. Data-mining techniques in detecting factors linked to academic achievement. *Sch. Eff. Sch. Improv.* **2017**, *28*, 39–55. [[CrossRef](#)]
31. Helal, S.; Li, J.; Liu, L.; Ebrahimie, E.; Dawson, S.; Murray, D.J.; Long, Q. Predicting academic performance by considering student heterogeneity. *Knowl. Based Syst.* **2018**, *161*, 134–146. [[CrossRef](#)]



32. Mhetre, V.; Nagar, M. Classification based data mining algorithms to predict slow, average and fast learners in educational system using WEKA. In Proceedings of the 2017 International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 18–19 July 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 475–479. [CrossRef]
33. Parkavi, A.; Lakshmi, K. Predicting the course knowledge level of students using data mining techniques. In Proceedings of the 2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), Chennai, India, 2–4 August 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 128–133. [CrossRef]
34. Cerezo, R.; Sánchez-Santillán, M.; Paule-Ruiz, M.P.; Núñez, J.C. Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. *Comput. Educ.* **2016**, *96*, 42–54. [CrossRef]
35. Heredia, D.; Amaya, Y.; Barrientos, E. Student Dropout Predictive Model Using Data Mining Techniques. *IEEE Lat. Am. Trans.* **2015**, *13*, 3127–3134. [CrossRef]
36. Fernandes, E.; Holanda, M.; Victorino, M.; Borges, V.; Carvalho, R.; Van Erven, G. Educational data mining: Predictive analysis of academic performance of public school students in the capital of Brazil. *J. Bus. Res.* **2019**, *94*, 335–343. [CrossRef]
37. Roy, S.; Garg, A. Predicting academic performance of student using classification techniques. In Proceedings of the 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON), Mathura, India, 26–28 October 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 568–572. [CrossRef]
38. Gonzalez, O.; O'Rourke, H.P.; Wurpts, I.C.; Grimm, K.J. Analyzing Monte Carlo Simulation Studies with Classification and Regression Trees. *Struct. Equ. Modeling* **2018**, *25*, 403–413. [CrossRef]
39. Schumacher, P.; Olinsky, A.; Quinn, J.; Smith, R. A Comparison of Logistic Regression, Neural Networks, and Classification Trees Predicting Success of Actuarial Students. *J. Educ. Bus.* **2010**, *85*, 258–263. [CrossRef]
40. Berlanga, V.; Rubio, M.J.; Vilá, R. Cómo aplicar árboles de decisión en SPSS. *REIRE* **2013**, *6*, 65–79.
41. Charron, N.; Lapuente, V. *Quality of Government in Eu Regions: Spatial and Temporal Patterns*; QoG Working Paper Series: Gothenburg, Sweden, 2018; ISSN 1653-8919.
42. OECD. *PISA 2018 Results (Volume I): What Students Know and Can Do*; OECD Publishing: Paris, France, 2020. [CrossRef]
43. AGAEVE. Cuestionario de Contexto Familia 2016–2017. Available online: <http://www.juntadeandalucia.es/educacion/agaeve/profesorado-primaria-escala-contexto.html> (accessed on 3 May 2019).
44. *IBM SPSS Statistics for Macintosh*; IBM: Armonk, NY, USA, 2017.
45. Escobar, M. *El Análisis de Segmentación: Técnicas y Aplicaciones de los Árboles de Clasificación*; Centro de Investigaciones Sociológicas: Madrid, Spain, 2007; ISBN 9788474764321.
46. García-Jiménez, J.; Rodríguez-Santero, J.; Torres-Gordillo, J.J. Annexed Result: Segmentation Tree for the Mathematical Reasoning Competence. Available online: <https://dx.doi.org/10.17504/protocols.io.bpepmjdn> (accessed on 4 November 2020).
47. García-Jiménez, J.; Rodríguez-Santero, J.; Torres-Gordillo, J.J. Annexed Result: Segmentation Tree for the Linguistic Communication Competence. Available online: <https://dx.doi.org/10.17504/protocols.io.bpenmjde> (accessed on 4 November 2020).
48. Wei, D. Parental influence on Chinese students' achievement: A social capital perspective. *Asia Pac. J. Educ.* **2012**, *32*, 153–166. [CrossRef]
49. Valle, A.; Pan, I.; Núñez, J.C.; Rosário, P.; Rodríguez, S.; Regueiro, B. Deberes escolares y rendimiento académico en Educación Primaria. *An. Psicol.* **2015**, *31*, 562–569. [CrossRef]
50. OECD. *Does Homework Perpetuate Inequities in Education? PISA in Focus*; OECD Publishing: Paris, France, 2014. [CrossRef]
51. Sigmundsson, H.; Eriksen, A.D.; Ofteland, G.S.; Haga, M. Letter-sound knowledge: Exploring gender differences in children when they start school regarding knowledge of large letters, small letters, sound large letters, and sound small letters. *Front. Psychol.* **2017**, *8*. [CrossRef]
52. Tobin, M.; Nugroho, D.; Lietz, P. Large-scale assessments of students' learning and education policy: Synthesising evidence across world regions. *Res. Pap. Educ.* **2016**, *31*, 578–594. [CrossRef]
53. Le, T.-T.-H.; Tran, T.; Trinh, T.-P.-T.; Nguyen, C.-T.; Nguyen, T.-P.-T.; Vuong, T.-T.; Vu, T.-H.; Bui, D.-Q.; Vuong, H.-M.; Hoang, P.-H.; et al. Reading Habits, Socioeconomic Conditions, Occupational Aspiration and Academic Achievement in Vietnamese Junior High School Students. *Sustainability* **2019**, *11*, 5113. [CrossRef]

54. Murillo, F.J.; Martínez-Garrido, C. Perfiles de segregación escolar por nivel socioeconómico en España y sus Comunidades Autónomas. *Rev. Electron. Investig. Eval. Educ.* **2019**, *25*. [[CrossRef](#)]
55. Rodríguez-Bailón, R. Inequality viewed through the mirror of COVID-19. *Int. J. Soc. Psychol.* **2020**, *35*, 647–655. [[CrossRef](#)]
56. Cáceres-Muñoz, J.; Jiménez-Hernández, A.S.; Martín-Sánchez, M. Cierre de Escuelas y Desigualdad Socioeducativa en Tiempos del Covid-19. Una Investigación Exploratoria en Clave Internacional. *Rev. Int. Educ. Justicia Soc.* **2020**, *9*, 199–221. [[CrossRef](#)]
57. Demetriou, A.; Kazi, S.; Makris, N.; Spanoudis, G. Cognitive ability, cognitive self-awareness, and school performance: From childhood to adolescence. *Intelligence* **2020**, *79*. [[CrossRef](#)]
58. Watts, T.W.; Gandhi, J.; Ibrahim, D.A.; Masucci, M.D.; Raver, C.C. The Chicago School Readiness Project: Examining the long-term impacts of an early childhood intervention. *PLoS ONE* **2018**, *13*, e0200144. [[CrossRef](#)] [[PubMed](#)]
59. Finders, J.K.; McClelland, M.M.; Geldhof, G.J.; Rothwell, D.W.; Hatfield, B.E. Explaining achievement gaps in kindergarten and third grade: The role of self-regulation and executive function skills. *Early Child. Res. Q.* **2020**, *54*, 72–85. [[CrossRef](#)]
60. Demetriou, A.; Kazali, E.; Kazi, S.; Spanoudis, G. Cognition and cognizance in preschool predict school achievement in primary school. *Cogn. Dev.* **2020**, *54*. [[CrossRef](#)]
61. Nelson, T.D.; Nelson, J.M.; James, T.D.; Clark, C.A.C.; Kidwell, K.M.; Espy, K.A. Executive control goes to school: Implications of preschool executive performance for observed elementary classroom learning engagement. *Dev. Psychol.* **2017**, *53*, 836–844. [[CrossRef](#)]
62. John, A.M.S.; Kibbe, M.; Tarullo, A.R. A systematic assessment of socioeconomic status and executive functioning in early childhood. *J. Exp. Child Psychol.* **2019**, *178*, 352–368. [[CrossRef](#)]
63. Kulic, N.; Skopek, J.; Triventi, M.; Blossfeld, H.P. Social Background and Children's Cognitive Skills: The Role of Early Childhood Education and Care in a Cross-National Perspective. *Annu. Rev. Sociol.* **2019**, *45*, 557–579. [[CrossRef](#)]
64. Roos, L.L.; Wall-Wieler, E.; Lee, J.B. Poverty and early childhood outcomes. *Pediatrics* **2019**, *143*. [[CrossRef](#)]
65. García-Jiménez, J.; Torres-Gordillo, J.J.; Rodríguez-Santero, J. What is Published in Impact Journals on School Effectiveness? A Systematic Review of Research Results and Methods. *Pedagogika* **2020**, *138*, 5–24. [[CrossRef](#)]

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