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Analysis of the Interest of Peruvian Schoolchildren in STEM Studies Based on Machine Learning

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In recent years, students and graduates in Science, Technology, Engineering and Mathematics (STEM) professions are the profiles most in demand by organizations, as they are compatible with the technological evolution occurring in society. However, despite governmental efforts to promote and generate STEM educational approaches to traditional education in various spaces and institutions, there is little interest on the part of young students and school leavers in directing their higher education towards the STEM area. This paper identifies the current study trends of school students, the causes of the low interest in STEM studies and develops a data analysis of the complex relationships between them to understand this process. The use of Machine Learning tools is proposed mainly to find patterns and the generation of an adequate prediction. It also proposes the use of samples of school students and supervised Machine Learning to develop the model of interest in STEM studies, and to predict this interest with high accuracy.

Keywords: STEM education, High School Students, Machine Learning, STEM interest, STEM carrer.

1. Introduction

The increasing importance of Science, Technology, Engineering, and Mathematics (STEM) education in shaping future economies and driving innovation has been widely recognized globally [1]. Despite this, numerous countries, including Peru, face challenges in fostering interest and participation in STEM fields among school-aged children, to which is added the gender gap in STEM careers [2-4]. Understanding the factors that influence students' engagement and interest in STEM is crucial for developing effective educational strategies and policies.

Globally, several exploratory studies have been conducted to investigate students‘ perceptions of STEM [5-6] and the factors that influence students’ interest both in pursuing STEM studies as eventual careers. Mostly of them using statistical analysis [7-11] and others recently considering Machine Learning (ML) as a powerful tool for analysing complex datasets and uncovering patterns that are not immediately apparent through traditional statistical methods. By leveraging ML techniques, researchers can gain deeper insights into the multifaceted aspects of educational engagement and performance [12].

Several studies have been conducted on interest and expectation in STEM based on students' gender, and the influence of parental and teacher support, as well as self-confidence and belief in one's own ability and value. In this sense, [13] studies the relationship between social support and STEM career expectations considering gender. As a result, a greater positive influence of parental support and STEM self-efficacy is found in male students. Similarly, in [14] the influence of educational, informal, social and media environment on gender STEM interest is studied. This results in marked differences between the two genders, with boys having a greater influence and interest in STEM.

On an exploratory basis, a quantitative assessment of a sample of 150 high school students has been developed in [15], which shows that according to parental education and gender of students there is an inequality in interest in STEM. In addition, student participation in STEM programmes outside school can help to promote student interest in STEM. In that sense, the relationship between student stimulation towards STEM fields and their participation in external STEM programmes is studied in [16]. The results show an increased interest and attitude in STEM careers of participating students, regardless of gender, race, socio-economic status, and socio-economic status.

An analysis of the environment and the influence of STEM domain course exams on student anxiety and attitude towards STEM is conducted in [17]. It results in a moderate to severe level of anxiety in more than 70% of students, which added to the learning environment (personal study space, access to technology) contributes to improved attitude, confidence and efficacy in the STEM domain.

It should be noted that in order to motivate and support student learning, various educational methodologies are being implemented in the teaching-learning process such as: flipped classroom, visual thinking, cooperative learning, gamification, competence-based learning, project-based learning, problem-based learning, among others. These learning plans are complemented in an interdisciplinary way by technological approaches such as Augmented Reality (AR) [18-19] and generative AI [20-22]; and pedagogical approaches such as STEM education [23-25]. Particularly the STEM education approach establishes student immersion in active learning experiences in diverse areas for the development of STEM competencies, which allow for the enhancement of students' positive perception of mathematics and science and their interest in STEM careers [26-27].

Peru presents a unique context for such a study due to its diverse cultural, socio-economic, and educational landscape. The country has made significant strides in improving its education system, yet disparities remain, particularly in rural versus urban areas and among different socio-economic groups. Understanding the factors that influence students' interest in STEM careers can provide valuable information to policy makers, educators and stakeholders.

The main objective of this work is to analyse the current level of Peruvian schoolchildren's interest in STEM studies using machine learning algorithms, identifying and interpreting the factors that significantly influence this interest. To this end, this paper is organised as follows: The fundamentals on ML topics applied to analysis are taken in section II. Section III describe the methodology used for data collection and analysis, and Section IV present the findings of our study, and discuss their implications for education. Finally, the conclusion of the work carried out is made.

Background

Young Students and STEM Careers in Peru

According to [28], in 2022 the population of Peru was 33,396,698 inhabitants, with a youth population of 23.58%. It is worth noting that 30.9% of these young people have successfully transitioned to higher education, comparatively lower than the 36.6% of the census conducted in 2019. However, as Table I shows, there are gaps in access to education.

Table I. Gaps in education

Young population	Gap
17 ~ 18 y.o.	80% complete secondary education
13 ~ 19 y.o.	5% discontinue secondary education
22 ~ 24 y.o.	21% complete higher education (university and non-university)
≤ 30 y.o.	46% discontinue their non-university higher education
≤ 30 y.o.	17% discontinue their higher education at university level

It is worth mentioning that the gap in access to STI is a multidimensional problem that includes gender. In this sense, it is evident that 53.92% of female adolescents surveyed do not consider orienting their studies towards STEM careers, while 32.25% of males indicate the same response [29].

According to the OECD study, when choosing a career, 35% of female students choose STEM careers, and of this population, 3% are oriented towards the ICT area. Thus, of the total number of students enrolled in Peruvian universities in 2022 in careers related to electronics and automation, only 7% will be women. The same trend occurs in degrees related to computing, civil engineering, physics, chemistry, mathematics, statistics, and economics. On the other hand, in health-related careers, women account for 60% and in biology careers they account for 55%.

On the other hand, at the end of the STEM university degree, men obtain 62% of the undergraduate degrees. Thus, the gap with women is 24%. This gap also exists for master's degrees with 26% and for doctoral degrees with 30%.

Several barriers have been identified that do not allow students to adequately perceive STEM fields of action and their interest in studying STEM careers. These include the following: gender stereotype, lack of role models, low self-efficacy, school curriculum, lack of educational resources, limited family support, little vocational guidance, non-inclusive learning environments, negative learning experiences, lack of information on STEM careers, social and cultural pressures, limited access to extracurricular programmes, perceived relevance low, cost of education, lack of connection to the labour market.

Addressing these barriers in a comprehensive manner is crucial to foster greater interest and participation in STEM careers, which is essential for the economic and technological development of the country. For this reason, several organisations have been deploying actions to foster the interest of adolescent students and, above all, to reduce the gender gap [30].

ML Algorithms applied to STEM Interest Analysis

ML encompasses a broad spectrum of computational techniques that enable systems to learn from data and improve their performance over time without being explicitly programmed. In the context of educational research, ML algorithms can analyze vast amounts of educational data to uncover patterns, make predictions, and derive insights that are not readily apparent through traditional analysis methods.

Table II proposes the key ML algorithms relevant to study on the interest of Peruvian schoolchildren in STEM studies. Supervised learning algorithms are designed to make predictions or decisions based on labeled training data. These algorithms learn a mapping function from input features to output labels and are particularly useful for classification and regression tasks. Unsupervised learning algorithms uncover hidden patterns in data without pre-existing labels. These techniques are crucial for exploratory data analysis and identifying inherent structures within the data. Neural networks, particularly deep learning models, have revolutionized many fields by their ability to model complex, non-linear relationships in data.

Table II. ML algorithms and student data

Category	Algorithm	Use
Supervised Learning	Linear Regression	It models the relationship between variables and it is useful for predicting continuous outcomes, such as test scores or engagement levels.
	Logistic Regression	Extending linear regression to classification tasks, logistic regression is used to predict binary outcomes, such as whether a student is interested in STEM subjects or not
	Decision Trees	They split the data into subsets based on the values of input features, creating a tree-like model of decisions. They are interpretable and can handle both categorical and numerical data.
	Naive Bayes	A probabilistic classifier based on Bayes' theorem, Naive Bayes assumes that the features are conditionally independent given the class label. Despite its simplicity, it performs well in various practical applications, particularly with large datasets. Naive Bayes is highly suitable for text classification tasks, such as analyzing survey responses to gauge student interest in STEM.
	Random Forests	An ensemble method that combines multiple decision trees to improve predictive accuracy and control over-fitting. Random forests are effective for handling complex, high-dimensional educational data.
	Support Vector Machines (SVM)	SVMs classify data by finding the hyperplane that best separates different classes. They are robust to high-dimensional data and effective for binary classification tasks.
Unsupervised Learning	K-Means Clustering	It partitions data into K clusters based on feature similarity. It is useful for grouping students with similar interest profiles in STEM subjects.

	Hierarchical Clustering	Builds a hierarchy of clusters by iteratively merging or splitting existing clusters. This technique provides insights into the nested structure of student interests.
	Principal Component Analysis (PCA)	PCA reduces the dimensionality of data while retaining most of the variance. It helps in visualizing and interpreting complex datasets by identifying key components that influence student interest.
Semi-Supervised and Reinforcement Learning	Semi-Supervised Learning	Combines a small amount of labeled data with a large amount of unlabeled data to improve learning accuracy. This is particularly useful when labeled data is scarce, as is often the case in educational datasets.
	Reinforcement Learning	Involves learning optimal actions through trial and error interactions with an environment. Although less commonly used in educational data analysis, reinforcement learning can model and improve adaptive learning systems.
Neural Networks and Deep Learning	Artificial Neural Networks (ANNs)	ANNs can capture intricate patterns in educational data, such as the non-linear relationship between various factors influencing STEM interest.
	Convolutional Neural Networks (CNNs) & Recurrent Neural Networks (RNNs)	While primarily used in image and sequence data, respectively, these networks can be adapted for specialized educational applications, such as analyzing temporal patterns in student performance data.

The selection of appropriate ML algorithms depends on the nature of the educational data and the specific research questions. Model evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve are essential for assessing the performance of classification models. For regression tasks, metrics like mean squared error (MSE) and R-squared are commonly used.

2. Methodology

The CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology was used for this research, being one of the most widely used for Big Data and Data Science projects, for which the following steps were considered:

- Understanding the business, understanding the current situation regarding the interest of students in basic education in pursuing a STEM career.
- Understand the data, knowing the data, its structure and quality. Identify the variables to be used.
- Data preparation, perform data cleaning, identify missing values and outliers for appropriate processing.
- Modelling, selecting the most appropriate techniques for our research, since we are dealing with a classification problem, so we will apply various supervised learning methods.
- Model evaluation, calculating a series of metrics on the selected dataset, we will analyse the results of accuracy, sensitivity and specificity, having used various methods.
- Implement, deployment of the results obtained in a way that disseminates them to end-

users and subsequent maintenance.

The procedure is shown in Fig. 1.

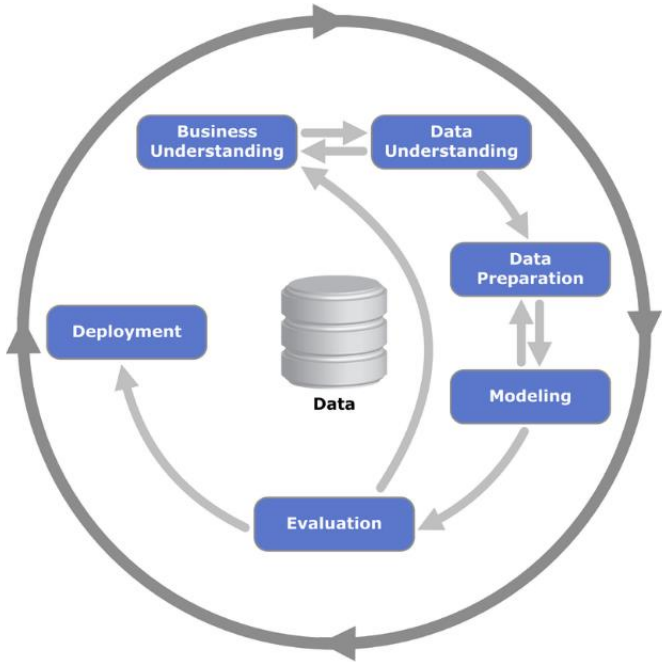

Figure 1. Flowchart of the CRISP-DM methodological process

The purpose of the study was to evaluate the suitability of Supervised Learning algorithms to determine the interest of Peruvian school students in STEM careers. The study involved 136 male and female students in the last two years of secondary school, who were selected by non-probabilistic purposive sampling. The study had the authorisation of the educational centre as it was applied through its vocational orientation programme.

The instrument used was a virtual survey of Peruvian schoolchildren developed ad-hoc which has questions in 2 target areas: 'Would you like to study Science, Technology, Engineering or Mathematics in the future' (called Study STEM) and 'Are you interested in a career in Science, Technology, Engineering or Mathematics' (called STEM Career). The instrument was administered to a random sample of students.

The study also covers the prior analysis of supervised learning algorithms: Logistic Regression, Decision Trees, Naive Bayes, Random Forests and Support Vector Machines (SVM) in order to find the most suitable algorithms according to our criteria. The results found Support Vector Machines (SVM), Logistic Regression and Naive Bayes as the most accurate, respectively (> 70%).

3. Results and Discussions

Analysis of Student Interest in STEM

In the present study, although the full instrument was applied, the analysis was carried out on the basis of the sub-set of data that considers 10 main attributes, in addition to the target variable:

- How old are you?
- Do you feel confident to solve problems?
- Do you feel confident to do science homework?
- Do you feel confident in using technology in school works?
- Do you do well in Science, Technology, Engineering and Mathematics related projects?.
- Do you find Science, Technology, Engineering and Mathematics homework or assignments easy?
- Would you like to participate in more after-school science and technology programmes?
- Do you find it easy to use technology and do coding/programming tasks?
- Are Science, Technology, Engineering and Mathematics important to you?
- Do you have family who study or work in Science, Technology, Engineering or Mathematics?
- Would you like to study Science, Technology, Engineering or Mathematics in the future?

As shown in Table III, the highest accuracy is achieved using the Support Vector Machines (SVM) model, followed by Logistic Regression and then Naive Bayes.

Table III. Algorithmic comparison

Algorithm	Accuracy	Sensitivity	Sensitivity
Logistic Regression	79.81%	87.10%	80.60%
SVM	81.73%	85.48%	84.13%
Naive Bayes	75.96%	80.65%	79.37%

There is no significant gap in accuracy between the models, all above 70%, which implies, by standard, that they are good models with high predictive power.

Sensitivity and specificity followed a similar trend with respect to performance classification. SVM was the best balanced prediction model with 84.81% on average in both sensitivity and specificity. Meanwhile RL was the most unbalanced with a sensitivity of 87.10% and a specificity of 80.60%, indicating a strong bias towards making positive predictions.

On the other hand, Fig. 2 shows the confusion matrix using the SVM algorithm, which had the highest percentage of prediction and whose results were used in the calculation of sensitivity and specificity, each related to predictions about two mutually exclusive classes, where 1 is a positive class and 0 is a negative class.

True positives (TP) = 53 are correct predictions of the positive class, while true negatives (TN) = 32 are correct predictions of the negative class. Likewise, false positives (FP) = 9 are incorrect predictions of the positive class, while false negatives (FN) = 10 are incorrect predictions of the negative class.

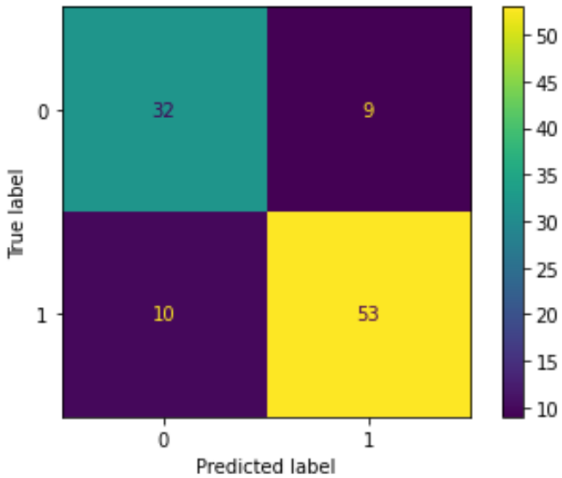

Figure 2. Confusion matrix

High sensitivity indicates that most positive cases are likely to be found, so that if a negative case is predicted, it is very likely that it is actually negative. Specificity refers to the proportion of negative TN instances predicted correctly, relative to the total number of negative TN+FP instances in the data. High specificity means that most negative cases are likely to be detected. Therefore, any positive prediction is very likely to be positive.

Strategies for Fostering Interest in STEM

High school students perceive various barriers to choosing STEM studies in colleges and universities. In view of this, Table IV proposes strategies to overcome these barriers and promote students' interest in STEM studies.

Table IV. Strategies to STEM studies

Barrier	Strategy	Implementation Examples
Gender Stereotype	Implement programmes and campaigns that promote gender equality in STEM	Awareness-raising workshops, talks by successful women in STEM, school media campaigns
Lack of Role Models	Connect students with STEM professionals who can serve as mentors	Mentoring programmes, school visits by STEM professionals, testimonials and motivational talks
Low Self-efficacy	Design activities that reinforce students' confidence in their STEM skills	Mathematics and science competences, collaborative projects, use of technology in the classroom
School Curriculum	Integrate more engaging and relevant STEM content into curricula.	Updating curricula, incorporating practical projects and experiments, problem-based learning

Lack of Educational Resources	Provide better tools and technologies for STEM education	Laboratory equipment, access to specialised software, creation of makerspaces
Limited Family Support	Involve families in the educational process and the importance of STEM careers	Workshops and information meetings for parents, family involvement programmes in school activities
Little Vocational Guidance	Provide appropriate advice on the opportunities and benefits of STEM careers	Vocational guidance programmes, STEM career fairs, information sessions with universities and colleges
Non-Inclusive Learning Environments	Promote a school culture that values diversity and inclusion in STEM	Inclusion policies, teacher training in inclusive pedagogies, inclusive science and technology clubs
Negative Learning Experiences	Ensure that STEM classes are engaging and rewarding for students	Active teaching methodologies, use of educational games, research projects and experimentation
Lack of Information on STEM Careers	Communicate to students about the various options and benefits of STEM careers	Informative talks, reading materials, visits to companies and universities, use of digital platforms
Social and Cultural Pressures	Educate the community about the importance of STEM careers and break down cultural barriers	Community campaigns, media talks, social awareness programmes
Limited Access to Extracurricular Programmes	Offer more STEM-related activities and clubs outside school hours	Robotics clubs, science fairs, STEM summer camps, programming and technology workshops
Perceived Relevance Low	To show the practical application and importance of STEM in everyday life and future employment	Projects that solve real problems, collaboration with local businesses, community projects
Cost of Education	Provide scholarships and financial aid to study STEM careers	Specific scholarships for STEM students, funding programmes, support in finding resources
Lack of connection to the labour market	Establish links between educational institutions and companies to showcase job opportunities	Internship programmes, company visits, conferences with professionals in the sector

4. Conclusion

The study provides evidence that the MVS, RL and nBayes algorithms are particularly well suited to predict, with a high rate of accuracy, high school students' interest in studying STEM.

Factors influencing high school students' interest in STEM careers are highlighted. Hands-on experiences, quality mentoring, the presence of role models and extracurricular activities stand out as key elements in fostering this interest. In addition, the elimination of gender stereotypes and institutional support are crucial to increase participation in STEM. The implementation of these proposed strategies can help to significantly increase student participation in STEM careers, contributing to the development of a competent workforce in these critical areas.

The development of projects that can be applied to the students‘ own reality or to their community can increase students’ interest in STEM careers by providing them with the opportunity to see the impact that the implementation of science, technology, engineering and mathematics has in a practical and tangible way. It also builds social awareness and responsibility.

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