# Predictive Model for STEM Vocational Guidance through Profile Analysis and Information Adaptation with a Gender Perspective

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***Abstract*–This article analyzes a predictive model for vocational guidance focused on identifying student profiles toward STEM careers (Science, Technology, Engineering, and Mathematics) with an explicit gender perspective. The study is based on data from students at University Tecnologica de Bolivar, considering academic variables such as standardized test results, socioeconomic background, and gender markers. Data preprocessing techniques, cluster analysis, and dimensionality reduction through Principal Component Analysis (PCA) were applied to identify significant patterns in academic behavior. The results allow the classification of students into specific profiles, highlighting those with skills aligned with STEM careers, cases where the model presents accuracy limitations, and differentiated trajectories mediated by gender. Importantly, the analysis reveals that, although female students demonstrate strong competencies in areas such as Mathematics, Critical Reading, and Natural Sciences, external factors such as socioeconomic conditions and gender roles influence their vocational decisions. By integrating this gender-sensitive analysis into the predictive framework, the study establishes a solid foundation for adapting information in future model iterations, improving the accuracy of inferences, and promoting vocational guidance processes that are not only personalized and adaptive but also explicitly oriented toward equity in STEM participation.***

***Keywords— STEM, PCA, Adaptive, Vocational Guidance, Gender Perspective, Education Engineering.***

## I. Introduction

Vocational guidance is essential for the development of human talent required for social and economic progress. STEM education has been consolidated as a strategic pillar in most Latin American countries due to its impact on innovation and competitiveness [1]. However, career choice remains a challenge for many students, particularly women, who face barriers in aligning skills, interests, and academic opportunities with labor market demands [2].

In Latin America and the Caribbean, women represent approximately 30% of STEM graduates. In disciplines such as engineering, participation rarely exceeds 20%, and in some countries, it falls below 15% [3]. These figures are not merely the result of individual decisions but rather reflect structural and cultural barriers: gender stereotypes, limited access to quality technical and scientific training, scarcity of female role models in professional fields, and gaps in access to digital resources [4]. This scenario not only reveals persistent inequality but also a systematic waste of talent and human capital that restricts the region's innovation and competitiveness [5][6]. Thus, the gender gap in STEM must be understood as a matter of social justice and sustainable development, not merely as an educational issue.

Colombia reflects these same trends: only 3% of students opt for STEM careers, and among those who do, only 32.3% are women. This calls for differentiated and adaptive interventions that consider socioeconomic, cultural, and academic factors [7], [8]. These data demonstrate that the gender gap is not automatically corrected by an increase in higher education enrollment; rather, it requires sustained actions and gender-sensitive policies.

From this perspective, predictive models constitute a promising alternative to enhance vocational guidance, provided they are designed with equity safeguards. International organizations have stressed that increasing diversity in STEM is already a priority on the agendas of governments, universities, and private entities, as female participation contributes to social inclusion and innovation[9] [10] . Therefore, we propose that the analysis of student patterns should not only classify profiles but also reveal the inequalities that limit women's participation and suggest adaptive pathways to reduce these gaps [11]. In this way, predictive models should not be conceived solely as technical tools but as instruments for educational equity.

The identification of student profiles is central to this objective. We define a profile as a structured representation that integrates performance in standardized tests, affinity with knowledge areas, self-efficacy, outcome expectations, access to resources, and socioeconomic conditions, along with the gender marker [12]. These profiles enable adaptive recommendations with a gender perspective. For example: mentoring programs with female role models in STEM when low self-efficacy is detected; remedial pathways in mathematics and programming when educational gaps are identified; and psychosocial and financial support when barriers are of socioeconomic origin.

We applied dimensionality reduction techniques, specifically Principal Component Analysis (PCA), to manage the complexity of educational and contextual variables. The retained components were selected to capture relevant structures for STEM affinity while preserving gender subgroup stability and predictive accuracy.

Within this framework, this study analyzes the results of a predictive vocational guidance model to identify gender-sensitive profiles and lay the foundations for an adaptive system. The main contribution consists in incorporating an adaptive component into vocational guidance with a gender perspective, which allows the model to evolve with new cohorts, dynamically adjust its recommendations, and prevent the reproduction of structural biases. In this way, progress is made toward a more flexible and inclusive vocational guidance system, aligned with the objectives of equity and sustainable development.

## II. Related Work

Guidance is the process of advising and supporting individuals in making appropriate decisions, considering both the characteristics and possibilities of the available options as well as their own capabilities and limitations. This section examines the fundamental concepts of vocational guidance and its development in previous studies, with the aim of understanding the theoretical and methodological foundations that support its application in adaptive systems. Vocational guidance is a psycho-pedagogical process that comprehensively evaluates students' skills and abilities before choosing a career. Its purpose is to guide students' vocational orientation and ensure academic success by identifying tasks and professional paths necessary to guarantee, to some extent, satisfactory performance [13].

Secondary education represents a decisive stage to guide students toward pathways that foster personal development and social contribution. An early approach facilitates the consolidation of interests and must consider labor market demands, recognizing that interests, aptitudes, and preferences do not always coincide. Furthermore, the influence of third parties plays a key role in fostering exploration and self-awareness, increasing the effectiveness of the process when approached comprehensively [14].

Vocational guidance has been transformed by the incorporation of adaptive technologies, which make it possible to respond to a labor market increasingly driven by innovation and the growing importance of STEM fields. These systems, supported by algorithms and computational platforms, offer multiple opportunities for personalization, adjusting to the characteristics of each student and optimizing decision-making toward high-demand careers [15][16]. In this context, personalization becomes a key tool, as it allows the delivery of content and recommendations tailored to students' abilities and preferences, particularly in specific areas such as STEM [17] .Adaptation is understood as the system's ability to modify information, conceived as a process of enriching the service [18], through algorithms that automatically adjust content based on the user's dynamic and contextual information.

These approaches are reinforced by machine learning, which enables increasingly accurate predictive trajectories. Within this framework, data analysis with a gender perspective has revealed significant differences: through explainable clustering, it was found that high-achieving female students show lower expectations of pursuing STEM careers compared to their male peers [19]. Complementary studies indicate that women tend to value the social and collaborative aspects of science, while men prioritize technical and salary-related factors[20]. Similarly, research in adaptive learning environments shows that female students achieve higher academic performance and make more intensive use of digital resources than men [21]. Altogether, these findings confirm the relevance of integrating a gender dimension into predictive models, avoiding the invisibilities of patterns that influence vocational decisions.

Globally, only 35% of STEM graduates are women, and fewer than 30% of STEM jobs are held by them [22]. In Latin America and the Caribbean, female participation rarely exceeds

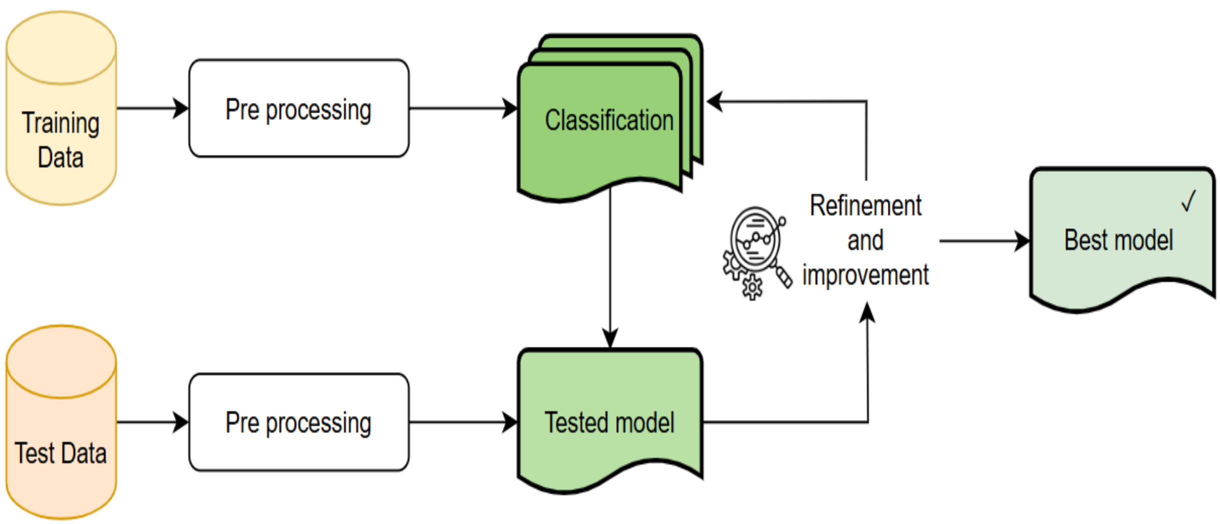


Fig. 1 Model components.

40%, and in fields such as ICT it drops to as low as 12% in Chile[23]. Although the region reaches 46% of women researchers, inequalities remain evident in engineering and technology, underscoring the urgency of adaptive systems that help to reduce these gaps. Beyond quantitative participation, structural and cultural barriers continue to restrict women's

Fig.2 Scree plot PCA N = 250.

Taken together, vocational guidance has evolved into adaptive systems capable of leveraging data analysis to provide personalized trajectories. Nevertheless, the persistent gender gaps in STEM and the influence of cultural barriers highlight the need for these models to incorporate an inclusive perspective that makes differentiated patterns visible and provides more equitable recommendations.

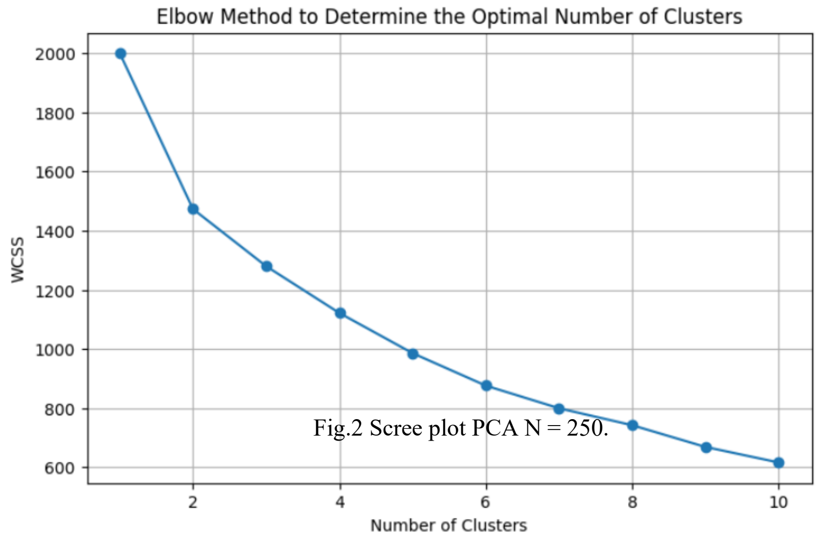

Fig.2 Scree plot PCA N = 250.

trajectories: in many STEM programs women represent

III. METHODOLOGY

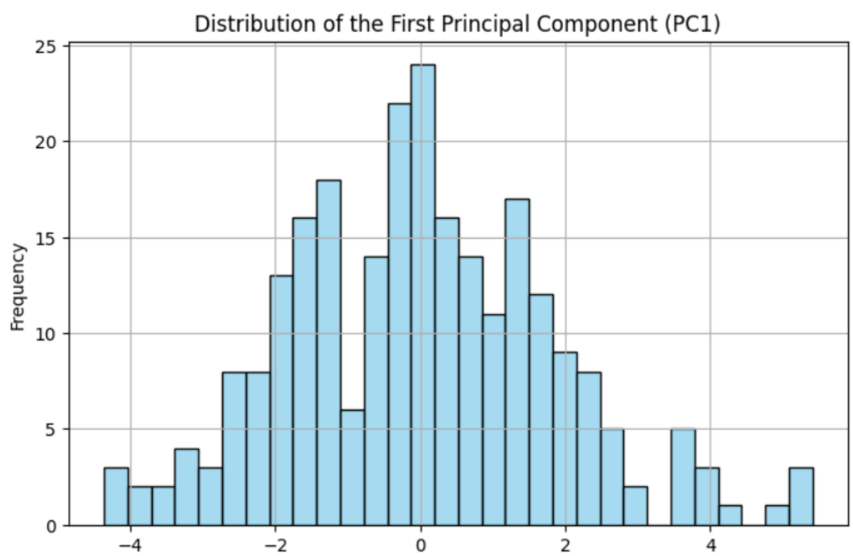

Fig.3 Variable distribution in PC1 (N=250).

less than 30%, largely due to stereotypes and cultural biases[24]. In Latin American neuroscience, women predominate in biology but remain underrepresented in exact sciences and leadership positions, with career delays often linked to pregnancy and family care responsibilities[25].Moreover, one-third of women in STEM report having faced harassment, sexism, or gender-based violence in their careers[26]

III. METHODOLOGY

We structured the development of the predictive model for vocational guidance towards STEM careers into a three-stage workflow: data preprocessing, model classification and validation, and refinement as an adaptive module to obtain the best system version. First, the training and test data were subjected to a normalization and cleaning process to ensure their quality. Subsequently, the classification module used the preprocessed data to train and validate the model, assessing its ability to identify affinities towards STEM careers. The results provide a comprehensive analysis that enables the achievement of optimal performance. This methodology, represented in Fig. 1, ensures a coherent integration between data analysis techniques and adaptive strategies, aimed at personalizing vocational recommendations.

facilitating the analysis by eliminating the need for imputation or additional cleaning processes.

We implemented clustering analysis using data preprocessing techniques, dimensionality reduction, and cluster quality assessment. The student data from the Universidad X includes individuals aged between 17 and 30 years and incorporates results from the 2014 updated ICFES tests. These tests evaluate key components such as Critical Reading, Natural

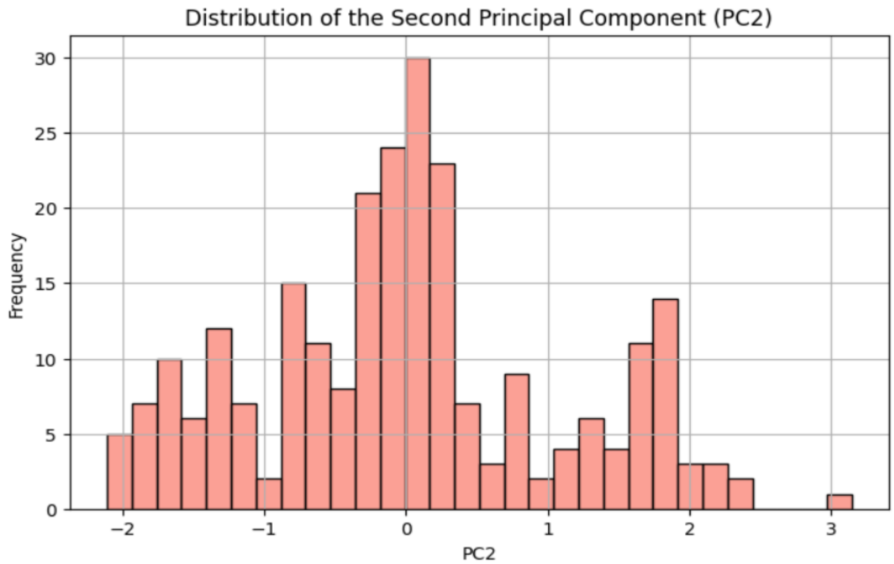


Fig.4 Variable distribution in PC2 (N=250).

Sciences, English, Mathematics, and Social and Civic Studies, providing a comprehensive view of students' academic abilities.

The process began by taking the model validation results and segmenting each resulting event to identify specific patterns within the data. Subsequently, we prepared the data, prioritizing the model's components and other complementary variables that defined more precise student profiles. In this case, the dataset contained no missing values, facilitating the analysis by eliminating the need for imputation or additional data-cleaning processes.

The first component focuses on data exchange between classification and adaptive modules. The classification module is based on a previously trained and validated model, following the approach described [27]. This module utilizes students' academic and socioeconomic data to make initial predictions about their affinity for STEM vocations. On the other hand, the adaptive module is responsible for adjusting recommendations based on the identified student profiles, allowing dynamic personalization as user data is updated.

The second component corresponds to the PCA process to understand the behavior of the results obtained during the predictive model's validation. This analysis began by taking the model validation results and segmenting each event to identify specific patterns in the data. The data were prepared by prioritizing the model's principal components and complementary variables, allowing for more precise student profiling. This study used a dataset without missing values,

We used the elbow method to determine the optimal number of clusters, which helps identify where the within-cluster sum of squares (WCSS) no longer decreases significantly. Based on this analysis, the K-means algorithm was applied to group the data into defined clusters, followed by an evaluation of clustering quality using the silhouette coefficient, which measures the internal consistency of each cluster and its separation from others. Finally, PCA was applied to reduce data dimensionality and facilitate visualization, representing the clusters in a two-dimensional space to identify relevant patterns in vocational guidance toward STEM careers.

The third component focuses on enhancing user services based on the information obtained from the previous modules. This component is based on identifying student profiles to analyze which personalized services can be offered, including consulting standardized test results, validating affinities toward STEM careers, and generating recommendations tailored to each student's profile. The precise identification of these profiles personalizes vocational guidance and provides additional resources that strengthen students' academic decision-making processes.

Within this analysis, three central profiles were identified to guide the implementation of the adaptive module. The first corresponds to students with high performance in STEM

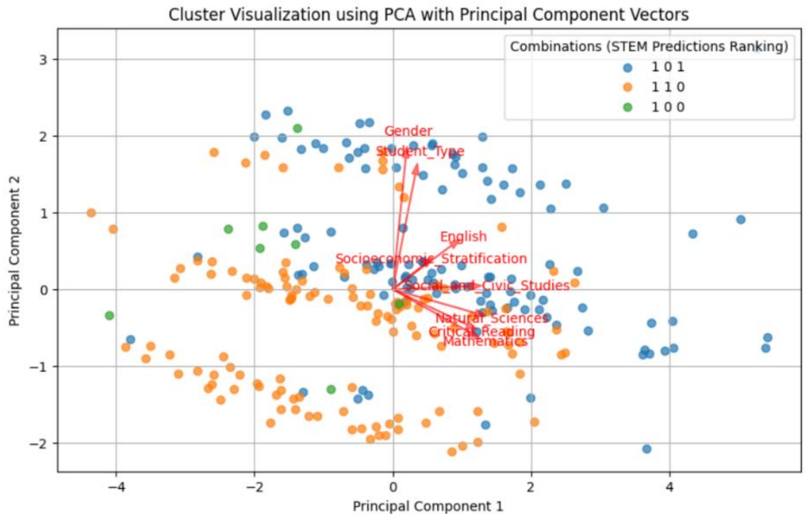


Fig.5 Principal component analysis.

competencies, for whom the strategy focuses on consolidating and enhancing their strengths through advanced mentoring, specialized tutoring, and early access to STEM-related experiences. The second group consists of students with strengths in humanities and social sciences, whose competencies translate into transferable skills of great value in STEM contexts. In this case, the adaptation seeks to highlight and leverage these abilities through interdisciplinary projects and activities that connect these areas with scientific and technological fields.

Within this analysis, three central profiles were identified to guide the implementation of the adaptive module. The first corresponds to students with high performance in STEM-related competencies; the second group consists of students with strengths in the humanities and social sciences; and finally, students with mixed profiles were identified, requiring a broader process of vocational exploration.

Through this analysis, not only is the technical accuracy of predictions refined, but it also ensures that each profile receives differentiated support, thereby strengthening the relevance and impact of vocational guidance in real contexts. The integration of these components establishes a solid methodological framework for the continuous analysis and improvement of the predictive model. The interaction between the classification and adaptive modules ensures a comprehensive approach to vocational guidance, while also enabling the iterative evaluation of the results obtained, identifying areas for improvement, and optimizing the system to provide more accurate and personalized recommendations toward STEM careers.

## IV. RESULTS

The analysis made it possible to identify three differentiated student profiles based on the validation of the model. The first profile corresponded to cases in which the prediction achieved high accuracy for students currently enrolled in STEM programs. These students showed outstanding performance in Mathematics and Critical Reading, competencies that are fundamental to ensuring strong performance in these types of academic trajectories. The second profile consisted of students enrolled in non-STEM programs who, according to the model, demonstrated strengths in transferable skills, reflected in good averages in areas such as English and Social and Civic Competencies, which suggests their capacity to adapt to different academic contexts. Finally, a mixed profile was identified, made up of students who, although not currently pursuing STEM programs, presented intermediate performance across several competencies. This group is characterized by a potential transition toward STEM programs, although conditioned by contextual and socioeconomic factors.

On the other hand, a detailed analysis was carried out on the cases in which the model did not predict accurately, with the purpose of improving its adaptability. Within this group, a PCA was applied to 250 students, selecting components based on the inflection point of the scree plot Fig. 2. The first component explained 42.53% of the variance, while the second represented 14.61%, accumulating a total of 57.14% of the variability in the data. Although these two components do not capture the entire structure of the data, they allow for a two-dimensional visualization of patterns and groupings. The first component was represented by variables such as Natural Sciences, Social and Civic Competencies, Mathematics, Critical Reading, English, Socioeconomic Stratum, Student Type, and Gender Fig. 3, while the second included Gender, Student Type, English, Mathematics, Critical Reading, Socioeconomic Stratum, Natural Sciences, and Social and Civic Competencies Fig. 4. Table 1 presents the percentage of influence of each variable with respect to all components.

This analysis identified students enrolled in STEM programs whom the model did not classify as possessing the necessary competencies for these fields. However, these students displayed good academic performance, with high participation in extracurricular activities and outstanding results in English, Civic Competencies, and Natural Sciences. Although they also achieved good results in Critical Reading and Mathematics, their strongest competencies were concentrated in the first three areas mentioned. Likewise, another profile was identified consisting of students with high competencies in Mathematics and Critical Reading but with lower-than-expected overall academic performance. In this case, the influence of student type was minimal, while socioeconomic stratum showed a significant correlation, together with a strong affinity in English and Civic Competencies, suggesting that external factors may be influencing their academic success.

When delving into the mixed profile through gender analysis, it became evident that women constitute the majority within this group (over 70% of cases). This finding reveals that, even though they possess relevant competencies for success in STEM, they choose to pursue different trajectories. The first component, explained mainly by Natural Sciences, Mathematics, Critical Reading, and Social and Civic Competencies, concentrates precisely on the areas in which these students show significant performance, reinforcing the idea that they have the cognitive abilities required to succeed in scientific and technological careers. However, their decision is mediated by external factors identified in the second component, such as gender, student type, and socioeconomic stratum, which take on a differential weight in shaping their trajectories.

As shown in Fig. 5, the vectors of the principal components indicate that academic competencies are strongly aligned with PC1, while contextual variables explain much of the dispersion in PC2. Complementarily, Fig. 6 provides a clearer visualization of the gender distribution in this two-dimensional space, where women are concentrated in the areas associated with the mixed profile, while men, although in smaller proportion, tend to be in regions where structural factors and English proficiency exert greater influence. These finding highlights that the low enrollment of women with academic potential in STEM careers is not due to a lack of abilities, but rather to the interaction between skills and social, economic, and cultural constraints. This reinforces the need to design gender-sensitive vocational guidance strategies that recognize these tensions and promote decisions more aligned with their strengths.

TABLE I
PERCENTAGE CONTRIBUTION OF EACH VARIABLE PER PRINCIPAL COMPONENT.

| Variable | PC1 | PC2 |
|---|---|---|
| Critical Reading | 16.92 | 8.38 |
| Natural Sciences | 18.86 | 5.64 |
| English | 13.35 | 10.39 |
| Mathematics | 17.63 | 10.27 |
| Social and Civic Studies | 17.84 | 0.76 |
| Gender | 2.98 | 31.25 |
| Socioeconomic Stratification | 7.25 | 5.98 |
| Student Type | 5.13 | 27.29 |

## V. DISCUSSION

The results highlight that vocational guidance systems must evolve beyond static predictions and move toward adaptive frameworks explicitly designed to address equity

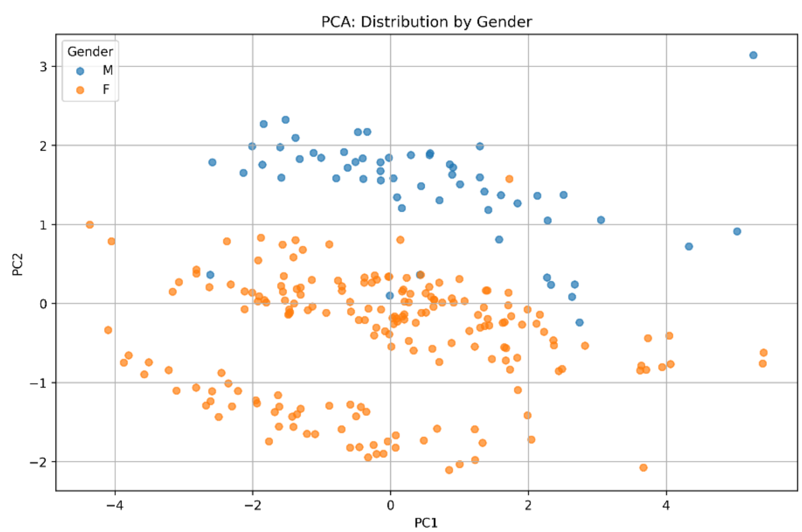


Fig.6 distribution by gender.

gaps. Traditional approaches are often limited to providing reasonably accurate classifications, but they fail to generate actionable recommendations that confront structural barriers such as gender and socioeconomic inequalities. By incorporating a gender perspective into the adaptive module, this study demonstrates how predictive findings can be translated into differentiated strategies that acknowledge and respond to these inequalities.

A key insight lies in the analysis of the mixed profile, where more than 70% of students are women who, despite demonstrating strong competencies in Mathematics, Natural Sciences, and Critical Reading, opt for non-STEM trajectories. This mismatch reveals that the barriers are not cognitive but contextual, shaped by socioeconomic conditions, gender roles, and cultural expectations. Consequently, adaptive systems must not only refine technical accuracy but also integrate mechanisms that expose and counteract these structural constraints. In doing so, vocational guidance can be transformed into a dynamic process that identifies hidden potential, ensures equitable participation, and aligns recommendations with both students' abilities and their social realities.

## VI. CONCLUSION

This study underscores the potential of predictive models to optimize vocational guidance toward STEM careers through the identification of student profiles based on academic patterns, individual characteristics, and contextual variables. The integration of clustering techniques and Principal Component Analysis (PCA) facilitated the effective classification of students, while also revealing critical areas where the model presents limitations—particularly in accounting for gendered trajectories. The gender-sensitive analysis revealed that women with high academic performance remain underrepresented in STEM choices, indicating that structural and cultural barriers, rather than lack of ability, drive these decisions.

Therefore, continuously adapting the model with gender, socioeconomic background, and performance dimensions is essential not only to enhance predictive accuracy but also to ensure that vocational guidance systems contribute to equity in STEM access. PCA plays a pivotal role in this adaptation, enabling the detection of patterns that expose inequities and guiding the design of recommendations that are inclusive and differentiated. Ultimately, this research advances a dual contribution: it provides a methodological foundation for scalable predictive systems and establishes a framework for integrating a gender-sensitive perspective into vocational guidance. This dual approach lays the groundwork for robust, fair, and adaptive systems capable of reducing gender disparities and fostering more informed and equitable academic decisions in STEM education.

## VII. FUTURE WORKS

In future work, we propose a recommendation system to optimize vocational guidance toward STEM careers based on the analysis of profiles generated through PCA. After training and validating the current model, the focus will shift to identifying complex patterns that influence career choices and facilitating the personalization of recommendations. This system is designed to adapt to students' individual characteristics, thereby improving prediction accuracy and increasing its impact across diverse educational contexts. Furthermore, with access to longitudinal data, it would be valuable to deepen the analysis of the long-term impact of these adaptive recommendations. Such efforts would enable the validation and scaling of the resulting model in authentic institutional contexts.

Additionally, we will develop a prototype or mock-up to serve as a pilot plan for the initial iterations of the recommendation system. This prototype will allow for evaluating the impact of information adaptation on the quality of recommendations, comparing the model's performance before and after its implementation. The objective is to demonstrate that integrating this adaptation improves the relevance of recommendations and strengthens the system's capacity to operate in adaptive ecosystems, contributing to the development of these ecosystems in STEM vocational guidance.

Fig.1 illustrates the steps to be followed in this process, highlighting the integration of information adaptation, predictive algorithms, and machine learning techniques within the recommendation system. This framework serves as a guide for the development and continuous improvement of the system, ensuring a dynamic approach to enhancing STEM career guidance through adaptive and personalized strategies.

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