

A machine learning approach to predict university enrolment choices through students' high school background in Italy

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Abstract

This paper explores the influence of Italian high school students' proficiency in mathematics and the Italian language on their university enrolment choices, specifically focusing on STEM (Science, Technology, Engineering, and Mathematics) courses. We distinguish between students from scientific and humanistic backgrounds in high school, providing valuable insights into their enrolment preferences. Furthermore, we investigate potential gender differences in response to similar previous educational choices and achievements. The study employs gradient boosting methodology, known for its high predicting performance and ability to capture non-linear relationships within data, and adjusts for variables related to the socio-demographic characteristics of the students and their previous educational achievements. Our analysis reveals significant differences in the enrolment choices based on previous high school achievements. The findings shed light on the complex interplay of academic proficiency, gender, and high school background in shaping students' choices regarding university education, with implications for educational policy and future research endeavours.

Keywords: gender gap, educational data, university enrolment, STEM, machine learning, gradient boosting

1. Introduction

Since the Second World War, there has been a remarkable expansion of educational opportunities worldwide, leading to an increased demand for education at all levels. This growth was expected to promote the development of democratic principles and reduce educational inequalities (Hadjar and Becker, 2009; Kromydas, 2017). However, despite this significant progress, disparities in educational attainment persist across various social groups.

An important area of focus in international research has been the examination of gender as a primary determinant of educational choices, particularly in higher education. For instance, numerous researchers in the US have shown that females generally outperform males in reading test scores, grade completion, and repetition rates at school (Stoet and

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Geary, 2018). Additionally, they exhibit a higher probability of opting for academic educational programs in high school, attending tertiary education, and achieving bachelor's degrees (Legewie and DiPrete, 2012).

Despite recent advancements in female educational attainment at the secondary and tertiary levels, there has been limited success in reducing gender horizontal segregation, that is, the different orientations of males and females in terms of educational choices worldwide (Macarie and Moldovan, 2015; Cheryan et al., 2017; Barone et al., 2019; Romito et al., 2020). Research reveals indeed significant gender differences, particularly along the humanistic-scientific divide, with females being underrepresented in Science, Technology, Engineering, and Mathematics (STEM) or STEM-related fields (Cheryan, 2012; Gabay-Egozi et al., 2015; Tandrayen-Ragoobur and Gokulsing, 2021). One notable statistic, derived from OECD countries in 2020, shows females accounted for only 31% of new enrolments in STEM fields at the bachelor's level (OECD, 2022). These patterns are consistently observed across countries, highlighting the existence of structural barriers that perpetuate gender segregation at different educational levels, such as master's (see Priulla and Attanasio (2023) for the Italian case) or doctoral levels (Lörz and Mühleck, 2019).

Research aimed to identify individual and contextual factors that lead males and females to make different educational choices (Regan and DeWitt, 2014). There has been a particular focus on the lack of female role models (González-Pérez et al., 2020) and the potential discouragement of females from pursuing careers in STEM, stemming from a heavily stereotyped culture and the influence of teachers, peers, and often parents (Archer et al., 2012; Tey et al., 2020; Porcu et al., 2022). Further research has highlighted the role of previous educational choices and achievements on the choice to pursue a specific university career (Priulla et al., 2023). In particular, the concept of primary and secondary effects introduced by Boudon (1974) has been adapted to the framework of gender inequalities in education. According to the literature (Hadjar and Buchmann, 2016; Hadjar, 2019), the primary effects of gender on educational attainment encompass disparities in performance and achievement between boys/men and girls/women that arise from personal attitudes exhibited by males and females. On the other hand, the secondary effects involve the considerations made by parents, teachers, and students regarding the probability of succeeding for males and females, shaping educational outcomes, influencing decision-making processes, and setting expectations based on gender. In this work, the direction followed is closer to the themes identified by the primary effects.

Focusing on the Italian case, some insights emerge from a recent report by the Italian National Statistical Institute (ISTAT), shedding light on Italy's considerable disparity in STEM participation compared to other European countries. Specifically, STEM graduates constituted 24.7% out of the total graduate population in Italy in 2021, trailing behind figures of 26.8% in France, 27.5% in Spain, and 32.2% in Germany. Notably, the data highlights that females show significantly lower participation than men towards STEM disciplines: out of 100 women earning a tertiary degree, only 15 obtained it in a STEM field, compared to 33 of males (ISTAT, 2023).

In this respect, the international literature has extensively highlighted the importance of adopting models capable of considering the intricate structure of educational differences

(Borman and Dowling, 2010; Giambona and Porcu, 2018).

Many classical statistical models have been employed in literature to study these differences. However, in the last decade, widespread adoption of flexible and non-parametric machine learning models has revolutionized various scientific domains. These models excel in capturing intricate and non-linear relationships within data, demonstrating adaptability to diverse data distributions without relying on specific assumptions. They also can automatically manage relevant features during training, exhibit robustness to overfitting when appropriately tuned, showcase high predictive performance, and efficiently handle large datasets. In recent years, the application of machine learning methods has also extended to the realm of education, where they play a pivotal role in analyzing educational data to offer valuable insights for enhancing the learning process (Fernandes et al., 2019; Yağcı, 2022; Suzuki et al., 2022).

Our research aims to investigate the relationship between high school backgrounds and university enrolment choices in Italy. Our primary focus lies in discerning the influence of previous educational achievement on the choices made by males and females concerning university enrolment and, subsequently, the choice of a specific field of study at university. Moreover, we focus on students who excel in both mathematics and Italian tests to identify further potential differences in their future academic choices. This investigation will provide a further understanding of the factors driving academic success and contribute to the ongoing discourse on gender-related differences within educational contexts. To this aim, we use longitudinal micro-data from two Italian administrative sources, namely the Ministry of University and Research (MUR) and INVALSI. This integrated database allows to follow students from the fifth and last year of high school up to the end of their first year of university career.

The paper is structured as follows. Section 2 provides a literature review on the topic of gender differences in STEM. Section 3 illustrates the data. Section 4 contains the methods employed. Section 5 provides an exploratory analysis, and Section 6 delves into the results of the gradient boosting procedure. The paper ends with some conclusions in Section 7.

2. Literature review

This section is devoted to the review of the international literature on the gender gap in STEM, with particular reference to the Italian case.

Most of the worldwide literature on such topics generally focuses on student performance in mathematics. Research has indeed shown that, among a variety of factors, overall academic achievement and proficiency in maths are crucial predictors of the choice to enroll in a STEM program at university. In detail, the gender gap in tertiary education arises from factors that manifest before this stage and shape students' interest towards a specific field. A recent strand of international literature has highlighted how students' educational choices conform to a gender divide as early as primary school (Bian et al., 2017; Makarova et al., 2019).

From a cultural point of view, a stereotype is that females possess an inherent inclination towards educational paths emphasizing humanistic and caring disciplines. Over the years,

various theories have been explored to elucidate these differences in educational preferences. For instance, [Sherman \(1980\)](#) proposed that family dynamics, school environments, and teachers' attitudes significantly shape the attitudes of males and females towards specific subjects and skills, influencing their educational decisions. Further research has delved into the examination of implicit gender stereotypes concerning individuals' mathematical identities ([Cvencek et al., 2011](#)) and has investigated the positive correlation between STEM identity and various outcomes, including persistence and career goals ([McNally, 2020](#)). According to balanced identity theory, if a girl holds stereotypes associating math and science with male proficiency, it is anticipated that she will disassociate herself from these domains and actively avoid pursuing advanced courses and careers within them. On the other hand, [Correll \(2001\)](#) argues that gender differences in mathematics are not solely responsible for the significant imbalances between the numbers of males and females entering fields requiring advanced mathematical competence. Cultural beliefs about gender and mathematics influence the choices of males and females toward STEM careers differently. The author suggests that some individuals may come to personally believe that males are inherently better at math, even though females are less likely than males to hold stereotypical views about mathematics. As a result, if a girl believes that males excel in math, she may perceive her mathematical competence as contradictory with her female gender identity, leading to self-doubt and decreased interest in careers requiring high mathematical competence. The perception that others hold these gendered beliefs about mathematics can lead to biased self-assessments and reduced performance. In this sense, since males tend to overestimate their mathematical competence relative to females, they are also more likely to pursue activities that pave the way for STEM careers.

While these results mainly come from research conducted in the United States, they also seem adaptable to European social structures. European literature has indeed widely addressed the topic of STEM engagement, analysing the factors affecting the choice to pursue a STEM career ([Smith and Gorard, 2011](#); [Regan and DeWitt, 2014](#)). In detail, research has shown that despite performing well in mathematics and literacy, males and females attribute different importance to their prior educational achievements when it comes to choosing their academic path. The influence varies by subject, as evidenced by studies. For instance, in the UK, boys tend to be more influenced by their comparative advantage in English and maths when making STEM-related choices compared to girls ([Delaney and Devereux, 2020](#)). Moreover, in an investigation of Israeli high school course preferences, girls were found to be more responsive to prior grades in biology and chemistry, while boys exhibited stronger reactions to grades in computer science and physics ([Friedman-Sokuler and Justman, 2016](#)).

[Barone et al. \(2019\)](#) presents another perspective concerning Italy, underscoring the lack of accurate information in high schools regarding the long-term job prospects associated with specific degree programs. This absence of information on economic rewards and career opportunities prompts students to base their choices solely on their preferred subjects or "dream" occupations, often influenced by gender stereotypes. From another perspective, the rational choice theory suggests individuals tend to favor educational options that enhance their chances of success ([Barone and Assirelli, 2020](#)). This theory posits that gender differentiation results from socialization processes and rational choice factors ([Gabay-Egozi](#)

et al., 2015). According to this theory, students with a more career-oriented mindset are less likely to enrol in non-STEM programs.

In Italy, as in many other European countries, the educational careers of the students are largely influenced by the choice of a specific curriculum in high school. The Italian high school system can be seen as a hierarchical tripartite structure. The system comprises “licei”, with a focus on humanities and sciences, serving as traditional institutions preparing students for potential university enrollment; technical schools and their diverse tracks are positioned as an intermediate choice, bridging academic and vocational pathways; vocational schools aim to equip students for direct entry into the labor market, providing training for various low-ability jobs. It is important to notice that since this choice occurs at the age of 13 in Italy, it is often not an independent choice made by students but is significantly influenced by their parents (Contini et al., 2016).

Despite universalist principles, European educational systems, including the Italian one, have indeed historically been organized to segregate students based on social class and gender. This structuring has compelled families to enrol their children in distinct educational institutions, each conforming to specific social, educational, and gender-based stratification and norms (Salmieri and Giancola, 2020). The academic achievements and gender-specific subject preferences observed at a particular educational stage, especially in a highly stratified high school system like the Italian one, serve as reflections of previous achievements and preferences in earlier phases of the students’ educational journey (Salmieri, 2022). In this regard, Contini et al. (2023) analysed the effect of previous achievement in mathematics and Italian on the choice of the high school curriculum in Italy, showing that female students require stronger prior signals of mathematical ability to choose STEM fields. Then, it is not surprising that in Italy, the gender distribution across different educational paths is notably heterogeneous. Females constitute broadly 70% in the classical curriculum, slightly less than 50% in the traditional scientific curriculum, and only 32% in the applied sciences one. The latter was established in the latest reform of the high school education system in Italy in 2010, aiming to provide extensive training in studies of scientific and technological fields. The distinction from the traditional scientific high school lies in the replacement of Latin language studies with more hours devoted to mathematics and other scientific subjects. In a recent paper, Priulla et al. (2023) has emphasized that attending the applied sciences track, which means attending more scientific-related classes in high school, positively influences the probability of enrolment in STEM.

3. Data

The dataset used for the analysis is built by linking two distinct administrative national sources:

- **INV-S**: micro-data sourced from the Italian National Institute for the Evaluation of the Education and Training System (INVALSI). INVALSI, operating as a research institution with legal status, conducts nationwide standardized computer-based tests to assess the overall quality of the Italian education system across different types of

schools. These tests are administered annually to students at five educational levels (grades 2, 5, 8, 10, and 13) to evaluate their proficiency in mathematics, Italian language skills, and, since 2018, English reading and listening skills. In this paper, we consider the maths and Italian language tests administered at grade 13. In addition to the test scores, INVALSI also collects information about socio-demographic status, family background, and further indicators of previous academic performance.

- **ANS-U:** micro-level longitudinal data from the Italian National Archive of University Students (ANS) ([MOBYSU.IT](https://mobysu.it), 2017). This comprehensive database contains detailed information about the university pathways of all students enrolled in Italian universities between 2010 and 2020. The database provides a comprehensive record encompassing their high school background and subsequent university career.

The linkage of these databases allows investigation of i) the transition from high school to university at the individual level and ii) the relationship between student performance in high school and university outcomes. We have access to data about all the students enrolled on the last year of high school in Italy in 2018/19, and we have information about those enrolled at university in the subsequent academic year, i.e. 2019/20. However, we are unable to differentiate between students who did not enrol in university and those who chose to enrol at university abroad.

In this paper, we focus on the subset of students attending humanistic and scientific curricula in high school. As for the latter, a further specification is adopted to distinguish the traditional scientific and the applied science tracks within the scientific curriculum. We decided to consider this specification following the results of [Priulla et al. \(2023\)](#) that highlighted differences in terms of academic outcomes of the students attending the two scientific tracks in Italy. We consider the following set of covariates in our analysis:

- **HS macroregion:** the macroregional location of the high school attended by the student
 - South & Islands (Abruzzo, Basilicata, Calabria, Campania, Molise, Apulia, Sardinia, Sicily)
 - Center (Latium, Marche, Tuscany, Umbria)
 - North (Emilia Romagna, Friuli Venezia Giulia, Liguria, Lombardy, Piedmont, Trentino Alto Adige, Veneto)
- **HS SES:** The overall socio-economic status of the school¹
- **Public/Private:** a variable indicating whether the student attended a public or private high school.

¹The OECD PISA surveys and INVALSI tests use the ESCS index (Index of Economic, Social, and Cultural Status) that synthetically defines the socio-economic and cultural status of the students' families. A negative (positive) value of the index indicates a lower (higher) SES than the Italian average.

- **Gender**
- **HS curriculum**: the type of high school curriculum attended by the student. We consider two curricula: the humanistic and the scientific curriculum, divided into traditional and applied sciences tracks.
- **INVALSI math score**: the scores² in the INVALSI math test at grade 13.
- **INVALSI Italian score**: the scores in the INVALSI Italian test at grade 13.

4. Methods

This section introduces Gradient Boosting (GBM) (Friedman et al., 2000; Friedman, 2001, 2002), a machine learning (ML) model employed to predict a response variable based on a set of covariates. In general, ML techniques provide a powerful framework for the analysis of high-dimensional datasets by modelling complex relationships, often encountered in modern data with many variables, cases, and potentially nonlinear effects. The impact of ML methods is still limited in the field of educational sciences but continuously growing as larger and more complex datasets become available (Hilbert et al., 2021).

GBM is an ensemble ML model that sequentially combines the predictions of multiple weak learners, which are typically decision trees. The goal is to find some function $\hat{F}(\mathbf{x})$ that best approximates the output variable y from the values of input variables $\mathbf{x}$. This is formalized by introducing a loss function $L(y, \hat{F}(\mathbf{x}))$ and minimizing its expectation:

$$\hat{F} = \arg \min_F \mathbb{E}_{\mathbf{x}, y} [L(y, F(\mathbf{x}))].$$

The GBM works seeking an approximation $\hat{F}(x)$ in the form of a weighted sum of B functions $h_m(x)$ from some weak learners:

$$\hat{F}(x) = \sum_{b=1}^B \alpha_b h_b(x),$$

where b is the iteration index. The process begins with a simple model, often a weak learner like a shallow decision tree, making predictions on the training data, $F_0(x)$. At each iteration, it fits a weak learner to the negative gradient of the loss function for the current model's predictions:

$$F_b(x) = F_{b-1}(x) + \left(\arg \min_{h_b} \left[\sum_{i=1}^n L(y_i, F_{b-1}(x_i) + h_b(x_i)) \right] \right) (x)$$

where n is the number of observations in the dataset, and L is a differentiable convex loss function that measures the difference between the true values y_j and the predicted values

²INVALSI, similarly to PISA tests, reports all the scores using the Rasch metric, setting the average for Italy at 200 and the standard deviation at 40.

$F_{b-1}(x) + h_b(x_i)$.

Given the computational challenges in selecting the optimal function h_b for an arbitrary loss function L , the steepest descent is employed via functional gradient descent. Iteratively updating the model $F_{b-1}(x)$ toward a local loss function minimum, the adjustment is made by a small distance α to maintain a valid linear approximation:

$$F_b(x) = F_{b-1}(x) - \alpha \sum_{i=1}^n \nabla_{F_{b-1}} L(y_i, F_{b-1}(x_i)).$$

This iterative process refines predictions based on ensemble errors, ensuring $L(y_i, F_b(x_i)) \leq L(y_i, F_{b-1}(x_i))$.

The GBM has proven to be robust to overfitting through techniques like shrinkage and the use of shallow trees and flexible to handle different types of data, capturing complex relationships and non-linear patterns. Popular implementations of GBM include the Gradient Boosting Machine (GBM), XGBoost, LightGBM, and CatBoost, each offering optimizations and enhancements to the original GB algorithm. The `gbm` package in R of the algorithm ([Ridgeway, 2007](#)) was chosen for its popularity and reliability.

4.1. Interpretability methods

The discussion now delves into various tools designed to interpret the model predictions effectively. It is essential to note that beyond their predictive capacity, these models serve a dual purpose in interpretation. These tools are instrumental in identifying the most influential factors and elucidating their impact on the response variable. Through this interpretative lens, the models contribute valuable insights into the determinants that significantly shape students' enrollment choices.

Understanding the inner workings of a ML model and interpreting its predictions are critical aspects of model deployment and decision-making ([Molnar, 2020](#)). In this section, we delve into three essential model interpretability tools: namely, the relative influence of predictors, the Accumulated Local Effects (ALE) and Multi-dimensional Partial Dependence Plots (PDP). These techniques offer valuable insights into the importance and impact of individual covariates on a model's predictions, aiding in the interpretation and selection of relevant variables.

The relative influence of a covariate in a GBM model is a measure indicating the relative importance of each variable in training the model. The relative influence of a covariate is calculated by taking each covariate's contribution for each tree in the model and calculating the relative contribution of the corresponding covariate to the model. Specifically, it is a reduction attributable to each variable in reducing the loss function in predicting the gradient on each iteration. The relative influence of a covariate is usually normalized so that the sum of the relative influences of all covariates is equal to one. The relative influence of a covariate can be used to rank the individual variables based on their importance in the model. The ranking can be used for covariate selection, where the most important covariates are selected for the final model. However, it is important to note that the relative influence of a covariate does not provide any explanations about how the variable actually affects the response, for this aim other methods need to be used.

Among others, the PDP (Friedman, 2001) stands as the most famous visualization tool to investigate how one or more covariates collectively shape the predictions of a ML model. PDP operates by marginalizing the model’s predictions over the distribution of the covariates in set X_C , the variables in which we hold no specific interest. This allows the function to reveal the relationship between the covariates in set x_S , the variables of interest, and the predicted outcome. The partial function $\hat{F}_S$ is obtained by computing average pointwise predictions for a grid of x_S values, within the training data:

$$\hat{F}_S(x_S) = \frac{1}{n} \sum_{i=1}^n \hat{F}(x_S, x_{i,C}).$$

This partial function yields insights into the average marginal effect on predictions for a grid of values of covariates x_S , while $x_{i,C}$ are the actual covariate values in the training set.

Unfortunately, the correlation between covariates in x_C and x_S introduces complexity, potentially leading to heavy interpolation, i.e. including data points that are highly improbable to observe. This correlation challenges the accurate reflection of the isolated impact of covariates in x_S due to their interdependence with covariates in x_C , as pointed out in the literature (Apley and Zhu, 2020). For this reason, the use of one-dimensional PDP plots is generally discouraged.

When more than one covariate is included in x_S , multi-dimensional PDP plots are obtained. Multiple PDPs can overcome one-dimensional PDP limitations by visualizing the joint effects of multiple covariates on the predicted outcome. This provides a comprehensive understanding of covariate interactions and their influence on the model’s predictions. Furthermore, to enhance the reliability of interpretations and mitigate the risk of extrapolation, the estimated response can be confined within the convex hull defined by the training values of relevant variables, to avoid interpreting the PDP outside the observed data boundaries. This approach ensures robust insights grounded in the empirical distribution of the training dataset, contributing to a more accurate understanding of relationships between variables and predicted responses. While Multiple PDPs can effectively address the challenge of visualizing the collective effect of multiple predictors on the response, limitations arise with continuous predictors, allowing visualization for only two variables at a time.

Additionally, the emphasis often lies in isolating and emphasizing the individual influence of each predictor. In these scenarios, ALE (Apley and Zhu, 2020) emerges as a valuable tool. ALE plots provide a faster and unbiased alternative to one-dimensional PDP and can be utilized to interpret the effects of individual covariates on a model’s predictions. For a single numerical covariate, the ALE value can be interpreted as the main effect of the covariate at a certain value compared to the average prediction of the data.

To estimate local effects, we divide the covariate X_j into k intervals driven by percentiles and compute the differences in the predictions. More specifically, for each $j \in \{1, 2, \dots, d\}$, let $N_j(k) = (z_{k-1,j}, z_{k,j}] : k = 1, 2, \dots, K$ be a partition of the sample range of $\{x_{i,j} : i = 1, 2, \dots, n\}$ into K intervals. Here we denote $z_{k,j}$ as the k -th quantile of the empirical distribution of $\{x_{i,j} : i = 1, 2, \dots, n\}$ with $z_{0,j}$ chosen just below the smallest observation, and $z_{K,j}$ chosen as the largest one.

For $k = 1, 2, \dots, K$, let $n_j(k)$ denote the number of observations that fall into the k -th interval $N_j(k)$, so that $\sum_{k=1}^K n_j(k) = n$. For a particular value x of the explanatory variable X_j , let $k_j(x)$ denote the index of the interval into which x falls, i.e., $x \in (z_{k_j(x)-1,j}, z_{k_j(x),j}]$.

To estimate the main ALE ($F_{j,ALE}(\cdot)$) of a predictor (X_j), we first compute an estimate of the uncentered effect $g_{j,ALE}(\cdot)$:

$$\hat{g}_{j,ALE}(x) = \frac{1}{n_j(x)} \sum_{k=1}^{n_j(x)} \sum_{i: x_{i,j} \in N_j(k)} [F(z_{k,j}, x_{i,\setminus j}) - F(z_{k-1,j}, x_{i,\setminus j})],$$

for each $x \in (z_{0,j}, z_{K,j}]$. In the preceding, $x_{i,\setminus j} = (x_{i,j} : j = 1, 2, \dots, d; j \notin J)$ denote the i -th observation of the subsets of predictors $X_{\setminus j}$. The uncentered effect of a covariate value that lies in a certain interval is the sum of the effects of all the previous intervals. This average in the interval is covered by the term Local in the name ALE. The left sum symbol means that we accumulate the average effects across all intervals. The (uncentered) ALE of a covariate value that lies, for example, in the third interval, is the sum of the effects of the first, second and third intervals. The word ‘‘accumulated’’ in ALE reflects this. The ALE main effect estimator $\hat{F}_{j,ALE}(\cdot)$ is then obtained by centering $\hat{g}_{j,ALE}(x)$ that the mean effect is zero.

$$\hat{F}_{j,ALE}(x) = \hat{g}_{j,ALE}(x) - \frac{1}{n} \sum_{i=1}^n \hat{g}_{j,ALE}(x_{i,j}).$$

One-dimensional ALE plots are not defeated in the presence of correlated predictors, unlike marginal plots (Grömping, 2020). The reason is that they analyze differences in predictions accumulating the average effects over a predictor’s range instead of the average of the predictions themselves. This cumulative approach helps mitigate issues arising from predictor correlation, providing a more stable and accurate representation of a predictor’s impact on the model’s predictions.

5. Exploratory analysis

In this section, we present an exploratory analysis of university enrolment choices made by female and male students, exploring the association between factors related to students’ previous educational attainment and their university careers.

In Table 1, we describe students enrolled on the fifth year of high school in Italy in 2018/19, giving a broad overview of how university enrolment choices of males and females differ according to the socio-demographic characteristics of the students and their high school careers. To aid interpretation, INVALSI test scores have been reported in Table 1 following the proficiency levels directly supplied by INVALSI, which range from 1 to 5. Students with a proficiency level below 3 are classified as low-performing, while those with a proficiency level of 5 are considered high-performing. Furthermore, the school SES has been classified using the quartiles of its distribution, with the 1st quartile representing low SES and the 4th quartile representing high SES. Throughout the remainder of the paper, these variables will be treated as continuous.

As anticipated, female students, on average, are more likely than males to enrol in university but less inclined to choose STEM programs. Further results reveal significant gender differences in enrolment choices. The well-known gap between the northern and southern Italian regions reemerges in students' enrolment choices. Specifically, the percentage of non-enrolled students increases from North to South, with a slightly wider gap observed among males. Interestingly, students from the North, especially males, show a higher inclination towards choosing STEM degree programs than their counterparts from the South. The overall socio-economic status of the school proves to be associated with university enrolment. Specifically, students coming from schools with an overall higher SES are more likely to enrol in non-STEM programs. This is particularly evident among male students, as female ones are generally more likely to opt for non-STEM programs. Regarding the type of high school attended, students from public schools are more likely to enrol in university, displaying a greater preference for STEM degree programs compared to their peers from private schools. As for the high school curriculum, the results show that students with humanistic backgrounds show minor differences in their choices, with a similar percentage of both males and females preferring non-STEM programs. On the other hand, females attending both scientific curricula are significantly less likely to enrol in STEM programs than their male counterparts. Finally, it is possible to observe that, as the INVALSI math and Italian scores increase, the percentage of students not enrolling at university decreases. In particular, a bad performance in maths tests appears to be more associated with males' choice not to enrol at university. Conversely, high performance in mathematics and Italian are associated with a higher probability of enrollment in STEM and non-STEM programs, respectively. This pattern appears to vary based on gender: high mathematics proficiency has a more pronounced impact on males' choice to enrol in STEM programs, while a higher score in Italian appears to be more associated with females' decision to pursue non-STEM programs. However, it's crucial to acknowledge that these associations are marginal and do not account for the joint influence of all variables.

The last results obtained in Table 1 regarding the effect of high school career on enrolment choices were reasonably expected. Nevertheless, it is necessary to consider an intersectional approach to have a deeper understanding of the gender differences characterizing the transition from high school to university.

In Figures 1 and 2, we show, respectively, the distribution of maths and Italian scores according to gender, the high school curriculum attended, and the enrolment choice. Regarding maths scores (Figure 1), students from scientific high schools generally exhibit better performance. This can be easily explained since humanistic high schools allocate fewer hours to science-related subjects. Moreover, the distribution of scores differs based on enrolment choices: students who opt for STEM programs consistently achieve higher scores in mathematics tests compared to others, but the gap appears to be more pronounced in scientific high schools, suggesting greater confidence in their mathematical abilities among those choosing to pursue STEM degrees. Additionally, it is observable that the gap between males and females is more evident in scientific high schools. In contrast to what is observed in humanistic high schools, male students demonstrate higher performance, even among those who opt not to pursue university enrollment.

Table 1: Student characteristics according to gender and enrolment choice. Cohort of students enrolled on the fifth year of high school in Italy in 2018/19.

Variable	Category	F				M			
		Not enr.	Non-STEM	STEM	Total	Not enr.	Non-STEM	STEM	Total
HS macroregion	North	13,7	46,9	39,4	25286	14,3	34,1	51,5	26559
	Center	14,4	47,8	37,8	14193	18,7	35,9	45,5	15570
	South & Islands	16,3	48,9	34,8	30979	19,5	35,8	44,7	29061
HS SES	Low	19,9	43,4	36,7	11390	22,9	29,6	47,5	12030
	Medium	14,5	46,7	38,8	42695	16,8	33,7	49,5	43537
	High	12,8	54,6	32,5	16373	14,6	43,7	41,7	15623
HS type	Private	26,7	47,7	25,7	4331	30,2	37,4	32,4	6268
	Public	14,2	48,0	37,8	66127	16,1	35,0	48,9	64922
HS curriculum	Humanistic	12,5	63,5	24,0	19904	15,3	61,6	23,0	9033
	Trad. scientific	15,5	44,0	40,5	40922	17,0	34,2	48,8	42032
	Applied sciences	17,9	33,0	49,0	9632	18,9	25,5	55,6	20125
INVALSI Math score	Low	27,3	51,3	21,4	13554	36,3	39,6	24,0	9307
	Medium	15,2	50,4	34,4	30564	21,3	39,6	39,1	25467
	High	8,4	43,5	48,1	26340	9,8	31,0	59,2	36416
INVALSI Italian score	Low	31,9	40,6	27,5	8497	35,1	30,5	34,3	10553
	Medium	14,4	47,6	37,9	43378	16,8	35,1	48,1	42649
	High	8,5	52,2	39,3	18583	8,2	38,2	53,6	17988
Total		15,0	48,0	37,0	70458	17,4	35,2	47,4	71190

Regarding the Italian scores (Figure 2), as expected, students attending the humanistic curriculum perform better than their scientific peers. Nevertheless, differently from what we observed for the maths scores, it seems the Italian scores are still associated with the choice to enrol at university, but not with the choice of the degree program. In fact, students who did not enrol at university show a worse performance in Italian, especially those attending scientific curricula. Moreover, the gap favouring females is slightly more evident among not-enrolled students from humanistic backgrounds.

Finally, we show in Figure 3 the bivariate joint distributions of maths and Italian test scores, categorized by gender and high school type. Each panel shows a contour plot, where the shapes resemble ellipses following the main bisector. This suggests a positive correlation between math and Italian test scores for both female and male students in each curriculum. In other words, students who perform well in one subject tend to perform well in the other. Additionally, the plot reveals differences in the densities among the students' profiles. In particular, students from the humanistic curriculum exhibit higher densities, especially females. This implies that the majority of students with this background tend to obtain average scores in both math and Italian tests.

6. Results

This section presents the key findings derived from our analysis based on GBM. We build two GBM models utilizing the same set of predictors listed in Section 3. In the first model (named Model 1), we predict the probability of enrollment at an Italian university. Therefore, the reference population for this model comprises all fifth-year high school students

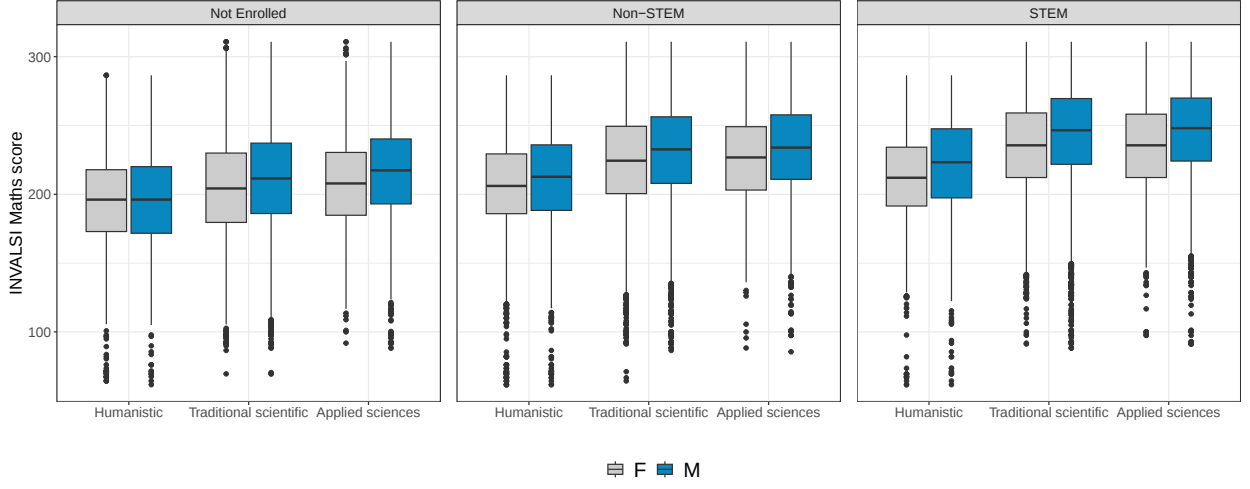


Figure 1: Distributions of maths scores according to gender, the high school curriculum, and enrolment choice.

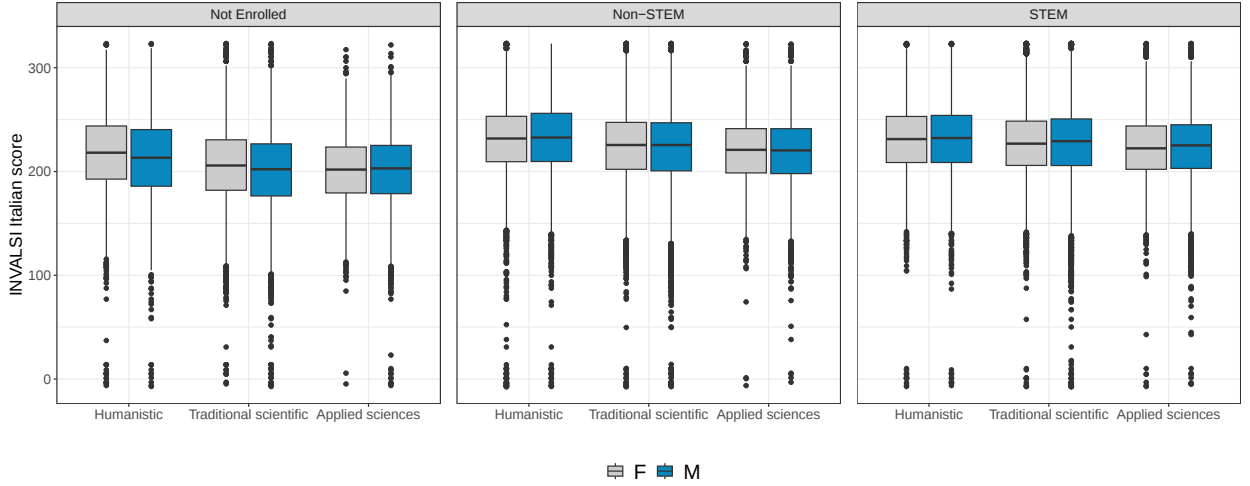


Figure 2: Distributions of Italian scores according to gender, the high school curriculum, and enrolment choice.

in 2018/19. Subsequently, in the second model (Model 2), we shift our focus to predicting enrollment in a STEM program. This model is built on the subset of students who enrolled at an Italian university in 2019/20 as the reference population. It is important to note that students with an INVALSI math or Italian score of 0 were excluded from the analysis (representing the 0.26% of the total) henceforth. This exclusion is twofold: firstly, based on the assumption that such scores may represent transcription errors; secondly, through sensitivity analysis during the training phase, we observed that including these scores degrades the model's performance.

In both model constructions, the dataset is partitioned into training and test sets, with 75% of observations allocated to training. The model undergoes hyperparameter tuning on the

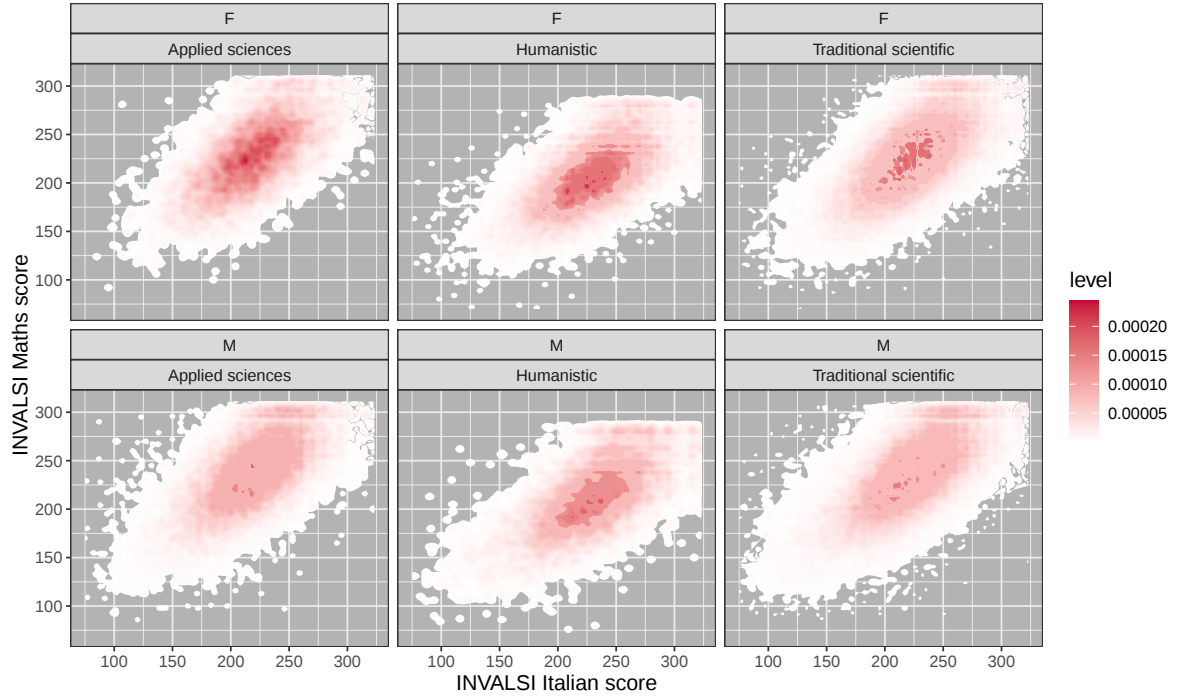


Figure 3: Bivariate distribution of maths and Italian test scores according to gender and high school curriculum.

training set through a 10-fold cross-validation procedure. After the final model selection, a thorough evaluation is conducted on the test set, computing the ROC curve and corresponding AUC to assess the model performance comprehensively. Figure 4 provides a visual representation of the ROC curves for the two distinct models on the test sets. Both models

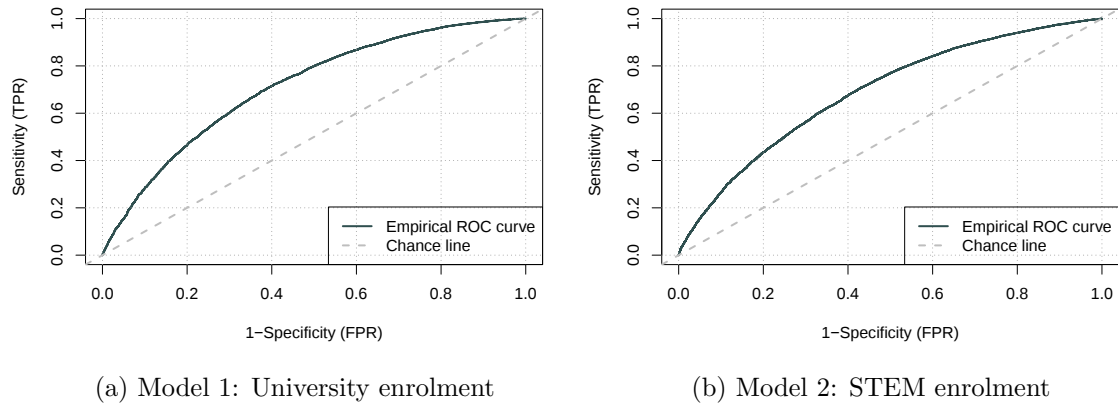


Figure 4: ROC curves.

present well-balanced ROC curves, demonstrating an effective trade-off between sensitivity

and specificity. They maintain high sensitivity with a relatively low false-positive rate, underscoring a balanced classification performance. Model 1 demonstrates robust performance with an AUC of 0.71, while Model 2 exhibits only a slightly less discriminatory capacity, with an AUC of 0.69.

We now turn to assessing the influence of predictors in the two models. Firstly, we examine the relative importance of predictors in Figure 5. In the first model, the most influential

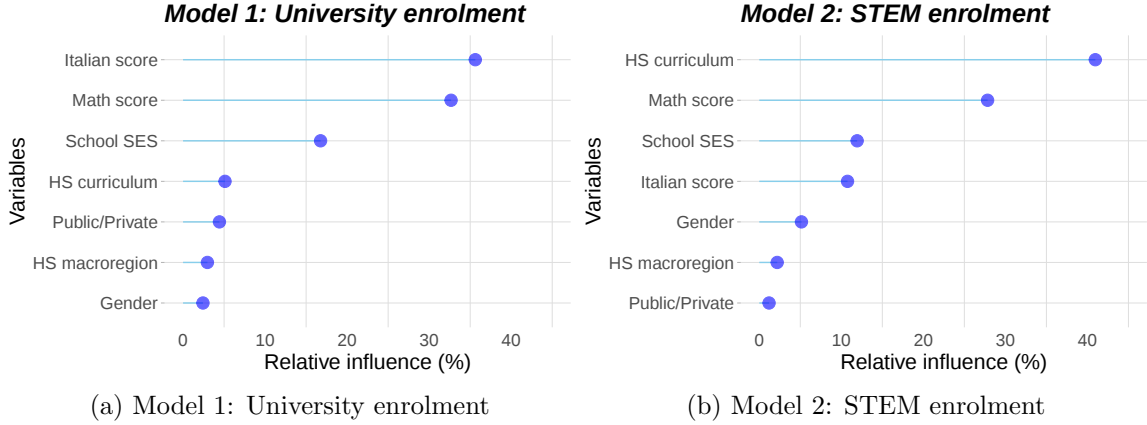


Figure 5: Relative influence of predictors.

variable for predicting university enrolment is the Italian score, accounting for 35.6% of the relative importance (Figure 5a). The math score follows closely at 32.7%, indicating the significance of high school performance on the university enrolment choice. School SES contributes substantially with 16.8%, while other factors such as HS curriculum, public/private high school attendance, macroregion, and sex play less significant roles. It is important to underline that the low relative importance accounted for by the HS curriculum in Model 1 was expected since we considered only those curricula that are more academic-oriented.

In contrast, Figure 5b reveals a different pattern of the variables' importance on STEM enrolment. HS curriculum accounts for 41.0% of the relative importance, highlighting its critical role in predicting STEM enrolment. Math score remains important but takes a secondary position with 27.8%. School SES, Italian score, and gender follow, contributing to a lesser extent. HS macroregion and Public/Private school attendance exhibit minimal impact in this context, emphasizing the specialized importance of the HS curriculum for STEM outcomes.

In Figure 6, the ALE (Accumulated Local Effects) of the three continuous explanatory variables in the two models are shown, offering some insights into the nonlinear relationships between probabilities associated with each enrolment choice and the predictors.

In line with the observations from Figure 5, emphasizing the relative importance of variables, it's worth noting that variables with higher importance tend to display more varied patterns in their ALE plots. This underscores the idea that variables of greater influence in the model's predictions often manifest more diverse patterns.

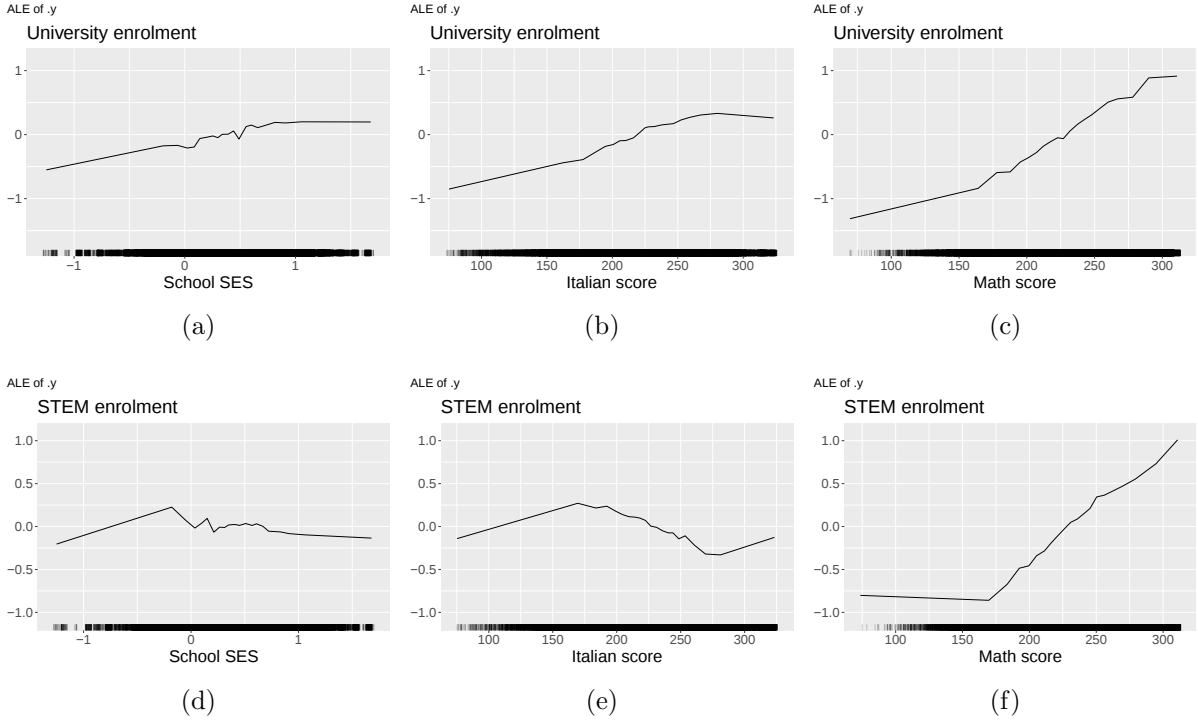


Figure 6: One-dimensional ALE plots of continuous predictors.

Beginning with the analysis of the socio-economic status of the school attended by the students (Figure 6a), the graph illustrates a general upward trend, indicating a moderate positive influence on university enrolment in Model 1. This upward trajectory stabilizes after reaching a value of 1. In Model 2, Figure 6d, the influence of the overall socio-economic status of the school initially rises, dipping slightly below 0, followed by a decreasing trend, ultimately stabilizing for values exceeding 1. While in both models, the observed variations are not drastic, they still serve as indicative cues, suggesting that the influence of a very high socio-economic status on university enrolment becomes more nuanced beyond a certain point. Focusing on STEM enrolment, the result indicates that an overall higher school SES negatively influences students' decisions to pursue a STEM career at university. This could be related to the hierarchical structure of the Italian high school system, where students from upper classes are more inclined to attend the humanistic curriculum (Panichella and Triventi, 2014).

Shifting the focus to the Italian score, the analysis reveals a highly nonlinear effect on the responses. In Model 1, Figure 6b, the influence of the Italian score increases up to a score equal to 250, after which it stabilizes. As regards STEM enrolment (Figure 6e), there is an initial ascending trend up to a score of 175, succeeded by a descending phase up to 275, and then a subsequent ascending trend. Beyond a critical threshold (175), proficiency in Italian appears to lead to a reduction in STEM enrolments. However, for top performers in Italian, there is once again an ascending trend, indicating that an increase in the score

results in more STEM enrolments.

Finally, examining the math score, the ALE analysis unveils an overall positive effect on both the probability of enrolling in any course (Figure 6c) and the probability of enrolling in a STEM course (Figure 6f). Particularly notable is the non-linear nature of these increments, especially in Model 2. The ALE exhibits a slightly negative trend between 70 to 170 before undergoing a noticeable sharp increase. It is essential to note that while there is a negative trend during this range, its impact is somewhat negligible, given its almost flat nature. Moreover, particular caution is warranted in the range of 70-100, as the data indicates a scarcity of students in this segment. Consequently, ALE values calculated in this region should be interpreted with due consideration, recognizing the limited sample size and the potential for increased variability in the estimates.

In the following, we shift from ALE to estimated probabilities. This shift aligns with the study’s objectives, wherein our primary aim is to investigate the variations in probabilities concerning the two specified academic outcomes. To achieve this, we compute multi-dimensional Partial Dependence Plots (PDP), focusing on the interplay of high school curriculum, gender, and performance in the INVALSI Italian and math tests. This method provides a comprehensive understanding of how changes in these variables collectively influence the estimated probabilities of our target outcomes.

Figures 7 and 8 illustrate the estimated probabilities of university and STEM enrolment, respectively. On the x-axis, we report the Italian score, and on the y-axis, the math scores are shown. The three top panels show the estimated probabilities for female students, while the bottom ones show those for males, both conditional on HS curricula. In each panel, the bisector indicates students who achieve the same score on both tests. We will refer to “top-achieving” students as those achieving high scores in both tests, namely those placed on the top-right corner of the panels. Conversely, the low-achieving students are found in the bottom-left region of the plots. As previously said, our analysis primarily focuses on those curricula that train students for a university pathway, more than other HS curricula in Italy. Consequently, the overall probability of university enrolment is notably high (Figure 7). Furthermore, the probability of enrolment increases as scores in both math and Italian tests increase. Although the estimated probabilities are similar for high-achieving students, some distinctions emerge across the different curricula. Notably, low-achieving students attending the applied sciences curriculum exhibit a lower probability of university enrolment (between 0.1 and 0.3) compared to their low-achieving peers from the other curricula. Specifically, the estimated probabilities for lower-achieving students coming from traditional scientific curriculum range between 0.3 and 0.5, while those with a humanistic background exhibit higher probabilities, ranging between 0.3 and 0.7.

Regarding gender differences, male students exhibit a slightly lower propensity to enrol in university compared to their female counterparts. Specifically, poor performance in Italian tests appears to be more effective on the enrollment decisions of male students than on those of female students. The observed scenario radically changes when it comes to the choice to enrol in a STEM program (Figure 8), where gender and HS curricula exert more influence. Notably, applied sciences students display a higher inclination to enrol in STEM programs. It is also noticeable that the difference between males and females in applied

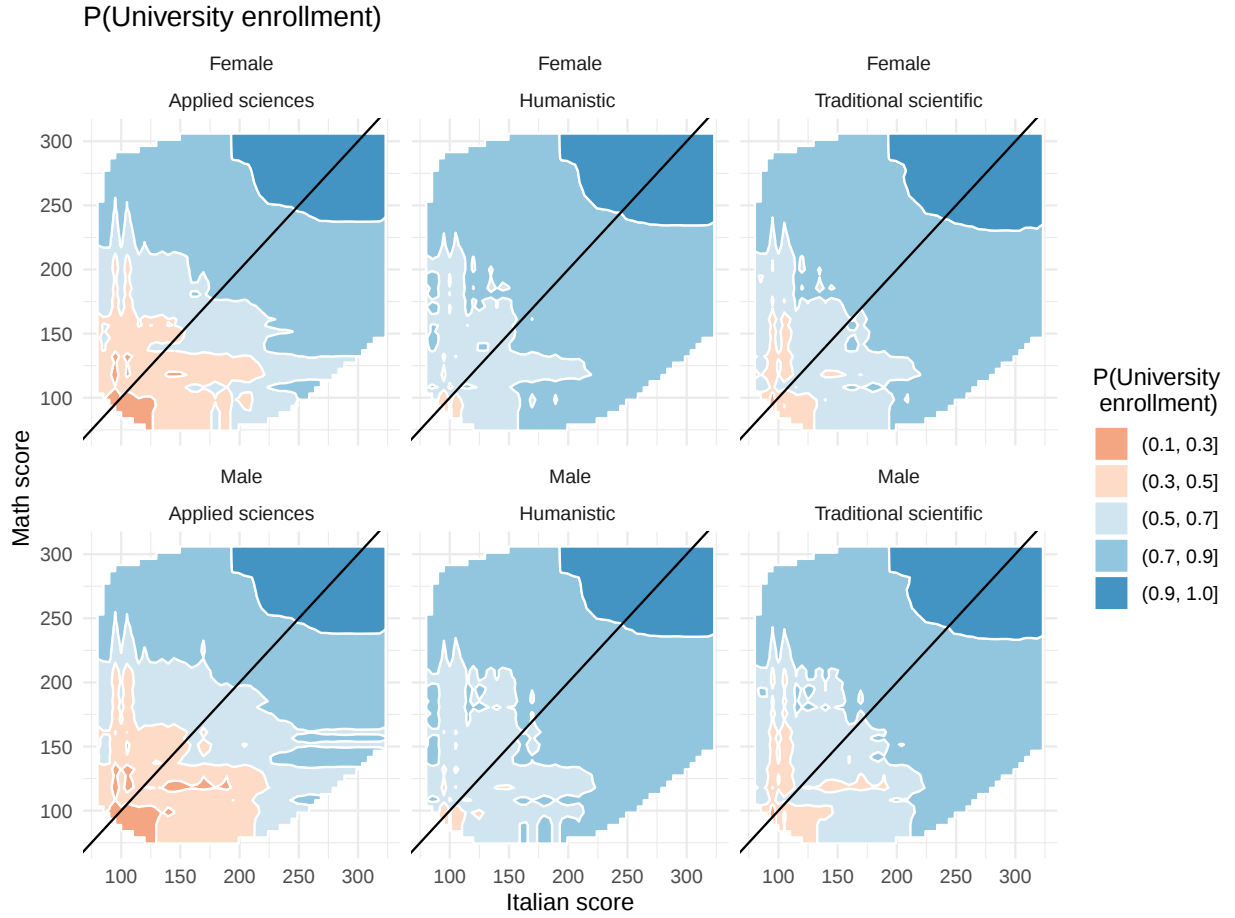


Figure 7: Multidimensional PDP Plot: Probability of enrolling at university based on Italian and math scores, gender and HS curriculum.

sciences increases as math scores increase. Specifically, male students with a robust math proficiency, scoring above 230, exhibit the highest probability of enrolling in STEM, ranging between 0.7 and 0.9, surpassing their counterparts in other curricula. While female students in applied sciences show a lower probability of enrolling in STEM compared to their male peers, their probability remains notably higher than peers from the humanities and similar to traditional scientific curricula. On the other hand, students with a humanities background consistently show lower probabilities of STEM enrollment. Across both panels, the estimated STEM probabilities range between 0.1 and 0.7, with individuals with low math scores falling within the 0.1 to 0.3 probability range. Again, males are more likely to enroll in STEM than females, especially when they exhibit high math scores alongside low Italian scores, reaching a probability range of 0.5 to 0.7. This suggests that, even within the humanities curriculum, a subset of male students with strong quantitative skills demonstrates a noteworthy interest in STEM fields when they perform well in mathematics tests and badly in Italian ones. Finally, estimated STEM probabilities for scientific curriculum students fall in between those estimated for the other two groups of students, with males exhibiting a slightly higher

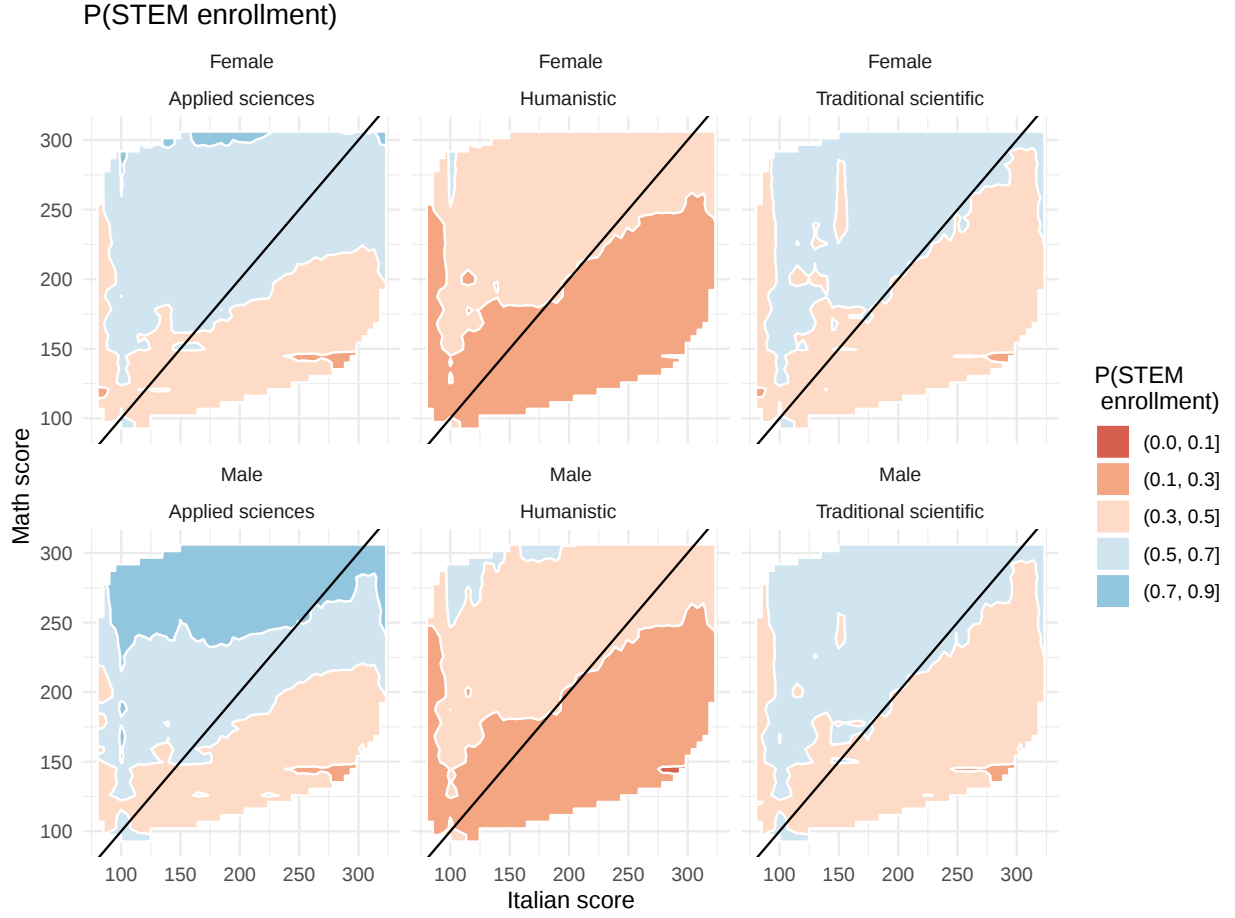


Figure 8: Multidimensional PDP Plot: Probability of enrolling in STEM programs based on Italian and math scores, gender and HS curriculum.

propensity to enrol in STEM.

7. Conclusions

This paper has undertaken a comprehensive exploration of the complex relationships between Italian high school students' proficiency in mathematics and in the Italian language, their gender, and their subsequent enrolment choices. The findings reveal compelling insights into the dynamics that shape students' educational choices and contribute to the broader discourse on gender disparities in higher education.

The statistical analysis, conducted using interpretable machine learning methods, specifically gradient boosting, underscores the significant influence of proficiency in both Italian and mathematics on university enrolment decisions. The differentiated impact of these factors on enrolment choices highlights the nuanced nature of students' decision-making processes. Importantly, the study reveals gender differences in enrollment patterns, with male students excelling in both subjects, especially in mathematics, showing a greater in-

clination toward STEM programs compared to their female counterparts. Additionally, the examination of high school backgrounds provides further valuable context, emphasizing the distinctive preferences of male and female students from applied scientific, traditional scientific, and humanistic backgrounds.

This intersectional approach contributes to a more comprehensive understanding of the interplay between academic performance, gender, and high school background in shaping students' choices. In summary, it becomes evident that students with high math scores are the ones predominantly associated with higher probabilities of enrolling in STEM programs. This trend is particularly pronounced when coupled with low or moderate Italian language scores, and it is more prominent among male students with a scientific background.

Nevertheless, in the intricate landscape of educational choices, these identified variables yet represent only a fraction of the myriad factors that contribute to students' decisions regarding university enrollment and choice of academic programs. The interaction between these variables may be nuanced and subject to contextual variations not captured in this analysis. Factors like individual aspirations, career guidance, and the socio-cultural landscape can also play pivotal roles, contributing to the intricate mosaic of university enrollment dynamics. In this framework, this paper also underlines the need for statistical methods that account for the intersectionality of educational data. Intersectionality should be a necessary aspect for scholars to include the diverse interconnections of various dimensions of factors such as socio-economic status, gender, and academic ability, among others.

The paper contributes not only to the academic understanding of educational choices but also holds implications for educational policy. The identified gender disparities and the role of academic proficiency emphasize the need for targeted interventions at the school level. Moreover, the insights into high school backgrounds shed light on the importance of tailoring educational pathways to individual strengths and interests.

Finally, the study has some limitations. In detail, the non-enrolment probability could be slightly overestimated since available data do not provide information about students enrolling at a university abroad.

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