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Are non-cognitive factors predictors of math performance of girls and boys? A Machine Learning approach[1]

Kewords: non-cognitive skills, machine learning, PISA test, gender gap

JEL Classification: I21, I24

Abstract

Non-cognitive factors are important predictors of students' academic performance. However, the quantification of this relationship is barely studied in economics of education. Using a Machine Learning (ML) methodology, we answer the following two questions: *i*) what factors (cognitive and non-cognitive) are better predictors of students´ academic achievement in math?, *ii*) to what extent does the importance of these factors hold when analyzing female and male students separately? To answer these questions, we propose the use of the information available in the PISA 2018 tests on non-cognitive variables (such as beliefs, behaviors, and attitudes) and context variables (demographic, family and school), in combination with the use of a Boosted Regression Trees (BTR) algorithm, developed within a Machine Learning methodology. We find that non-cognitive features are important predictors of math performance, with some of them even on top of socioeconomic features. For instance, believes on *intelligence is manageable*, *students´ cooperation* and *life satisfaction* result in superior predictor of math performance than *family wealth* and *parents´ education*. Estimations by gender show some few noteworthy contrasts between females and males: whereas *mother education* is in the top of (positive) predictors for females, for males it is *exposure to bullying* a strong (negative) predictor math performance. Findings reveal that, encouraging children for a growth mindset and lessoning them on managing non-cognitive skills can be powerful tools to improve students´ cognitive outcomes.

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1. **Introduction**

Academic performance can be strongly influenced by socioeconomic and socioemotional factors. The influence of socioeconomic characteristics of the students (such as the family income or the parents' education) on their academic performance have been widely studied in economics of education literature (Fetler, 1989; Considine & Zappalà 2002; Boston, 2013; Graven, 2014). In contrast, non-cognitive factors (including the socioemotionals), such as beliefs, feelings, and attitudes, have had less attention in economics of education literature. However, in the fields of psychology and pedagogics, there is extensive evidence (Haynes, Ben-Avie & Ensign, 2003; Dobbs, Doctoroff, Fisher & Arnold, 2006; Diekstra & Gravesteijn, 2008) that socioemotional factors are important predictors of academic performance and general wellbeing (Marsh, et. al, 2006)[2].

Unlike socioeconomic variables, non-cognitive competencies can differ between boys and girls belonging to the same community, and by extension, they could have gender-differentiated relationships with academic performance. For instance, the correlation between fear to failure and math performance is negative for boys, but positive for girls (PISA, 2018). Therefore, there are reasons to test the hypothesis that differences between non-cognitive aspects could influence mathematics performance differently for boys and girls, and this analysis should be considered in a comprehensive way where cognitive and non-cognitive are led to play a role without imposing any restriction on the linearity of relationship or their importance (as Machine Learning –ML- allows).

Previous studies have considered that the success of students in math can be influenced by several factors including socioeconomic (Perry & McConney, 2010; Chiu & Chow, 2015; Westrick, Le, Robbins, Radunzel & Schmidt, 2015; O'Connell, 2019; Ortiz, Hincapié & Paredes, 2020) and socioemotional ones. In particular, from the non-cognitive perspective it is found that aspects such as attitudes and feelings towards math (Gottfried, 1985; Maloney & Beilock, 2012; Dweck, 2014), as well as beliefs about intelligence (Claro, Paunesku, & Dweck, 2016), self management (Claro & Loeb, 2019) or culture (Stew, Mount, Sapienza & Zingales, 2008) can determine math performance. Likewise, extensive literature in psychology about socioemotional

[2] In the PISA test, the OECD defines socioemotional skills as the "social and emotional skills that refer to capabilities to regulate thoughts, emotions and behavior". Note that the terms of socioemotional and non-cognitive factors used in this proposal, indistinctly refer to variables related to behaviors, attitudes, and student feelings.

differences between men and women (Grossman & Wood, 1993; Pohl, Bender & Lachmann, 2005; Acosta, Muller & Sarzosa, 2015) supports the need to study these interactions differentiated by gender.

In economics of education, there are only two previous papers that analyze at the same time an extensive variety of factors, some non-cognitive included, using ML techniques and its interrelation with the student's academic performance (Gabriel, Signolet & Westwell, 2018; Masci, Johnes & Agasisti, 2018); nevertheless, none of these two studies have focus either in socioemotional aspects or gender approach. They focuses in the interactions of variables and both are in the context of developed countries. This research is intended to fill this gap by answering the following two questions: *i*) what socioemotional (and non-socioemotional) factors are better predictors of students´ academic achievement in math?, *ii*) to what extent does the importance of these factors hold when analyzing female and male students separately? In doing so, we consider the use of PISA 2018 tests, in combination with an automatic computational learning methodology known as Boosted Regression Trees (BRT).

On the one hand, the PISA 2018 test collects a high number of variables that concern cognitive and non-cognitive aspects of the student, as well as his/her context. On the other hand, the BRT methodology, associated with ML techniques, provides the unrestricted possibility of incorporating all the information provided by the student within the algorithms, with data and non-models with predetermined rules that guide the results. The BTR models exceed some restrictions on the classic models (for instance, Ordinary Least Squares), such as non-collinearity between variables or pre-established parameterization, which helps improve their forecast capacity of the target variable (Gabriel et al., 2018). The BRT estimates allows to discover, classify, and ponder the factors associated with the best performance differently and according to the particular patterns for each gender. However, a limitation of BRT models is the difficulty in interpreting the coefficients (for example, the magnitude), which will be overcome using the *Shapley Additive Explanations* (SHAP) *Methodology*.

This research aims to contribute to the literature with at least three aspects. First, it contributes to the literature of socioemotional analyses and math performance, with an emphasis on the gender perspective. Second, by using a ML approach, the research contributes to the incipient literature that seeks to study multidimensional explanatory factors and predictors of academic performance. Third, this study could contribute to inform educational authorities, parents and teachers on aspects to focus to increase success in mathematics. In particular, this research reveals that believes of *intelligence is manageable*, *students´ cooperation* and *life satisfaction* results is superior predictor of math performance than *family wealth* and *parents´ education*. Moreover, in separated analysis by gender, findings are relatively similar between them, with some few remarkable contrasts: whereas mother education is in the top of (positive) predictors for females, for males it is exposure to bullying which is a strongly (negative) predictor of math performance. Results indicate that there is room to improve performance from developing the non-cognitive aspects, regardless the socioeconomic status of children´s families. Colombia represents an interesting case of study because it exhibits high learning lags in math (69 out of 78 participating countries in PISA assessment), the highest mathematical gender gap in the countries participating in the PISA 2018 tests (Schleicher, 2019), and incipient exploration of socioemotional relation to performance from an economics of education perspective.

2. **Literature Review**

Educational research has widely studied the relevance of multiple factors in predicting academic performance. Among them, non-cognitive factors have been classified as relevant in the educational process of developing academic and interpersonal skills (Marsh et al., 2006; Diekstra et al., 2008). Some researchers have shown that these socioemotional factors are strongly related to not only students' success in secondary and higher education (Poropat, 2009; Lindqvist & Vestman, 2011; Richardson, Abraham & Bond, 2012), but also to their success in the labor market (Heckman, Stixrud & Urzua, 2006). Additionally, non-cognitive factors' predictive validity over multiple life achievements have been compared to socioeconomic status (SES) and cognitive factors (Roberts, Kuncel, Shiner, Caspi & Goldberg, 2007). Particularly, students' attitudes towards mathematics (Maloney et al., 2012; Dweck, 2014), students' implicit beliefs about their intelligence (Claro et al., 2016), and students' self-management (Claro et al., 2019) have been classified as very important predictors of academic achievement in mathematics.

Nevertheless, one of the challenges in this field of study is to unravel the effects of socioemotional and cognitive factors, as they are inherently linked inside every student. Some literature has suggested that, when studying the effect of non-cognitive and cognitive elements over academic achievement, these factors are constantly and mutually supplementing each other, implying an endogenous relationship between them (Cunha, Heckman & Schennach, 2010; Eisenhauer, Heckman & Mosso, 2015; Heckman & Corbin, 2016). This endogeneity makes it complex to establish a causal relationship between socioemotional skills and academic achievement. Still, this relationship offers an interesting challenge for researchers, especially when new computational techniques appear, which could improve non-linear predictive analyses with multiple non-cognitive factors, such as beliefs, feelings towards a particular subject, personality traits, and cognitive factors.

Considering the previous, some researchers have studied exogenous variations in non-cognitive factors and their effects on educational success. For example, Aronson, Fried & Good (2002) conducted an experiment in the US, where students were encouraged to see intelligence as malleable, aiming to diminish racial stereotypes; similarly, Paunesku et al. (2015) and Yeager et al. (2016), designed interventions to test the efficacy of academic mindset and sense-of-purpose over achievement.[3] They concluded that these interventions had an impact on better academic achievement, particularly when students had to face difficulties or contextual disadvantages in their learning processes.

Consequently, the relevance of socioemotional factors, in a supplementary relationship with SES and cognitive factors, has been recognized not only by the global academic community, but also by the educational policy authorities around the world (OECD, 2019). Stiglitz, Sen and Fitoussi (2009) have suggested that it is necessary to incorporate standardized questions about well-being in national and international survey questions, which could give a better view about development and the design of high-quality public policies, including educational programs. Hence, some initiatives around the world, such as the PISA program and the Colombian Institute for the Promotion of Higher Education (ICFES), have incorporated new survey modules that include and validate questions and measures that relates students' well-being and non-cognitive factors.

In relation to the PISA test, the incorporation of non-cognitive variables brings opportunities to study how these factors (including socioemotional features, socioeconomic

[3] Interventions aimed to develop a "growth mindset" (the belief that intelligence is malleable and could be changed over time), in opposition to a "fixed mindset", among students.

status, school environment, perceptions toward teachers and classmates, etc.) relate to academic achievement. Literature in Psychology has observed differences in socioemotional factors across genders (Kring & Gordon, 1998; Wager & Ochsner, 2005; Kret & De Gelder, 2012; Parkins, 2012). For example, Šolcová and Lačev (2017) suggest that women tend to perceive socioemotional experiences more severely and they tend to classify negative stimuli more adversely than men. Hence, studying gender differences in contexts were non-cognitive factors have an effect on academic success should be relevant for parents and teachers on daily-basis and for policymakers in the design of policies. Cornwell, Mustard and Van Parys (2013) discuss this issue, using data from US primary and secondary students, showing that boys who perform equally as well as girls on reading, math, and science tests are graded less favorably by their teachers, but this less favorable behavior vanishes when non-cognitive factors are taken into account. Additionally, they show evidence of a "grade bonus" for boys with test scores and behavior like their girl counterparts. Gustavsen (2017) studied the relationship between social skills and academic achievement with a gender perspective, concluding that teachers' grading appeared to be based not only on students' knowledge but also their social skills and behavior, and teachers tend to assess girls as having better social skills than boys. However, as these authors consider how teachers mark their students, it is possible that teachers' biases are having important shocks over students' final grades, which could differ from scores on a standardized test. For that reason, it is important to investigate about gender differences in non-cognitive factors and their relationships with academic success, particularly in settings where scores or results are not screened by teachers.

Colombia has been part of the growing interest in the role that socioemotional factors have over students' learning process. For example, Niño, Hakspiel, Mantilla, Cárdenas and Guerrero (2017) adapted the EDEX tool, which is used to measure soft skills, to the Colombian background, aiming to have an available tool that could assess psychosocial skills and healthy habits in the school system. Along with this, Huerta (2019) has pointed out the growing relevance of accumulating data of socioemotional factors and skills in Latin America, highlighting the initiative of including questions about (self-)identification, (self-)regulation, and expression of emotions and empathy in surveys from "Acciones y Actitudes Ciudadanas de las pruebas SABER 3,5,9", done by the Ministerio de Educación de Colombia (Colombian Ministry of Education) and ICFES. It is designed and applied to assess emotional competencies and integrative competencies. It is a survey-type questionnaire made up of a set of qualitative questions of perception scales (agree / disagree) or frequency (never / usually), for which there are no correct answers (ICFES, 2018). Additionally, some regional studies in Colombia have depicted and characterized the importance of socioemotional skills in primary and secondary education, emphasizing the relationship between emotional intelligence and reading comprehension and mathematical reasoning (see Hung (2013) for the Atlantic administrative region, and Rendón et al. (2016) for the Antioquia administrative region).

Regarding the ML techniques, researchers have recently incorporated them to expand the computational tools to analyze large educational datasets. Rastrollo-Guerrero, Gómez-Pulido and Durán-Domíngues (2020) analyzed near 70 papers to show how these computational methods were used in educational studies, concluding that this kind of research has appeared only in the last decade. Nevertheless, few of them have focused on primary or secondary education. one study that stands out is that of Yoo (2018), who uses the Elastic Net method (EN method) with the TIMSS dataset (Trends in International Mathematics and Science Study) to predict primary school students' achievement in mathematics. The author concluded that the EN method can be successfully applied to large-scale educational datasets by selecting a subset of variables with reasonable prediction accuracy, sensitivity, and specificity[4].

ML techniques have also been applied to PISA datasets. Damaso and Martínez-Abad (2020) explore the factors linked to academic performance in PISA 2018 through data mining techniques, building a decision-tree algorithm with a school-level unit of analysis for all countries. Their results show the existence of two main branches in the decision tree according to the schools' mean SES: while performance in high-SES schools is influenced by educational factors such as metacognitive strategies or achievement motivation, performance in low-SES schools is affected in greater measure by country-level socioeconomic indicators such as GDP. Masci et al. (2018) used multilevel tree-based methods, which can depict non-linear relationships between the predictor variables and the scores, to understand students' PISA 2015 performance in nine countries (Australia, Canada, France, Germany, Italy, Japan, Spain, UK, and USA). At the student level, they found that SES, motivation, and anxiety were the most influential factors. At the school level, the determinants of academic accomplishment varied among countries, though the proportion of

[4] Among 162 TIMSS variables, 12 student and 5 teacher variables were selected in the Elastic Net model, and the prediction accuracy, sensitivity, and specificity were 76%, 70%, and 80%, respectively.

disadvantaged students was one the most important factor: schools with a higher proportion of disadvantaged students were related to lower scores. Gabriel et al. (2018) analyzed the Australian context, using BRT algorithms with non-cognitive dispositions variables and demographics variables, to predict mathematical literacy scores in the PISA 2012. Their results showed that there is a strong relationship between mathematics self-efficacy and mathematical literacy, and that this relationship was linear. Other interesting relationships were found with students' SES and mathematical anxiety, but they were non-linear (they even portrayed complex interactions among them). Thus, the authors concluded that ML techniques might provide evidence for new ways of associating multiple variables, which can show novel underlying patterns of interaction that would have been otherwise missed in linear models, as Masci et al. (2018) also suggest.

Some authors have studied the disparities between boys' and girls' variables and their effects on educational achievement. Though they consider a different context, Golsteyn & Schils (2014) and Cornwell, Mustard & Van Parys (2013) have studied non-cognitive variables and gender gaps in US primary schools. They find: 1) that girls typically outperform boys in languages and boys typically outperform girls in math; 2) boys are better equipped with important non-cognitive resources though girls' returns to cognitive- related attributes are larger; 3) boys who perform equally as well as girls on reading, math, and science tests are graded less favorably by their teachers, but this disappears when non-cognitive skills are taken into account; and 4) there is evidence of a grade bonus for boys with test scores and behavior like their girl counterparts. These results must be read carefully, as they consider how teachers grade and interact with students in this process, which differs from a "blind testing" setting. In China, Song (2021) studies gender gap patterns in language and math during primary school periods and, using administrative data, shows that girls on average outperform boys in language and in math. They find, once using a survey, that non-cognitive variables can reduce the gender gap in both subjects; that females' efforts, measured in concentration and participation in class, are significantly higher than those of males; and that the reducing effect is greater for students in the bottom quantile.

Regarding the PISA test, Lee and Stankov (2018) examined the predictability of non-cognitive variables for students' mathematics achievement and showed that "self-efficacy" and "educational aspiration" in PISA were the best predictors of student achievement. Borghans and Schils (2019) also documented the importance of non-cognitive skills in predicting performance in the test, though they mainly disentangle different types of variables and they do not focus on gender variances. Nevertheless, these results are important, as gender differences in those variables, once studied, might expose important consequences on achievement. Brozo et al. (2014) summarize major gender differences trends during the years 2000-2009, showing a pattern of boys' underachievement in reading and lower reading engagement relative to girls. Additionally, Arellano, Cámara and Tuesta (2017) explore the gender gap in financial literacy, for 15-year-old students in Spain, concluding that the gender gap decreases when the model includes the effect of non-cognitive skills, though residual differences remain statistically significant. Anaya and Zamarro (2020) analyze the extent to which student effort helps to explain test scores heterogeneity across countries and by gender groups. Their main results show that, once accounting for differential student effort across gender groups, the estimated gender gap in math and science could be up to 6-12 times wider, respectively, and up to 49 percent narrower in reading, in favor of boys, and that this even holds among some of the most gender-equal countries.

To sum up, there are no systematic analyses that explore comprehensively how gender differences in socioemotional variables could be important factors when studying the phenomenon of gender gaps in PISA achievement. Additionally, despite the importance of the scopes and methods described previously, there are no studies that use ML techniques to explore non-cognitive factors that affect academic achievement in Colombian students. Therefore, a gender approach would also be pioneering in comparison to previous national and international research. This study intends to give a new way of studying these elements as a complementary source of educational information for researchers, policymakers, teachers, and parents.

3. Methodology and Data

In recent years, ML algorithms have proven themselves as better predictors than classical statistical methods for both classification and regression problems. In particular, black-box non-linear algorithms, such as Neural Networks, Random Forests and Gradient Boosted Trees are capable of discovering and modelling complex relations between independent variables and the target.

In this research, we aim to exploit the capabilities of these models to identify student's features that better predict math performance from a pool of cognitive and non-cognitive variables measured in the PISA test. Particularly, we make use of the Gradient Boosted Machine (GBM), a tree-based algorithm that sequentially creates regression trees that slowly learn and correct the errors of previous models, to then average their predictions to create a final answer (James, Witten, Hastie & Tibshirani, 2013).

Since we aim to determine which features predict better performance, we make use of Shapley Additive Explanations (SHAP) to interpret the results of the GBM. This methodology allows the ranking of features by importance, as well as determine the direction of the effect.

3.1 Gradient Boosted Trees

As mentioned in the previous section, the GBM is a tree-based algorithm that sequentially creates weak learners in such a way that each new learner decreases the overall loss in the model (Friedman, J., 2001). Following Chen and Guestrin (2016), a GBM model can be represented as

$$\widehat{y_i} = \widehat{y_i}(X_i) = \sum_{k=1}^{K} f_t(X_i),\ \ f_k \in \mathrm{F},$$

in which K is the number of regression trees, f_k is the kth regression tree model, and F is the set of all possible regression trees. The number of necessary trees is determined by each model, in such a way that each new tree included decreases the loss function

$$L = \sum_{i=1}^{n} l\left(y_{i,}\widehat{y_i}\right) + \sum_{k=1}^{K} \Omega(f_k),$$

where $l(.)$ is a convex and differentiable function that measures the distance between the prediction, $\widehat{y_i}$, and the target value, y_i, and $\Omega(.)$ is a function that penalizes the complexity of each tree. By minimizing the L, it is possible to train a GBM that minimizes the overall discrepancy between actual and predicted values, while minimizes model complexity by allowing the construction of simple yet predictive trees.

Nevertheless, this model must be trained in an additive manner, in which the inclusion of the next tree, f_t, if any, helps to reduce the loss function by improving the prediction based on the previous models, $\widehat{y_i}^{(t-1)}$,

$$L^t = \sum_{i=1}^{n} l\left(y_{i,}\widehat{y_i}^{(t-1)} + f_t(X_i)\right) + \Omega(f_t).$$

The final model is obtained after there is no more room to improvement on L^t, or the maximum number of trees is reached. Details on the training of each individual decision tree are presented in James, Witten, Hastie and Tibshirani (2013) and Friedman, Hastie and Tibshirani (2001).

3.2 SHAP for Model Interpretation

Many ML models are considered as black boxes that outperform classical statistical models in prediction tasks by sacrificing its interpretability (Ribeiro, Singh & Guestrin, 2016). To address this issue, many authors have developed methods to extract knowledge on why model predicts the way it does. In particular, we focus our attention to the work presented in Lundberg and Lee, (2017), and Lundberg, Erion, Chen, DeGrave, Prutkin, Nair and Lee, (2020), in which global model explanations are obtained by using Shapley Additive Explanations (SHAP) values.

The objective behind SHAP is to measure feature importance by computing Shapley Values of a conditional expectation function of the model of interest (Lundberg, S. M., & Lee, S. I., 2017). This task is represented as an additive feature attribution method over a simplified model,

$$g(z') = \phi_0 + \sum_{j=1}^{M} \phi_j {z_j}',$$

in which g is called the explanation model, defined as a linear function of binary variables, $z_j' \in \{0,1\}$ correspond to simplified inputs, such that $x = h_x(x')$, and $\phi_j \in \mathbb{R}$ corresponds to the attribution of feature j.

These feature attributions are estimated in such a way that they are Shapley Values, therefore being *locally accurate* by matching the output of the model and its explanation model, possess *missingness* by forcing zero impact of missing features (i.e. $z_j' = 0 \rightarrow \phi_j = 0$), and *consistency* in which the feature attribution is consistent between two different models regardless of other features. Overall, the feature importance obtained by the SHAP methodology helps the interpretation of complex ML models. In particular, if a feature has a positive (negative) impact on the prediction, the SHAP methodology assigns a positive (negative) Shapley Value, and a zero Shapley Value if it has no effect.

4. **Data**

We used databases of the Colombian students from PISA 2018 assessment. PISA is an international exam promoted by the OECD that assesses the competencies and skills of 15-year-old students in different countries, regardless the grade. In Colombia, it is administrated by ICFES. Our sample contains information of 7522 students, 51% are females. This database includes information about student´s opinions and perceptions, school's climate, teacher's direction, competitiveness, resources and parent's education. These variables and indices had been tested and validated by PISA from its initial questionnaire application in 2000. Validation process on the questionnaire has tracked developments in psychometric theory and survey research methodology to provide increasingly valid and reliable measures of non-cognitive constructs that are not sensitive to cultural differences in response style (OECD, 2019). Table 1 shows the groups of variables or indices we used in the analysis, whereas Appendix displays the entire list of indices and variables.

Table 1 – Categories of the variables used in the analysis

Categories	**Description**
Simple questionnaire indices	Grade, Age, and school information
Educational level of parents	Measuring highest level of education completed
Household possessions	Variables related to access to basic necessities, computers, internet
Students' well-being	Variables asking for student's feelings, or how they're perceived by others
Value of school	Asking what students believe they may get from studying at their school
Attitudes towards competition	Questions related to scenarios that involve competition
Motivation to master tasks	Asking how the student feels about hard work and struggling
Fear of failure	Questions related to how the student feel about uncertainty and failure
Meaning in life	Single question asking if the student believes that life has a meaning
Learning goals	Questions asking what are the student's goals at school
Self-Efficacy	Questions related to student's self-efficacy
Sense of belonging	Questions asking for student's feeling of acceptance in their school and with their classmates
Parents' emotional support	Variables measuring student's perception on parent's support
Student competition	Questions about student's perception of competition in school
Exposure to bullying	Questions asking if the student has suffered of some specific forms of bullying
School climate	Questions measuring the sutent's perception on bullying in their school
Student co-operation	Questions related to the student's perception on cooperation in their school
PISA WLE Indices	Compound indices that measure specific traits and perception of the students, based on the questions in the test
Math score	Using the average of the 10 plausible values

Two kind of variables were included in the analysis: indices and individual variables. The indices group variables that are measuring a similar construct (e.g. Attitudes towards competition includes the questions "I enjoy working in situations involving competition with others"; "It is important for me to perform better than other people on a task"; and "I try harder when I'm in competition with other people").[5] According to PISA, among the indices, there are three types: simple indices, new scale indices and trend scale indices. Simple indices are the variables that are constructed through the arithmetic transformation or recoding of one or more items in exactly the same way across assessments. Scale indices are the variables constructed through the scaling of multiple items. Indices are scaled using a two-parameter item-response model and values of the index correspond to Warm Likelihood Estimates (WLE). Basing on all students from equally-weighted countries and economies, the item parameters were estimated. Finally, some of the WLE are WLE standardized afterwards, with mean equal zero and standard deviation equal one (OECD, 2019). The individual variables are not included in the index and are instead included in its original form (e.g. intelligence is something that can´t be change very much). Individual variables are measured and reported as ordinal variables (e.g. the students were asked if they "strongly disagree", "disagree", "agree", or "strongly agree" with the following statement: "Your intelligence is something about you that you can't change very much").

We aim to establish the relationship of all these variables to predict average math score obtained at the PISA test.

Table 2 presents some descriptive statistics. For simplicity in displaying the statistics, we standardized the index (with mean =0 and standard deviation =1) and categorical variables were collapsed into two variables. Notice that for estimation, we use the variables and indeces in its original scale. Moreover, in Table 2, we only show the top twenty variables resulting as strong predictors of performance (although the model was feed with all variables and indices listed in Appendix 1). Column 1 show the statistics for all students. Highlights that most pupils belong to low socioeconomic status families, and have positive beliefs on non-cognitive outcomes (more often agree with non-cognitive positive statements). Almost half of the students are in 10th grade (46%) with the rest spreading in grades 7th, 8th, 9th, and 11th, which is atypical because PISA takers in the other countries concentrate into one particular grade. Moreover, performance is low

[5] https://www.oecd-ilibrary.org/sites/0a428b07-en/index.html?itemId=/content/component/0a428b07-en

compared to other OECD economies (22% lower score than the OECD average). The share of females (51%) is slightly higher than males. When dividing the sample by gender (columns 2 and 3), males perform slightly better in math tests than their female counterparts. In addition, when it comes to school's climate, male students tend to have a higher exposure to bullying and are more competitive than females. In the learning area, female students tend to have more ambitious learning goals, and enjoy reading more than their male counterparts. This is in line with PISA results in the world as in most assessed economies, boys outperform girls in mathematics, and some beliefs and perceptions about themselves of the school are statistically different between gender (OECD, 2019).

Table 2. Descriptive Statistics. All, females and males.

		1	2	3	4
Category	**Variable**	**All** **Mean/SD**	**Male** **Mean/SD**	**Females** **Mean/SD**	**Difference (Male-female)**
Binary (b)	Intelligence Is Something That can´t be changed	0.349	0.338	0.36	-0.022*
		[0.477]	[0.473]	[0.480]	
Binary (b)	Life Has Clear Meaning	0.869	0.85	0.887	-0.037***
		[0.337]	[0.357]	[0.317]	
Binary (c)	Students Are Cooperative	0.914	0.92	0.907	0.013
		[0.281]	[0.271]	[0.290]	
Binary (d)	How Many Cars	0.345	0.365	0.325	0.040***
		[0.475]	[0.482]	[0.468]	
Binary (d)	How Many Cell Phones	0.895	0.9	0.891	0.01
		[0.306]	[0.300]	[0.312]	
Binary (e)	Mother Education	0.501	0.533	0.471	0.062***
		[0.500]	[0.499]	[0.499]	
Binary (e)	Father Education	0.473	0.493	0.455	0.038***
		[0.499]	[0.500]	[0.498]	
Binary	Gender Femenin	0.513	0	1	N/A
		[0.500]	[0.000]	[0.000]	
Binary	Computer	0.664	0.677	0.652	0.025**
		[0.472]	[0.468]	[0.476]	
Binary	Books	0.782	0.765	0.798	-0.034***
		[0.413]	[0.424]	[0.401]	
Binary	Proportion Grade 7	0.039	0.053	0.026	0.027***
		[0.193]	[0.223]	[0.159]	
Binary	Proportion Grade 8	0.098	0.121	0.075	0.046***
		[0.297]	[0.327]	[0.263]	
Binary	Proportion Grade 9	0.215	0.228	0.202	0.026***

		[0.411]	[0.420]	[0.401]	
Binary	Proportion Grade 10	0.456	0.431	0.48	-0.049***
		[0.498]	[0.495]	[0.500]	
Binary	Proportion Grade 11	0.193	0.167	0.218	-0.051***
		[0.395]	[0.373]	[0.413]	
WLE (a)	Joy Like Reading	0	-0.247	0.234	-0.481***
		[1.000]	[0.895]	[1.037]	
WLE (a)	Exposure To Bullying	0	0.14	-0.137	0.277***
		[1.000]	[1.036]	[0.944]	
WLE (a)	Competitiveness	0	0.116	-0.11	0.226***
		[1.000]	[1.028]	[0.960]	
WLE (a)	Mastery Goal Orientation	0	-0.076	0.072	-0.148***
		[1.000]	[1.015]	[0.980]	
WLE (a)	Family Wealth	0	0.069	-0.065	0.134***
		[1.000]	[0.993]	[1.002]	
WLE (a)	General Fear Of Failure	0	-0.089	0.084	-0.172***
		[1.000]	[1.003]	[0.990]	
WLE (a)	Teacher Directed Instruction	0	0.024	-0.023	0.047*
		[1.000]	[0.984]	[1.015]	
WLE (a)	Adaptation Of Instruction	0	0.004	-0.003	0.007
		[1.000]	[1.003]	[0.997]	
WLE (a)	Teachers Stimulation	0	-0.022	0.021	-0.042*
		[1.000]	[0.986]	[1.013]	
WLE (a)	Work Mastery	0	-0.078	0.073	-0.151***
		[1.000]	[1.011]	[0.984]	
Continuous (a)	Life Satisfaction	0	0.085	-0.08	0.165***
		[1.000]	[0.982]	[1.010]	
Continuous	Math Score	400.019	410.706	389.863	20.843***
		[75.452]	[77.371]	[72.140]	

The value displayed for t-tests are the differences in the means across the groups.

***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

(a)Standardized (with the mean and stantard deviation of colombia).

(b)Strongly agree and agree =1. Strongly disagree and disagree =0.

(c)Extremely true, very true, slightly true =1. Not at all true =0.

(d) One or more =1. None =0.

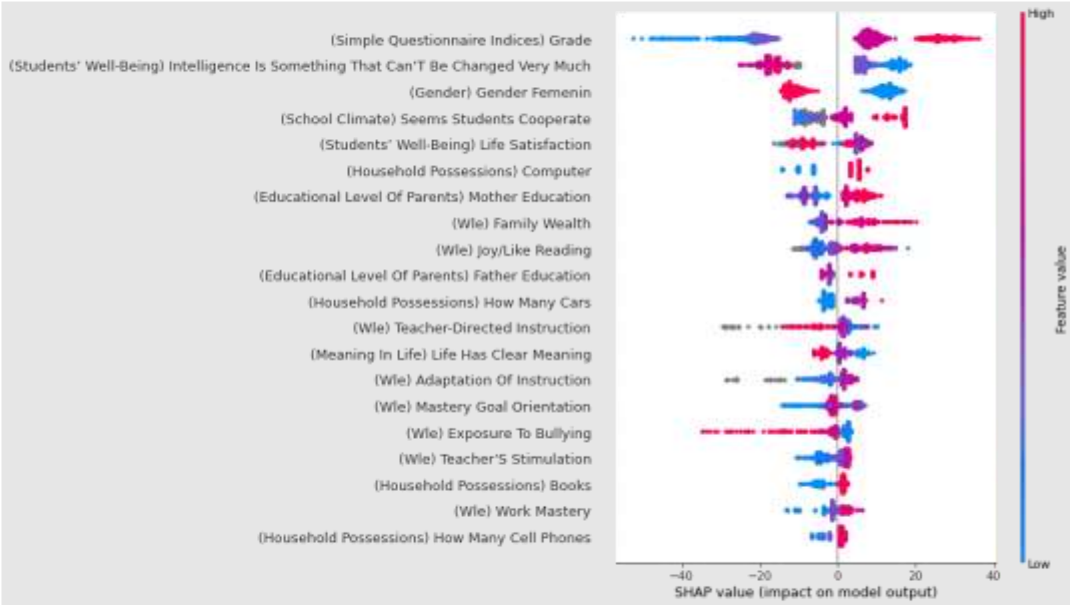
(e) ISCED level is 4 (post secondary not superior) or higher =1. ISCED level is 3 (upper secondary education) or lower =0.

5. **Results**

Using the BRT technique described before, we identify student's features that had better predict math performance from a pool of non-cognitive and cognitive variables measured in the PISA test. As follows, we show the results of the SHAP models which rank variables and indices by importance and determine the direction of the effect. The indices are labeled by WLE, whereas individual variables are not. We first show the result using the entire sample: females and males. Further, we estimate separate models by gender. We feed all models with the same set of variables described in section 3, leading the data "speak" without forcing any functional form or pre-conceive relationship.

Figure 1 describe the results to the first research question: what socioemotional (and non-socioemotional) factors are better predictors of students´ academic achievement in math. Figure 2 has three components for interpretation. First, the indices/variables ranked by the model in the left. Second, the SHAP value scale in the bottom, where negative (positive) scale represents a negative (positive) relationship between the variable and math performance. Third, the color scale in the right side, where intense-blue color represents low values of the index/variable and intense-pink color represent high values of it (e.g., in variables with Likert scale, "strongly disagree" will take an intense-blue color, whereas "strongly agree" will take an intense-pink color).

Figure 1 – Ranking of variables that better predict math performance



For interpretation, it is important to have into account: (i) the variable ranking and (ii) the color mix in front of each variable. Both give different information. The former ranks the importance that a particular variable has on the prediction of math score. The further described the direction or relation between the values of the variable and the prediction of math score. For instance, *grade* is the most important variable that predicts math performance. The gathering of blue points in negative values of SHAP indicates that students in low grades are predicted to have lower score compared to students in higher grades. The latter is represented by intense-pink displayed in positive values of the SHAP. As PISA evaluates 15 years old students regardless the course, this is a logical result: those with 15 years in 6th grade would be predicted to obtain negative result in math compared to those with 15 years in 10th grade. The purple color emerged next to the zero SHAP value means that, for in-middle values of grade (i.e., 10th grade where most 15 years old should be) SHAP values are only slightly positive or slightly negative and variation in math score prediction is not high among 10th graders. Similar analysis can be made for every index/variable with a caveat that the scale can be different: whereas grade goes from 6th to 11th grade, females is binary (high value=female), indices are continue and variables are in a Likert scale. Notice that a variable that is highly ranked but not clear color division is perceived (e.g., life satisfaction) mean that it is important to the prediction, but the direction/relationship is not clearly defined to math score.

In terms of index/variable ranking to predict math score, both socioemotional and socioeconomic features appear to be important predictors of performance. Figure 1 shows that two socioemotional variables are on top of any socioeconomic feature. In order, aside the *grade* (which is the first features), the 10 most important predictors of performance given PISA datasets are: *believes on intelligence* (i.e., intelligence is something that can´t be changed very much), *gender, students cooperation, life satisfaction, have computer, mother education, family wealth, enjoy reading and father education.*

Notice that believes about intelligence (ranked 2) is a strong predictor even over *computer possession* (ranked 6) or *mother and father education* (ranked 7 and 10). From the color scale in front of intelligence variable, it can be inferred that those students who think, "Intelligence is something that cannot be changed" (strongly agree=intense-pink) obtain lower scores in math (under 0 in the SHAP scale). In contrast, those who think the opposite (strongly disagree=intense-blue) obtain high scores in math. The presence of some blue points in the pink region and the fuzzy purple color next to the zero SHAP value reveals some overlap (i.e., students who believe intelligence cannot be change might have a relatively positive result in math represented by purple colors). However, since a rather clear visual division of colors is present (prevalence of intense-pink in the left and intense-blue in the right), it can be inferred that there is an existing strong relationship between believes on intelligence and performance. That is, those who believe that *intelligence is something that cannot be changed* are highly predicted to get low math scores; and those who believe this statement is false, are highly predicted to have high math scores. Color division pattern is perceived in socioeconomic features: having computer and high levels of mother education are predicted to have high positive influence on students' performance on math. Likewise *enjoy reading* is an important factor in predicting math performance. Students who declare an environment of cooperation among students (ranked 4) are predicted to have better scores.

A variable that puzzles is *life satisfaction*. Ranked 5, it indicates that it is an important predictor of performance, but the direction is not clear. The prevalence of bright colors in the extremes and mix of colors in the middle indicates that extreme levels of satisfaction or dissatisfactions have a negative relation to math performance, whereas those intermediately satisfied with life are predicted to get better scores in math than their peers. Possible explanations will be offered in the discussion section. Moreover, *exposure to bullying* displays a rather asymmetric pattern. Students who have high exposure to bullying will be predicted to underperform in math (SHAP values reaching -40). For those reporting low levels of bullying, the relationship to positive results in math is positive but less strong (SHAP values reaching 10).

The general picture presented in Figure 2 indicates that some socioemotional and other non-cognitive features are strong predictors of performance, sometimes surpassing socioeconomic, teachers and school´s environmental features. Beliefs that intelligence is something manageable is the most powerful predictor of performance. Other important non-cognitive features on the top 20 index/variables are: *student's cooperation, life satisfaction, teacher directed instruction, life has clear meaning, adaptation to instruction, mastery goal orientation, exposure to bullying, teacher stimulation, and work mastery*.

Next, a similar analysis as in Figure 1 was run dividing the sample by females (Figure 2a) and males (Figure 2b). From Figure 1 gender is an important predictor of performance (ranking 3), females underperforming males. This gap has been widely documented. However, less has been explore and contrast in terms of the features that predict well math performance by gender, which our second research question: Does the ranking and direction of factors explored in Figure 1 hold similarly for females and males?

Figure 2a and 2b shows that the tendency to have socioemotional determinants in the first places of the ranking holds for both genders. Nevertheless, there is variations in the order of importance of the features. For both genders, their *believes over the manageability of intelligence* occupies the second place in importance, after *grade* variable (which naturally determines the student´s level of knowledge). Nevertheless, the subsequent ranking of the index/variables resulted different by gender. For girls this is followed by *mother education*, *enjoy reading*, *family wealth*, *sense of belonging*, *life satisfaction*, *perceived feedback*, *work mastery* and *cars possession* (Figure 2a); whereas for males, manageability of intelligence is follows by *life satisfaction*, *enjoy reading*, *possession of cellphone*, *family wealth*, *student's cooperation*, *teacher instruction*, *exposure to bulling* and *irritated by bullies* (Figure 2b). Colors in front of the features are similar distributed as in the Figure 1. In general, there are coincidences in some socioemotional and socioeconomic features that determines math performance. Two contrasting aspects highlights though. First, *mother education* is particularly important predictor (ranking 3) for female´s performance whereas not as much for males. Second: *exposure to- and irritated by bullying* is particularly important in predicting bad performance for males, but significant less important for females.

Figure 2a- Ranking of variables that better predict math performance, females.

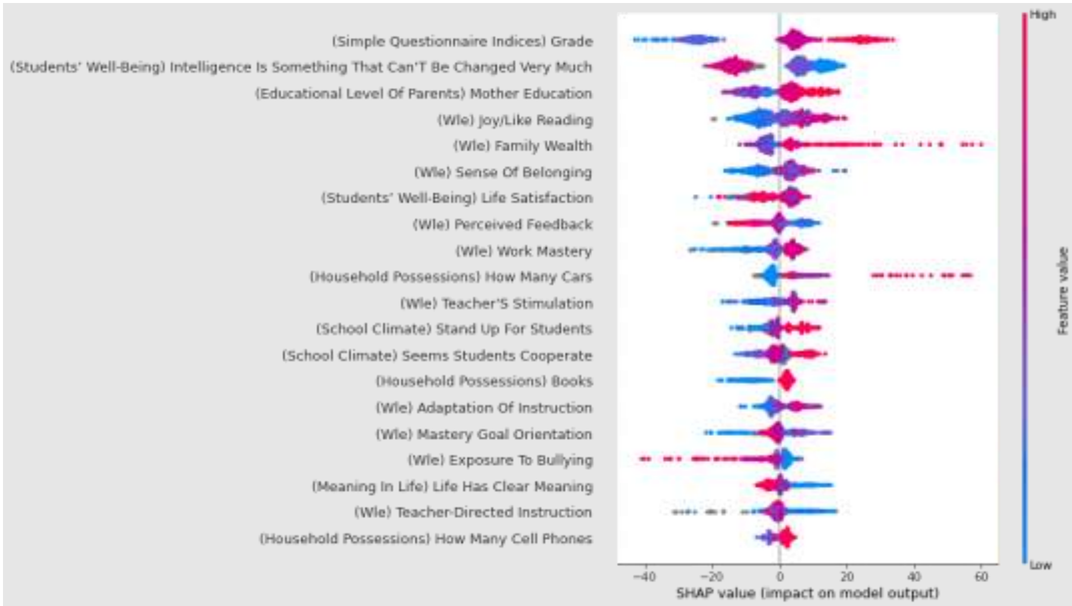
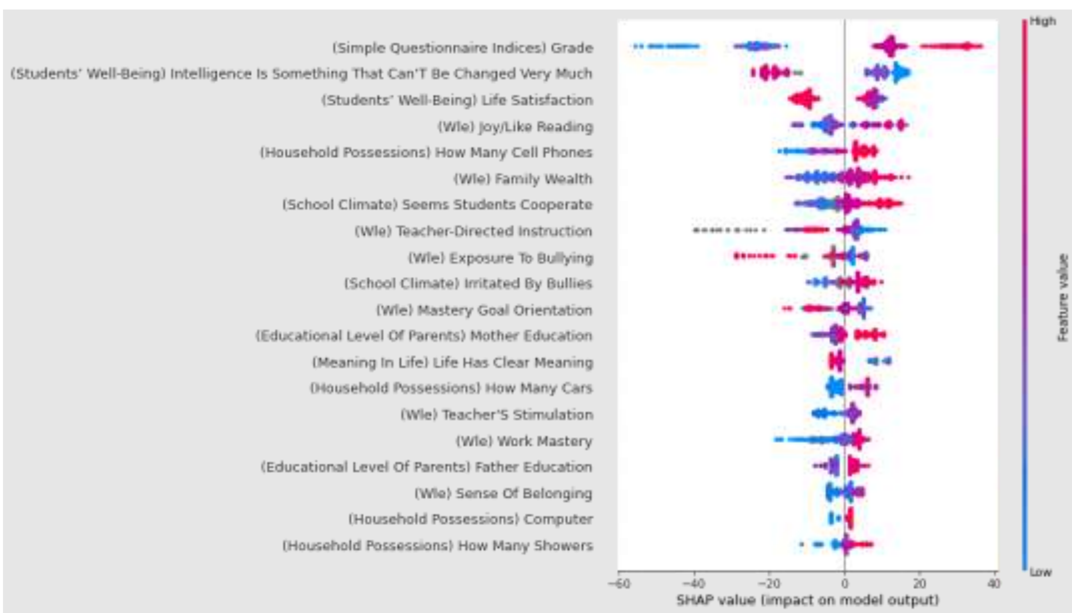


Figure 2b – Ranking of variables that better predict math performance, males.



5.c. Comparison to Latin-Americans Countries and the rest of the world and OECD economies

For the sake of comparison, we run similar analysis as in Figure 1 (i.e. shows the ranking of variables that had better predict math performance) for two groups of countries: a) Latin-American countries and b) all economies participating in PISA test in 2018. Figure 3a shows similarities between the importance and order of predictors between Colombian and Latin-American region: grade, gender, manageability of intelligence, likeness of reading and life satisfactions are in the top 5, and family wealth is in the 7th place.

Figure 3a. – Ranking of variables that better predict math performance

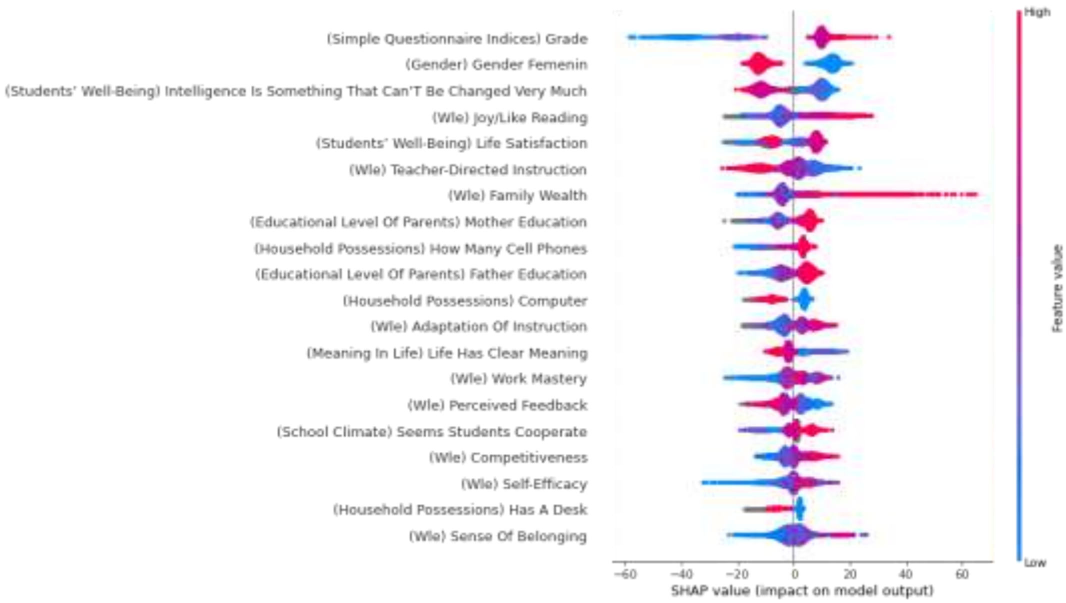
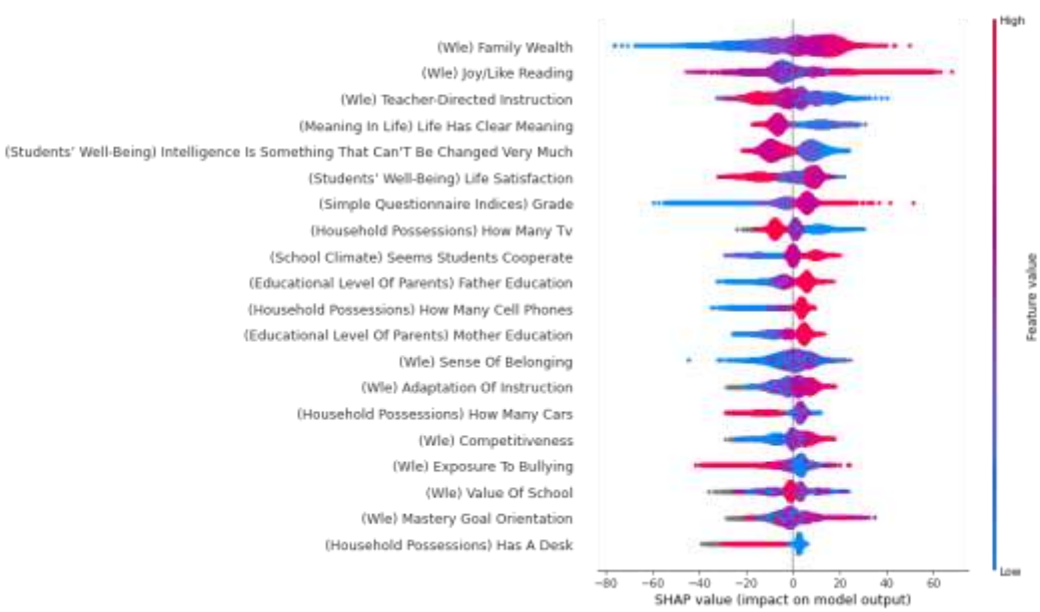


Figure 3b. – Ranking of variables that better predict math performance



These results quite contrast to Figure 3b, where all assessed economies were merged. Here, *family wealth* (socioeconomic), *gender* and *like reading* (cognitive) are the three biggest predictors of performance. The following 4 most important aspects in predicting math successful are non-cognitive: *life has a clear meaning, teacher directed instruction, life satisfaction, intelligence is something that can´t be changed very much*. Although some of the variables and the order are dissimilar to Colombia results, it is a consistency: non-cognitive factors are important predictors of math success.

6. **Discussion**

Using an extensive set of variables and a machine learning method we analyze the factors that better predict math performance in Colombia. The use of a rich set of variables reported in PISA (which includes cognitive and non-cognitive student´s characteristics linked with their habits, perceptions on classmate, teachers, family and school climate, habits of the students, etc.) allows the inclusion of several dimensions and interactions presented in the complex educational process. Beyond classical methods, the BTXX method enables the opportunity to study all the accessible information and interactions at once, without imposing any functional relationships among the available variables. Although they have the limitation of not establishing causal relationships, BTXX display more accurate predictions than other classical methods, which could imply a step forward to discovering the importance of particular variables as math performance predictors.

The results notably stablish that, for the case of Colombia, non-cognitive features are important predictors of math performance, with some of them even on top of socioeconomic features. In particular, believes on *intelligence is manageable, students´ cooperation* and *life satisfaction* result in superior predictor of math performance than *family wealth* and *parents´ education*.[6] This evidence is of paramount importance given that the factors weighting more in predicting math are not necessarily socioeconomic (which is rather difficult to change) but socioemotional, that are within reach of change by the school, families, and/or students.

[6] Notice that grade is not listed given that is xxx that students in higher grade display higher results in math, as they have covered more topics.

The highly ranking places that non-cognitive skills reach on predicting math support the extensive literature that well developed non-cognitive aspects are significant influences on cognitive outcomes (Roberts et al., 2007; Maloney et al., 2012; Dweck, 2014; Claro et al., 2016; Claro et al., 2019). Our results also reveal a potential challenge for policy as it supports the claim that educational plans need to be strong in promoting socioemotional manage developments, as it was previously mentioned on the literature review (Stiglitz et al., 2009; OECD, 2019). This could be crucial when analyzing the contexts (both at school and inside families) where students engage along their educational path, and, like what Niño et al. (2017) and Huerta (2019) studied, new available data for Latin America and Colombia could promote a new culture that enhances the importance of these factors.

Furthermore, the gender approach that we study reveals important facts. Mainly, that socioemotional variables are relevant for both genders. Overall, for girls and boys, our study shows that particular factors of interest should be the development of a growth mindset, cooperation skills, and life satisfaction. This recalls what other authors have exposed (Rellano et al., 2017; Anaya et al., 2020), but it also opens a novel analysis that explores extensively how socioemotional variables affect academic results. Nevertheless, differential actions can also take place by gender. For girls we find that mother's education is particularly strong predictor of math performance, in line with previous literature (Törrönen, 2019). This can be due to role model theory (Almquist & Angrist, 1971). Therefore, in environments where mothers have low levels of education, provision of policies to empowering girls into academic achievement can be important to compensate mothers absent of education and lessen the current high gender gap in math. For males on the other hand, exposure to bullying highly marks deterioration in math performance. For them, self-behavioral plans (with consequences to others) need to be particularly enforced for boys (Murillo & Román, 2011).

This research, using contemporary quantitative tools, can be viewed alongside other research drawn from the literature on the importance of non-cognitive inputs and multidimensional interactions for learning. From several decades ago, constructuivistic psychologist had been posted theories pointing that learning process is not linear and complex (Gardner,1995, Ausubel, Novak & Hanesian, 1978). It long depends on intrapersonal, situational, cognitive and affective-social factors (Ausubel, et al., 1978) where interactions with other is fundamental for transmission of different knowledge (Bruner, Mercer & Edwards, Rogoff). The present research, which develops in the field of applied economics, using a ML methods allows for the study of cognitive outcomes incorporating such connections, which results in quantitative evidence supporting previous statements in psychology, where non-cognitive factors play an important role in learning.

Finally, a particularly salient aspect of this research is the relationship of variables that are not usually thought to pertain to educational policy on educational performance. This research supports that educational policy should include, as important aspect, orientation to schools over the importance and management of non-cognitive variables. Ultimately, they are not only contributing to mental health and well-relationship among students, but they are also directed and important predictors of achievement.

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Appendix 1 – Indices by category used in the analysis

VARIABLES

Variables by models

i) General model

Name	Type	sub-group	scale
Grade	Variable	Simple questionnaire indices	.
Birth month	Variable	Simple questionnaire indices	.
Mother Education (Decreasing)	Variable	Simple questionnaire indices	.
Father Education (Decreasing)	Variable	Simple questionnaire indices	.

Has a Desk	Variable	Household possessions	.
Own Room	Variable	Household possessions	.
place to study	Variable	Household possessions	.
Computer	Variable	Household possessions	.
Education software	Variable	Household possessions	.
Internet	Variable	Household possessions	.
Books	Variable	Household possessions	.
How Many TV	Variable	Household possessions	.
How Many cars	Variable	Household possessions	.
How Many showers	Variable	Household possessions	.
How Many cell phones	Variable	Household possessions	.
Life satisfaction	Variable	Students' well-being	.
School helps get good job	Variable	Students' well-being	.
School helps get into good college	Variable	Students' well-being	.
Trying hard at school is important	Variable	Students' well-being	.
Enjoys competition with others	Variable	Students' well-being	.
It is important to perform better than others	Variable	Students' well-being	.
Tries harder when is competing	Variable	Students' well-being	.
Satisfaction in working	Variable	Students' well-being	.
Persistence in task completition	Variable	Students' well-being	.
Enjoy improvement	Variable	Students' well-being	.
Keeps struggling to master sth	Variable	Students' well-being	.
Worry of others opinion when failing	Variable	Students' well-being	.
Afraid not having enough talent when failing	Variable	Students' well-being	.
When failing, he/she doubts of future plans	Variable	Students' well-being	.
Intelligence is something that can't be changed very much	Variable	Students' well-being	.
Life has clear meaning	Variable	Students' well-being	.
Described as Happy	Variable	Students' well-being	.
Described as Afraid	Variable	Students' well-being	.
Full of energy	Variable	Students' well-being	.
Unhappy	Variable	Students' well-being	.
Proud	Variable	Students' well-being	.
Worried	Variable	Students' well-being	.
Cheerful	Variable	Students' well-being	.
Sad	Variable	Students' well-being	.
Contented	Variable	Students' well-being	.
Goal: Learn	Variable	Students' well-being	.
Goal: Master study material	Variable	Students' well-being	.
Goal: Master classes content	Variable	Students' well-being	.
Manage	Variable	Students' well-being	.
proud of acocmplished	Variable	Students' well-being	.
Handle multiple things	Variable	Students' well-being	.
believe in myself	Variable	Students' well-being	.
find way out of difficulty	Variable	Students' well-being	.

feel like outsider	Variable	School climate	.
make friends easy	Variable	School climate	.
belong to school	Variable	School climate	.
feel awkward in school	Variable	School climate	.
others like me	Variable	School climate	.
feel lonley	Variable	School climate	.
parents support EDU	Variable	School climate	.
parents support Difficulties	Variable	School climate	.
parents support Confidence	Variable	School climate	.
students value competition	Variable	School climate	.
students are competitive	Variable	School climate	.
students are equally competitive	Variable	School climate	.
Students compared	Variable	School climate	.
Students left me out	Variable	School climate	.
made fun of	Variable	School climate	.
threaten by	Variable	School climate	.
misstreated by	Variable	School climate	.
hit by	Variable	School climate	.
rummors of me	Variable	School climate	.
irritated by bullies	Variable	School climate	.
help students	Variable	School climate	.
against bullying	Variable	School climate	.
against bullying	Variable	School climate	.
stand up for students	Variable	School climate	.
Value cooperation	Variable	School climate	.
students are cooperative	Variable	School climate	.
students are cooperative	Variable	School climate	.
students encourage	Variable	Student co-operation	.
family wealth	Index	WLE	.
Gender Femenin	Variable	Simple questionnaire indices	.
lectura	Index	WLE	.

ii) WLE model

Name	Type	sub-group	scale
Grade	Variable	Simple questionnaire indices	.
Birth month	Variable	Simple questionnaire indices	.
Mother Education (Decreasing)	Variable	Simple questionnaire indices	.
Father Education (Decreasing)	Variable	Simple questionnaire indices	.
Has a Desk	Variable	Household possessions	.
Own Room	Variable	Household possessions	.
place to study	Variable	Household possessions	.
Computer	Variable	Household possessions	.
Education software	Variable	Household possessions	.

Internet	Variable	Household possessions	.
Books	Variable	Household possessions	.
How Many TV	Variable	Household possessions	.
How Many cars	Variable	Household possessions	.
How Many showers	Variable	Household possessions	.
How Many cell phones	Variable	Household possessions	.
Life satisfaction	Variable	Students' well-being	.
Intelligence is something that can't be changed very much	Variable	Students' well-being	.
Life has clear meaning	Variable	Students' well-being	.
parents support EDU	Variable	School climate	.
parents support Difficulties	Variable	School climate	.
parents support Confidence	Variable	School climate	.
irritated by bullies	Variable	School climate	.
help students	Variable	School climate	.
against bullying	Variable	School climate	.
against bullying	Variable	School climate	.
stand up for students	Variable	School climate	.
family wealth	Index	WLE	.
Gender Femenin	Variable	Simple questionnaire indices	.
Teacher-directed instruction	Index	WLE	.
Perceived feedback	Index	WLE	.
Teacher's stimulation	Index	WLE	.
Adaptation of instruction	Index	WLE	.
Teacher support	Index	WLE	.
Joy/Like reading	Index	WLE	.
Perception of competitiveness	Index	WLE	.
Perception of cooperation	Index	WLE	.
Value of School	Index	WLE	.
Competitiveness	Index	WLE	.
Work mastery	Index	WLE	.
General fear of failure	Index	WLE	.
Self-efficacy	Index	WLE	.
Mastery goal orientation	Index	WLE	.
Respect for other cultures	Index	WLE	.
Sense of belonging	Index	WLE	.
Exposure to bullying	Index	WLE	.
Reading	Index	WLE	.