

## RESEARCH ARTICLE

# Gender and Academic Indicators in First-Year Engineering Dropout: A Multi-Model Approach

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**ABSTRACT** Student attrition during the first academic year remains a critical issue in engineering education, with implications for equity and institutional effectiveness. This study explores early dropout patterns across five engineering degree programs using data from 3889 first-year students spanning seven academic cohorts at one public and one private university in Spain. A multi-method analytical strategy—comprising logistic regression, artificial neural networks, and propensity score matching—was used to examine how gender and academic performance relate to early attrition. Findings challenge prevailing assumptions in the literature by showing that gender is not a statistically significant factor in first-year dropout, a result consistent across methods and after adjusting for confounders. In contrast, academic variables—such as entrance exam scores, failure rates, and exam absenteeism—exhibited strong associations with attrition. Institutional context also shaped dropout patterns: academic failure played a particularly salient role in the private university, while disengagement, measured through no-show rates, was more relevant in the public institution. Notably, an exception emerged in the Mathematical Engineering program, where gender moderated the link between academic failure and dropout, pointing to potential interaction effects in specific curricular settings. These results underscore the importance of understanding the conditional and context-dependent nature of early dropout, supporting targeted interventions grounded in academic, rather than demographic, indicators.

**INDEX TERMS** Academic performance, dropout, engineering, first year engineering students, gender, machine learning, neural networks, NeuralSens, propensity score matching, student retention.

## I. INTRODUCTION

Student attrition during the first year of university poses a major challenge for institutions, as it directly affects academic planning, the return on public and private investment, and the equitable distribution of educational opportunities [1]. Beyond its institutional impact, dropout disproportionately affects certain student populations, raising concerns about equity and access in higher education [2]. In particular, gender equity emerges as a central issue,

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especially in fields such as engineering, which have traditionally been characterized by low female representation [3]. Although women's participation in STEM programs has increased notably, the debate persists as to whether female students are at higher risk of academic dropout at any stage [4], particularly within the field of engineering [5] and specifically during the first year [6].

The contrast between institutional discourse and empirical findings is evident in the mixed results regarding gender-related dropout in STEM. While educational policies stress the need for gender equity [7], [8], empirical studies often report no significant gender differences

**TABLE 1. PICOC-based inclusion and exclusion criteria for study selection.**

RQ id	PICOC Element	Included Requirement	Excluded Requirement
RQ1	P – Population	Study is conducted in higher education (college or university students).	Studies conducted in secondary education, vocational training, or general population.
RQ2	I – Intervention or Exposure	Study focuses explicitly on first-year students or includes specific analysis of first-year outcomes.	Studies with no focus on first-year students, or where data for that year is not analyzed separately.
RQ3	C – Comparison	Study includes gender as a comparative variable (e.g., compares men and women).	Studies that only include one gender (e.g., only women or only men).
RQ4	O – Outcome	Study addresses dropout, attrition, retention, persistence, or withdrawal, whether measured directly or indirectly (e.g., intention to persist, proxies like academic well-being).	Studies that do not address student dropout, attrition, retention, persistence, or withdrawal, either directly or through indirect measures (e.g., intention to persist, academic integration, belonging).
RQ5	C – Context	Study population is exclusively engineering students, or results for engineering are disaggregated from STEM.	Studies where engineering is not separated from other STEM fields in gender-related results.
RQ6	Article	Study is published in a peer-reviewed journal	Reports, conference papers or posters, or non-peer-reviewed journals.
RQ7	Language	Study is written in English.	Studies written in languages other than English.

in dropout rates [9]. However, a critical issue lies in the frequent generalization of results from engineering to the broader STEM domain, despite growing evidence that gender-related dynamics vary substantially across disciplines. Overgeneralizing findings from engineering to the broader STEM field can obscure important disciplinary differences, such as gender disparities observed in computing [10]. This highlights the importance of conducting disaggregated, discipline-specific analyses to support more accurate and equity-oriented educational interventions.

This study addresses this gap by applying robust methods to a large sample of first-year students from five engineering programs across public and private universities, spanning seven academic cohorts. Its primary objective is to empirically examine the existence of a gender effect on academic dropout during the first year, a critical period for institutional intervention. The hypotheses addressed are: (H1) there are gender differences in first-year dropout rates in engineering; (H2) the gender effect persists after adjusting covariates using PSM; and (H3) the relevance of gender and academic factors, such as university entrance examination score, remains stable throughout the first year.

The main contributions of this study are fourfold:

1. It provides a systematic literature review covering the past ten years to examine whether gender differences in first-year engineering dropout are consistently supported by empirical evidence.
2. It applies a rigorous multi-method analytical framework, combining logistic regression, artificial neural networks, and propensity score matching to assess the causal impact of gender on first-year engineering dropout, while controlling for academic confounders.
3. It provides discipline-specific insights by disaggregating dropout data across five engineering programs and using administrative enrollment records to ensure outcome validity.

The cross-institutional design—spanning public and private universities—adds contextual depth to the analysis.

4. It contributes evidence-based guidance for institutional interventions, emphasizing that academic indicators—not gender—should guide early retention strategies in first-year engineering education, at least in these contexts.

## II. LITERATURE REVIEW

### A. GENDER, DROPOUT AND FIRST YEAR OF ENGINEERING

To examine whether *significant gender differences exist in first-year engineering dropout*, a systematic literature review was conducted following the PRISMA guidelines [11], covering publications from 2015 to June 2025. To enhance methodological rigor, we applied the Quasi-Gold Standard (QGS) approach as outlined by [12], and recently adopted in related educational research [13], [14]. Searches were performed across six major academic databases frequently used in studies on academic performance and retention in higher education [15], [16], such as IEEE Xplore, Scopus, Web of Science (WoS), ACM Digital Library, Springer Link, and Science Direct.

To construct the QGS, an initial manual search was conducted on Google Scholar, following the same methodology as [13], using the following query: (“*dropout*” OR “*attrition*” OR “*retention*” OR “*persistence*”) AND (“*first-year*” OR “*freshmen*” OR “*first year*”) AND (“*higher education*” OR “*university*” OR “*college*”) AND (“*gender*” OR “*women*” OR “*female*” OR “*sex*”) AND “*engineering*”.

We reviewed the first 100 results, identifying 12 studies meeting all PICOC-based inclusion criteria [17], as detailed in Table 1. From these, 9 high-impact studies were selected for the QGS based on relevance and expert consensus. Additionally, we manually reviewed eight top-tier

journals in the field—e.g., Journal of Engineering Education, IEEE Transactions on Education, European Journal of Engineering Education—identifying 8 further studies. The final QGS thus comprised 17 benchmark articles (Appendix - Table 7).

We then constructed a synonym table based on the PICOC framework (Table 2) to support comprehensive keyword coverage. Following iterative testing, the final search string was defined as: (“engineering”) AND (“first-year” OR “first year” OR “freshman” OR “freshmen” OR “early-stage”) AND (“gender” OR “female” OR “women” OR “sex”) AND (“dropout” OR “attrition” OR “retention” OR “persistence” OR “withdrawal”). This string was subsequently adapted to the specific syntax requirements of each database (Appendix - Table 8). We restricted the search to English-language, peer-reviewed journal articles published between 2015 and 2025, resulting in 45 studies selected for full-text analysis after applying inclusion criteria and removing duplicates (Figure 1).

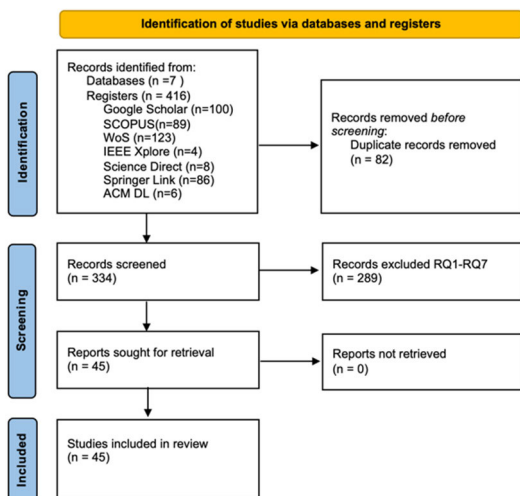
the validity and interpretability of dropout research—especially since the validity of inferred relationships may be context-dependent.

**TABLE 2. PICOC-based search terms and synonyms used in the revised search strategy.**

PICOC Element	Conceptual Term	Synonyms and Related Terms
Population (P) / Context (C)	Higher education engineering students	"engineering"
Intervention (I)	First-year students	"first-year", "first year", "freshman", "freshmen", "early-stage"
Comparison (C)	Gender	"gender", "female", "women", "sex"
Outcome (O)	Dropout-related concepts	"dropout", "attrition", "retention", "persistence", "withdrawal"

In the studies presented in Table 3, where dropout is measured directly, most works examine student persistence across the full duration of the degree or focus on graduation outcomes. Four studies — [21], [23], [26], and [29]—include measurements of student attrition during the second academic year. Among them, only [23] focuses exclusively on the transition to the second year, reporting no significant gender differences. The remaining studies consider second-year attrition alongside other academic stages: [21] addresses non-persistence across both the first and second year but does not specify gender-related differences; [26] analyzes dropout rates in the first three years and finds no gender gap in electrical engineering, though it reports higher attrition among women in computer engineering; [29] similarly examines multiple academic years and finds higher dropout rates among male students. Study [24], which focuses on non-persistence in an engineering major after the first year, also finds no significant gender differences; however, its definition may classify students who switch majors within engineering as retained, potentially affecting comparability. More broadly, findings on gender and engineering dropout are inconsistent. Some studies report higher dropout among women, others among men, and many find no significant differences. As shown in [28], retention rates vary notably by discipline within the same institutional context: women are less likely to persist in computer engineering but more likely to persist in telecommunication engineering. These findings are consistent with broader research showing that women’s dropout patterns in engineering differ from those in other STEM fields, such as the biological or physical sciences [18], underscoring the need to disaggregate results by program and context.

Table 4 presents 33 studies that examine gender-related patterns in variables theoretically associated with student dropout—such as academic performance, self-efficacy, or identity—rather than measuring dropout directly. These studies are organized into three categories: academic ([30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40]),



**FIGURE 1. PRISMA flow diagram of the study selection process for the systematic literature review.**

To assess the robustness of our search strategy, we compared its performance against our QGS, consisting of 17 key studies. Fourteen of these were successfully retrieved, resulting in a sensitivity of 82% and a precision of 31% (14 out of 45 studies), which confirms the methodological adequacy of our approach according to the criteria proposed [12]. For comparative purposes, the 45 included studies were classified by how dropout was measured. Table 3 presents 12 studies using direct indicators, such as administrative enrollment data, offering stronger validity by capturing actual withdrawal events. Table 4 compiles 33 studies using inferred indicators—academic, motivational, or psychological constructs—linked to dropout risk based on prior literature. This classification points to a key methodological distinction in the field and highlights the importance of using objectively observable outcome variables to strengthen

**TABLE 3. Gender and directly measured dropout indicators in higher education.**

Id	Indicator*	Higher Dropout	N Sample	N Universities	N Disciplines
[18]	Non persistence in their enrollment in engineering across eight academic years	F*	3097	1	NS
[19]	Non persistence in their enrollment in engineering across 4 academic years	ND	5894	1	NS
[20]	Non persistence in their enrollment in engineering	ND	474	1	2
[21]	Non persistence in their enrollment in engineering (first and second year)	NS	82	1	NS
[22]	Non persistence in higher education program	NS	5951	2	NS
[23]	Non persistence into the second year of the same program	ND	243	1	NS
[24]	Non persistence in an engineering major after the first year	ND	682	1	NS
[25]	Non persistence in the second fall semester	NS	1488	1	NS
[26]	Attrition rates in the first, second, and third year	F*ND	119979	NS	2
[27]	Attrition rates and final graduation	M*	559	1	NS
[28]	Attrition rates, graduation on time, graduation within 6 years	F*M*	12260	1	4
[29]	Attrition rates in the first, second, and third year, as well as 4-year graduation rates	M*	2098	1	2

\*D=Direct indicator, I=Indirect indicator, NS=Not specified, ND=Not difference. F\* =Female significance

**TABLE 4. Gender and inferred dropout indicators in higher education.**

Id	Indicator*	Higher Dropout	N Sample	N Universities	N Disciplines
[30]	Academic changes: changes of major and selection of program of study	ND	827	1	NS
[31]	Academic performance (spatial skills)	NS	3948	1	1
[32]	Academic performance (first-year) and self-efficacy	NS	3982	1	6
[33]	Academic performance in courses, career intentions	ND	2420	1	NS
[34]	Academic performance in a specific course	ND	472	1	3
[35]	Academic performance in first-year introductory courses	NS	11195	1	NS
[36]	Academic performance in first-year introductory courses	ND	1738	2	21
[37]	Academic performance in first-year introductory courses	NS	2463	1	12
[38]	Academic performance, and integration in peer academic/social networks	NS	582	1	NS
[39]	Academic performance, units taken per term, and progress toward graduation	ND	12053	1	NS
[40]	Academic success (credits)	M*	353	5	NS
[41]	Motivational constructs: Academic well-being	NS	258	1	4
[42]	Motivational constructs: Belonging and role identity	NS	834	1	NS
[43]	Motivational constructs: Confidence, self-efficacy and team satisfaction	NS	29	1	NS
[44]	Motivational constructs: Engineering identity	NS	186	1	NS
[45]	Motivational constructs: Engineering identity	NS	598	1	NS
[46]	Motivational constructs: Engineering identity	NS	295	1	NS
[47]	Motivational constructs: Engineering identity and intention to persist	NS	2897	4	NS
[48]	Motivational constructs: Engineering values	NS	72	1	NS
[49]	Motivational constructs: Intent to persist	ND	2186	11	NS
[50]	Motivational constructs: Mathematics self-efficacy and mathematics anxiety	F*	593	1	9
[51]	Motivational constructs: Participation, sense of belonging, and intentions to persist	F*	589	1	NS
[52]	Motivational constructs: Self-efficacy	NS	96	1	NS
[53]	Motivational constructs: Self-efficacy	NS	339	1	NS
[54]	Motivational constructs: Self-efficacy	NS	343	1	NS
[55]	Motivational constructs: Self-efficacy and innovation	NS	2678	32	15
[56]	Motivational constructs: Self-efficacy, academic self-confidence	NS	102	2	NS
[57]	Motivational constructs: self-efficacy, interest, perceived recognition, identity	ND	761	1	NS
[58]	Motivational constructs: Self-efficacy, utility value, engineering identity	NS	278	1	3
[59]	Motivational constructs: Socialization, sense of belonging, harassment and others	NS	12	9	1
[60]	Psychological factors: Person-thing orientation	NS	383	1	NS
[61]	Psychological factors: Gender-biased self-evaluations	NS	383	1	NS
[62]	Psychological factors: Self-perceptions of resilience, grit, and persistence	NS	167	1	NS

\*D=Direct indicator, I=Indirect indicator, NS=Not specified, ND=Not difference. F\* =Female significance

motivational [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59]),

and psychological indicators ([60], [61], [62]). While most report no significant gender differences, some identify

patterns suggesting higher risk among women or men. However, these patterns refer to potential predictors rather than confirmed dropout behavior, and the strength of their association with dropout is often grounded in prior literature and may vary by context.

Most dropout studies—whether using direct or inferred measures—are based on single institutions and seldom provide disaggregated analyses by engineering discipline. These limitations, also noted in prior reviews [15], often stem from restricted access to longitudinal student data due to ethical and legal constraints such as General Data Protection Regulation.

In addition to the literature review results on gender-related dropout among first-year engineering students, various interventions have been proposed to address gender barriers in this field. These include gender-targeted housing initiatives [63], comprehensive academic support programs [64], peer-led learning strategies [65], and the enhancement of spatial skills, which have been linked to dropout and exhibit gender differences [66]. These initiatives are grounded in the assumption of a gender gap in engineering persistence, the existence of which, specifically in first-year engineering dropout, is examined in this study. Additionally, many gender-focused studies address broader underrepresented populations, such as Latinx students [67], rural students [68], or those experiencing microaggressions [69], [70], often reporting indirect associations between these factors, gender, and dropout.

Psychosocial factors play a crucial role in engineering dropout more broadly and justify the need for context-sensitive, gender-informed analyses—an aspect often overlooked in general studies. A Chilean study [71] found that female students tend to become more risk-averse after poor academic outcomes. A Central European study [72] found that high-achieving women may still drop out due to the “ironic threat” effect, where good grades reduce self-criticism but increase social discomfort and disidentification—especially among those with low self-expectations. In Spain, qualitative research [73] comparing women who dropped out, men who dropped out, and women who persisted revealed that non-persistence is often linked to hostile classroom environments, excessive academic demands, lack of female role models, and perceived misalignment with traditional gender roles. These findings highlight psychological pressure and social integration challenges as key drivers of female attrition, beyond academic ability. Finally, a 40-year longitudinal study in California [74] showed that the factors influencing students’ intention to pursue engineering have evolved significantly over time, challenging the notion of a static engineering student profile and highlighting the shifting nature of gendered experiences in the field.

Given these diverse and context-dependent findings, the relationship between gender and first-year dropout in engineering remains inconclusive. This study contributes to clarifying this issue by analyzing administrative enrollment

data from two universities across five distinct engineering disciplines. Dropout is directly measured as non-enrollment in the second academic year, and gender is examined as a potential causal factor while controlling for multiple covariates.

## **B. PROPENSITY SCORE MATCHING AND GENDER EQUITY IN HIGHER EDUCATION**

Several studies have utilized machine learning techniques to explore the impact of gender on academic dropout rates in engineering degrees [75]. Likewise, research in other fields [76] has emphasized the importance of considering equity metrics when evaluating predictive models, particularly when analyzing groups defined by gender. To prevent artificial intelligence tools from exacerbating existing inequalities—especially in sensitive fields such as STEM—it is recommended to conduct stratified analyses and employ predictive parity metrics [77]. Given that most of these studies utilize observational data, careful consideration of confounding biases that may affect these estimations is necessary [78].

In this context, Propensity Score (PS) methods offer robust solutions by condensing multiple covariates into a single score that allows for balancing comparable groups [79]. Among these techniques, Propensity Score Matching (PSM) stands out, being especially useful when randomized controlled trials are not feasible due to ethical or logistical constraints [80]. The PSM method has well-established applications in medicine [81], [82], pharmacy [83], and it has recently been applied to analyze gender-related issues in higher education. For example, the study [84] employed PSM to examine gender-based salary differences in STEM fields in the United States, identifying greater economic benefits for high-performing men, a factor contributing to the underrepresentation of women in these disciplines. Additionally, [85] applied PSM to evaluate women-only learning communities, demonstrating that these significantly reduce dropout rates in STEM disciplines. Recent studies [25], [30] and [86] also utilized PSM-based methods to assess transition programs, integration strategies, and academic advising for engineering students, reporting improvements in retention and academic performance, particularly for women and other underrepresented groups, although [30] found no significant effects specifically related to gender.

Traditionally, gender is included as an explanatory variable within conventional statistical models. However, studies applying PSM treating gender explicitly as a treatment variable are less frequent. The present study proposes precisely this methodological approach, employing PSM to estimate, in a controlled manner, the effect of gender on academic dropout in engineering. According to [87], although the term “treatment” originates from the clinical field, it is also applicable to binary categorical variables such as gender when evaluating their effect on specific outcomes—in this case, academic dropout. This strategy complements traditional logistic analysis and provides additional verification of the

robustness of the findings. Additionally, this study incorporates neural networks (NN), commonly used in educational research [88], with post hoc analyses validated previously in social sciences studies [89]. This approach allows for the interpretation of variable sensitivity and reinforces the consistency of the results. To the best of our knowledge, this is the first study to jointly apply PSM, LR (Logistic Regression), and NN within a multi-model framework to analyze the role of gender in first-year engineering dropout, explicitly treating gender as a treatment variable within the PSM component.

### III. MATERIALS AND METHODS

#### A. DATA AND STUDY DESIGN

This study focuses on analyzing academic dropout rates during the first academic year in five undergraduate engineering degrees offered by two Spanish universities: one public (from academic years 2014/2015 to 2022/2023) and one private (from academic years 2014/2015 to 2021/2022).

The study analyzes academic data from both institutions. For the private university, the project was approved by the Research Ethics Committee of Universidad Pontificia Comillas in accordance with the established procedure. After evaluating the project, the committee issued a favorable opinion, concluding that the research complies with Organic Law 3/2018 on Personal Data Protection and other applicable regulations. The study relied exclusively on academic data that had been irreversibly anonymized prior to their use. These data were provided to the research team by the University's Office of Data Governance and Intelligence (*Oficina de Gobierno e Inteligencia del Dato*) in a format that permanently prevents any form of personal identification. Furthermore, all analyses were conducted using aggregated data, and the results were used solely for academic and research purposes, as outlined in the project's objectives. For the public university UCM (Universidad Complutense de Madrid), the data sets were obtained thanks to an agreement signed by the Institutional Intelligence Center of the UCM and the research group, which contained among its clauses all the requirements to comply with data protection regulations. These datasets were also fully and irreversibly anonymized before being accessed by the research team and were used strictly for academic and scientific purposes. Given the use of fully anonymized and aggregated data in both cases, and the absence of any personally identifiable information, the Research Ethics Committee of Universidad Pontificia Comillas waived the requirement for informed consent. This approach ensures strict compliance with ethical standards in research and guarantees the full protection of participants' rights.

The study sample comprises a total of 3889 students, whose distribution by degree program and gender is detailed in Table 5. The considered degree programs are: Bachelor's in Industrial Technologies Engineering (ITE) and the Double Degree in Industrial Technologies Engineering and Business Administration (ITEBA), both offered by a medium-sized

TABLE 5. Descriptive statistics by degree program and gender.

Degree	N	G	%	Avg.UEE	DR (%)	FR (%)	N-SR(%)
ITE	1737	M	74	8.2	25.5	27.9	7.1
		F	26	8.6	19.9	26.2	5.7
ITEBA	504	M	65	8.7	24.6	15.8	3.6
		F	36	9.0	29.1	15.6	3.6
CE	710	M	52	7.7	29.2	32.2	10.8
		F	48	7.8	24.7	35.0	8.7
MatE	374	M	74	6.7	36.0	29.3	20.0
		F	26	6.8	34.3	28.9	14.8
MathE	564	M	55	8.5	26.1	14.9	9.2
		F	45	8.6	20.5	14.5	9.1

M=MALE, F=FEMALE, DR=DROPOUT

private university; and Bachelor's in Chemical Engineering (CE), Bachelor's in Mathematical Engineering (MathE), and Bachelor's in Materials Engineering (MatE), offered by a large public university. These degrees represent different orientations within engineering, varying levels of mathematical rigor, and distinct institutional contexts, enabling a broader and more robust comparative analysis of academic dropout with a gender perspective.

The primary objective of this study is to analyze the relationship between gender and academic dropout in engineering degrees, distinguishing two critical moments during the first year: the Start (S) and the End (E). This dual perspective allows examining, on the one hand, students' initial conditions upon university entry, and on the other, their academic performance progression throughout the first year. For the analysis corresponding to the beginning of the academic year, two main predictive variables have been considered: the student's gender (Female, F) and the university entrance examination score (UEE), known in Spain as the "*Prueba de Acceso a la Universidad*" (PAU). These variables reflect characteristics prior to university enrollment. At the end-of-year analysis, the model also incorporates variables related to academic performance achieved in the first examination session: the failure rate (FR), defined as the percentage of failed subjects, and the non-show rate (N-SR), understood as the percentage of subjects in which the student did not attend the exam during that session. Both variables are based on performance during the initial scheduled exam session (first sitting). The dependent variable in all models is academic dropout, operationally defined as the student not enrolling in the second academic year, neither to progress nor to repeat the first year. This definition allows objective and homogeneous identification of dropout cases within a consistent temporal framework.

#### B. METHODOLOGY

To analyze the relationship between gender and academic dropout, a multi-model strategy combining classical statistical techniques with advanced machine learning approaches

was employed. The role of gender was studied using three complementary analytical methods: as a direct predictor variable in a logistic regression model, as a treatment variable in a PSM analysis, and as a variable for sensitivity analysis in predictive models based on NN with post-hoc analyses [90]. This methodological triangulation allows controlled evaluation of gender's influence on academic dropout. Dropout is consistently defined here as non-enrollment in the second academic year. Other terms that appear in the discussion, such as academic redirection, non-submission, or disengagement, are treated as explanatory mechanisms or related behaviors, not as alternative definitions. Specific versions of the models within these three methodological approaches were tailored for each phase of the study (Start and End).

To account for differences in admissions profiles, curricula, and gender distributions across programs, all analyses were conducted independently for each undergraduate degree: ITE, ITEBA, CE, MatE, and MathE. This disaggregation was applied consistently across all three methodological approaches—LR, PSM, NN—to ensure that potential degree-specific patterns, including gender effects, were properly captured without aggregation bias.

Firstly, LR was employed, chosen for its interpretability and frequent use in educational research [91], allowing estimation of the probability of academic dropout and interpretation of the magnitude and direction of effects for each explanatory variable. Secondly, a PSM analysis was implemented, considering being female as a treatment condition. The matching method used was nearest neighbor matching without replacement. Balance between matched groups was subsequently evaluated to ensure comparability of covariates after matching implementation. This analysis was conducted using the R statistical environment, following methodological recommendations from previous literature [87]. The third modeling approach consisted of a supervised predictive model based on a feedforward neural network, trained using K-fold cross-validation. Model optimization was performed through a grid search, varying both the number of neurons in the hidden layer and the regularization parameter (decay). The optimal hyperparameters were determined independently for each degree program as follows: for ITE, 3 neurons with 0.1 decay at the start and 2 neurons with 0.01 decay at the end; for ITEBA, 2 neurons with 0.001 decay at the start and 1 neuron with 0.00001 decay at the end; for CE, 4 neurons with 1 decay at the start and 2 neurons with 0.01 decay at the end; for MathE, 1 neuron with 0.1 decay at the start and 1 neuron with 1 decay at the end; and for MatE, 4 neurons with 0.01 decay at the start and 2 neurons with 0.1 decay at the end. To interpret NN results, post-hoc analysis using the NeuralSens tool [90], was applied, providing mean sensitivity (MS), standard deviation (SD), and mean squared sensitivity (MSQ) for each predictor variable. The combination of these three approaches (LR, PSM, and NN with post-hoc analysis) constitutes a robust methodology for assessing gender's influence on academic dropout in engineering degrees.

#### IV. RESULTS

The following results from the Logit, PSM, and NN models are structured according to the three proposed hypotheses. Detailed information is available in Table 6.

Regarding H1, the coefficients associated with the variable gender (F) are not statistically significant in all degree programs nor across any of the applied methods. However, in the analysis corresponding to the MathE degree program, the use of the NeuralSens tool enabled the identification of a significant interaction effect between F and both, FR and N-SR. These interaction effects were detected only in the model estimated at the end of the first academic year and were not present in the initial model. The inclusion of interaction terms notably altered key coefficients in the logit model. The intercept remained at a similar value ( $-1.172$ ,  $p = 2.89 \cdot 10^{-15}$ ), and the effect of F remained largely unchanged ( $-0.422$ ,  $p = 0.0882$ ). However, the coefficient for FR increased to  $0.368$  ( $p = 0.0051$ ), reaching statistical significance, indicating a stronger impact on dropout when accounting for interaction effects. At the same time, the coefficient for N-SR slightly decreased to  $0.904$  ( $p = 5.73 \cdot 10^{-9}$ ) but remained a robust predictor. The interaction model revealed two moderating effects associated with gender. First, the FR\*F interaction showed a coefficient of  $-0.637$  ( $p = 0.0157$ ), indicating that the impact in dropout of FR is significantly lower for female students compared to their male counterparts. Second, the N-SR\*F interaction yielded a positive coefficient of  $0.739$  ( $p = 0.0139$ ), suggesting that the effect in dropout of non-show rate is more pronounced among women. In other words, although N-SR is generally a strong predictor of dropout, its impact is amplified for female students. As a conclusion, overall, and except for the MathE degree program mentioned above, the results indicate no significant gender differences in dropout rates during the first year in any of the analyzed degrees.

In relation to H2, the PSM approach does not substantially alter the magnitude or direction of the coefficients associated with F compared to the LR. Across all degrees and time points, the coefficients obtained using PSM for F are like those from the LR and remain statistically non-significant. This confirms that gender's effect remains non-significant, even after balancing covariates—highlighting the consistency of the Logit-based findings.

When testing H3, the results indicate that academic variables do not behave homogeneously throughout the first academic year. While F consistently shows a lack of significance across all models and degrees, the UEE variable exhibits temporal variation in its predictive capacity regarding dropout. UEE is significant at the beginning of the academic year in all programs except ITEBA, with negative coefficients and p-values  $< 0.01$  in both LR and PSM models. This suggests that higher entrance scores are associated with lower dropout probability during early course stages. However, by the end of the year, UEE loses relevance in most degrees, and its statistical significance diminishes.

TABLE 6. Student dropout by degree program: Logit, PSM and neural networks.

	Coef	Logit			PSM			NN Sens			
		Est	Est	p-val	Est	Est	p-val	Mean	SD	MSQ	
ITE	S	Int.	-1.341	<2e-16	***	-1.30	<2e-16	***	0.010	0.004	0.011
		F	0.075	6e-01	.	0.03	8e-01	.			
		UEE	-0.884	<2e-16	***	-0.83	<2e-16	***			
	E	Int.	-2.348	<2e-16	***	-2.41	<2e-16	***	-0.016	0.094	0.095
		F	-0.165	4e-01	.	-0.08	7e-01	.			
		UEE	-0.185	3e-02	*	-0.26	4e-02	*			
FR		1.970	<2e-16	***	1.91	<2e-16	***				
N-SR	1.528	<2e-16	***	1.52	<2e-16	***	0.184	0.333	0.381		
ITEBA	S	Int.	-1.123	<2e-16	***	-1.10	3e-10	***	0.112	0.232	0.258
		F	0.236	3e-01	.	0.23	3e-01	.			
		UEE	-0.027	8e-01	.	-0.05	7e-01	.			
	E	Int.	-1.198	<2e-16	***	-1.39	3e-11	***	-0.013	0.009	0.016
		F	0.150	5e-01	.	0.32	2e-01	.			
		UEE	0.452	1e-03	**	0.60	2e-03	**			
FR		0.578	3e-07	***	0.62	2e-05	***				
N-SR	0.780	2e-07	***	0.95	2e-06	***	0.079	0.054	0.097		
CE	S	Int.	-0.942	2e-15	***	-0.98	9e-15	***	-0.147	0.016	0.148
		F	-0.205	2e-01	.	-0.19	3e-01	.			
		UEE	-0.453	3e-07	***	-0.43	8e-06	***			
	E	Int.	-1.164	1e-12	***	-1.10	2e-10	***	-0.257	0.255	0.361
		F	-0.215	3e-01	.	-0.27	2e-01	.			
		UEE	-0.105	4e-01	.	-0.15	3e-01	.			
FR		0.685	2e-08	***	0.67	5e-07	***				
N-SR	1.814	<2e-16	***	1.74	<2e-16	***	0.877	0.864	1.231		
MatE	S	Int.	-0.605	2e-06	***	-0.65	2e-03	**	0.043	0.447	0.448
		F	-0.022	9e-01	.	0.00	1e+00	.			
		UEE	-0.322	6e-03	**	-0.27	9e-02	.			
	E	Int.	-0.855	2e-07	***	-0.72	1e-02	*	0.275	0.234	0.361
		F	0.330	3e-01	.	0.22	6e-01	.			
		UEE	-0.016	9e-01	.	-0.08	7e-01	.			
FR		0.770	2e-07	***	0.74	4e-04	***				
N-SR	1.467	<2e-16	***	1.76	9e-09	***	0.692	0.401	0.800		
MathE	S	Int.	-1.071	3e-16	***	-1.00	3e-12	***	-0.258	0.092	0.274
		F	-0.281	2e-01	.	-0.33	1e-01	.			
		UEE	-0.275	4e-03	**	-0.25	2e-02	*			
	E	Int.	-1.143	3e-14	***	-1.15	10e-12	***	-0.244	0.127	0.275
		F	-0.421	7e-02	.	-0.43	9e-02	.			
		UEE	0.001	1e+00	.	-0.05	7e-01	.			
FR		0.189	9E-02	.	0.18	1e-01	.				
N-SR	1.152	<2E-16	***	1.12	5e-14	***	0.182	0.095	0.205		
							0.581	0.303	0.655		

Signif. codes: '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
S = Start / E = End

For example, in CE (E), the estimated coefficient for UEE in the Logit model is -0.11 with a p-value of 0.40. By comparison, FR and N-SR stand out as the strongest predictors of academic dropout at the end of the first year. Both indicators show positive, large, and highly significant coefficients ( $p < 0.001$ ) across all degrees and models. Moreover, the NN models also reflect high sensitivity values for these variables. For example, in CE (E), the variable N-SR reaches a Logit coefficient of 1.814, with a mean sensitivity in NN of 1.236. This confirms that F has no influence on dropout, with near-zero coefficients, high p-values, and low NN sensitivity throughout. The academic relevance of UEE declines over time: although a significant predictor early on—especially in ITE, CE, MatE, and MathE—its statistical impact weakens notably by year-end. Finally, although the neural network models produced consistent results across most degree programs, an exception was observed in ITEBA. In this case, the model showed a limited ability to fit the data, especially toward the end of the academic year.

V. DISCUSSION

Regarding the effect of gender (H1 and H2), the obtained results indicate that gender is not a significant factor in predicting academic dropout in any of the analyzed degree programs or institutional contexts. This finding is robust, remaining consistent after applying PSM. In this line, recent studies such as the one conducted in Egypt [92] include gender among the variables for which the literature shows varied perspectives and a lack of consensus regarding its role as a key success factor in the first year. Notably, in that context, characterized by a different institutional and geographical setting and a distinct methodological approach, gender was likewise not identified as a significant contributor to student success.

Our finding is also consistent with previous studies conducted in Spain [23], in Colorado [19], in Texas [20], in Arkansas [24], along with [21] and [93] in Portugal—although the latter reports aggregated results across STEM fields. Among these, only the Spanish study [23] uses a definition of dropout comparable to ours, based on

non-enrollment in the second academic year of the same degree program.

However, our findings contrast with studies conducted in Latvia [94], Kosovo [27], Malaysia [28]—limited to specific engineering branches—and Spain [29], which reported higher dropout rates among male students. In contrast, research from other international contexts, such as the United States, [18] and [26], identified female gender as a factor associated with increased dropout risk. Notably, the study in [26] was based on a large, longitudinal sample covering multiple institutions and disciplines. In such contexts, gender effects may emerge at later stages or under institutional conditions. Given the structural differences across educational systems, caution is needed when generalizing the absence of gender effects to other settings.

A considerable number of studies, as shown in Table 4, do not examine academic dropout directly but instead focus on indirect indicators—such as persistence intentions, course performance, or program satisfaction. This is often due to ethical, legal, or technical barriers that limit access to comprehensive administrative records. In this regard, the present study offers a valuable contribution by using verified administrative records of enrollment and academic performance, providing a direct and objective measure of dropout. Moreover, including degree programs from both public and private institutions of different sizes adds diversity to the sample and reinforces the external validity of the findings, that is, gender has no effect on dropout. However, an exception to this general pattern was found in the MathE program, where interaction effects involving gender emerged at the end of the first academic year. In this case, gender moderated the relationship between specific types of academic failure and dropout: FR had a weaker impact on dropout risk for women, whereas the N-SR had a stronger negative effect. These interactions—FR\*F and N-SR\*F—suggest that, while gender is not a significant predictor on its own, it can influence how academic difficulties translate into dropout risk. This pattern, observed only in MathE and absent from the other engineering degrees analyzed, underscores the importance of modeling conditional rather than main effects. It suggests that gender-related differences may only emerge in specific academic contexts. This finding is consistent with a large-scale study [10] covering 19 universities and 33 engineering disciplines, which reported similar overall persistence rates between genders, but discipline-level differences in the first year. Women in computer and computational engineering showed lower “stickiness,” while gender gaps were smaller or reversed in fields like chemical, civil, or mechanical engineering. The study also noted the influence of performance in introductory math and science courses—especially for women with lower grades—highlighting the need to account for interactions between academic and sociodemographic factors when analyzing attrition.

About H3, the findings show that the predictive capacity of the variables changes notably over the course of the first academic year. While gender consistently lacks statistical

significance throughout the period analyzed, academic variables display a dynamic evolution in their predictive power. Early in the year, the UEE score stands out as a relevant indicator, negatively associated with dropout—suggesting that students with higher entrance scores are less likely to withdraw at initial stages. However, as the academic year progresses, the influence of UEE weakens, and cumulative academic performance becomes increasingly relevant in explaining student persistence. This perspective refines previous contributions such as [76], which highlighted the role of prior academic background, and complements studies like [95] where pre-semester data are valued for developing early warning systems. Considering our results, while entrance scores may offer a useful early indication of risk, it is the student’s academic trajectory during the first year that ultimately provides the strongest signal for identifying potential dropout. This finding aligns with studies such as [96], which highlight the importance of continuous monitoring—from enrollment through each semester—to better understand dropout dynamics.

An exception to the general trend was observed in the ITEBA program, where a positive association between UEE scores and dropout emerged—an unexpected result given the typical protective role of entrance scores. In this case, the neural network showed a weaker fit than in the other programs, with marked difficulties in achieving satisfactory output convergence toward the end of the academic year. This limitation is likely related to the sample size, as neural networks tend to reach their limits with relatively small datasets, which constrains the robustness of the conclusions for ITEBA. It should also be noted that the pattern may be linked to the program’s high academic entry thresholds: students with stronger academic profiles are more likely to have alternative educational or professional opportunities and may voluntarily redirect their academic paths, which in practice often translates into not enrolling in the second academic year of the same degree program. This underscores the importance of considering academic redirection [20]—not only academic failure—when interpreting dropout behavior particularly in programs that attract high-achieving students. Recent literature reviews on engineering student dropout confirm a growing interest in this field [97], but according to our research we also emphasize the critical importance of clearly defining what constitutes dropout, to compare results. The interpretation of results can vary widely depending on the definition of dropout adopted. It may refer to leaving during the first year, failing to enroll in the second year, withdrawing at any point across the full duration of the degree, non-completion, a change of specialization within engineering, a switch to a non-engineering program, or a complete departure from university. Each of these definitions captures different dimensions of student trajectories and failing to distinguish among them can lead to misleading or contradictory conclusions.

On the other hand, the decisive importance of recent academic performance as a dropout predictor aligns with prior research. For instance, [75], reported significant predictive

TABLE 7. QGS list of studies.

Ref	Title
[22]	Analysis of first-year university student dropout through machine learning models: A comparison between universities
[27]	Analysis of the Student Dropout Rate at the Faculty of Electrical and Computer Engineering of the University of Prishtina, Kosovo, From 2001 to 2015
[50]	Assessing engineering students' mathematics self-efficacy and mathematics anxiety levels in Latino contexts
[30]	Data Analytics and STEM Student Success: The Impact of Predictive Analytics-Informed Academic Advising Among Undeclared First-Year Engineering Students
[62]	Differences in the Self-Perceptions of Resilience, Grit, and Persistence among First-Year Engineering Undergraduates
[54]	Effects of a first-year undergraduate engineering design course: survey study of implications for student self-efficacy and professional skills, with focus on gender/sex and race/ethnicity
[23]	Effects of pre-college variables and first-year engineering students' experiences on academic achievement and retention: a structural model.
[25]	Examining the impact of the engineering successful/unsuccessful grading (SUG) program on student retention: A propensity score analysis
[19]	Longitudinal Study of Engineering Student Persistence at the University of Colorado
	Multi-Institution Study of Student Demographics and Outcomes in Electrical and Computer Engineering in the USA
[24]	Predicting Engineering Student Attrition Risk Using a Probabilistic Neural Network and Comparing Results with a Backpropagation Neural Network and Logistic Regression
[20]	Predicting Persistence in Engineering through an Engineering Identity Scale
[29]	The better performance and higher retention rates of women in electrical engineering studies
[36]	The Effect of Gateway Course Completion on Freshman College Student Retention
[33]	The multiplicative function of expectancy and value in predicting engineering students' choice, persistence, and performance
[37]	The potential of Supplemental Instruction in engineering education – helping new students to adjust to and succeed in University studies
[48]	University-elementary school partnerships: Analyzing the impact of a service-learning freshman engineering course on students' engineering values and competence beliefs

accuracy improvement when including first-semester academic data compared to models solely based on pre-entry data. Similarly, [22] found that failure rates, particularly those related to low mathematics scores, are associated with dropout probability during the first year in engineering degrees. Likewise, [23] acknowledges the role of pre-university preparation but emphasizes that first-year academic performance is the true determinant of student retention. From complementary perspectives, [98], in a Russian context, concludes that academic integration during early semesters is key to preventing dropout, thus supporting the observed relevance of early engagement indicators—which, in our study, may be represented by FR and N-SR—as measures of student engagement levels. Additionally, a Chilean study [99] significantly differentiates between formal and informal dropout, highlighting the importance of early behaviors such as absence from classes or assessments, which anticipate institutional disengagement. This aligns with findings from studies that explore students' perspectives on dropout. For example, [100] reports that 46% of engineering students surveyed acknowledged having considered dropping out at some point, with the main reasons being academic difficulty and poor performance—factors that resonate with the objective indicators analyzed in our study, such as FR and N-SR.

Finally, notable differences emerge depending on the institutional context, although the patterns are not entirely

clear-cut. In the private university analyzed, FR exerts a particularly strong influence on dropout, as seen in ITE, although N-SR also contributes substantially. In the public university, N-SR consistently shows a strong predictive role across all programs, yet failure rates also remain relevant in some cases. These findings suggest that dropout dynamics are shaped not only by academic performance but also by institutional context and student profiles. In the private university, attrition tends to follow from clear instances of academic failure, reflecting the weight of performance expectations. In the public university, by contrast, dropout is more systematically associated with N-SR patterns, which may reflect gradual disengagement and delayed withdrawal rather than immediate failure, although academic failure also remains relevant in certain programs. Overall, these results suggest that while institutional context shapes dropout dynamics, the relationship between FR, N-SR, and dropout is more nuanced than a simple public–private divide.

## VI. CONCLUSION AND FUTURE WORK

The results allow several conclusions. Firstly, gender does not appear as a significant predictor of academic dropout during the first year, neither at the beginning nor the end, and this finding remains consistent even after balancing covariates using PSM. This supports the robustness of the result across the studied contexts.

TABLE 8. Adapted search strings and results by database.

Database	Search String (Adapted)	Search Level	Found	Included	In OGS
Google Scholar	"(dropout" OR "attrition" OR "retention" OR "persistence") AND ("first-year" OR "freshmen" OR "first year") AND ("higher education" OR "university" OR "college" ) AND ("gender" OR "women" OR "female" OR "sex") AND "engineering""	Full text	100	12	9
Web of Science	"TS=("engineering") AND TS=("first-year" OR "first year" OR "freshman" OR "freshmen" OR "early-stage") AND TS=("gender" OR "female" OR "women" OR "sex") AND TS=("dropout" OR "attrition" OR "retention" OR "persistence" OR "withdrawal")"	Topic (Title, Abstract, Keywords)	123	32	12
Scopus	TITLE-ABS-KEY ( "engineering" ) AND TITLE-ABS-KEY ( "first-year" OR "first year" OR "freshman" OR "freshmen" OR "early-stage" ) AND TITLE-ABS-KEY ( "gender" OR "female" OR "women" OR "sex" ) AND TITLE-ABS-KEY ( "dropout" OR "attrition" OR "retention" OR "persistence" OR "withdrawal" )	Title, Abstract, Keywords	89	25	9
IEEE Xplore	("All Metadata": "engineering") AND ("All Metadata": "first-year" OR "All Metadata": "first year" OR "All Metadata": "freshman" OR "All Metadata": "freshmen" OR "All Metadata": "early-stage") AND ("All Metadata": "gender" OR "All Metadata": "female" OR "All Metadata": "women" OR "All Metadata": "sex") AND ("All Metadata": "dropout" OR "All Metadata": "attrition" OR "All Metadata": "retention" OR "All Metadata": "persistence" OR "All Metadata": "withdrawal")	All metadata	4	3	3
ScienceDirect	("first year" ) AND ("gender" OR "female" OR "women") AND ("dropout" OR "attrition" OR "persistence" OR "retention" ) AND (" engineering")	Title, Abstract, Keywords	8	4	1
SpringerLink	( "first-year engineering" OR "first year engineering" OR "freshman engineering" OR "freshmen engineering" OR "early-stage engineering" ) AND ( "gender" OR "female" OR "women" OR "sex" ) AND ( "dropout" OR "attrition" OR "retention" OR "persistence" OR "withdrawal" )	Full-text adapted	86	4	1
ACM Digital Library	[Abstract: 'engineering'] AND [[Abstract: 'first-year'] OR [Abstract: 'first year'] OR [Abstract: 'freshman'] OR [Abstract: 'freshmen'] OR [Abstract: 'early-stage']] AND [[Abstract: 'gender'] OR [Abstract: 'female'] OR [Abstract: 'women'] OR [Abstract: 'sex']] AND [[All: 'dropout'] OR [All: 'attrition'] OR [All: 'retention'] OR [All: 'persistence'] OR [All: 'withdrawal']]	Abstract + full-text adapted	6	0	0

Secondly, there is a clear shift in the relevance of academic predictors over the course of the year. The analysis also reveals institutional differences. That means that rather than broad gender-based measures, institutions should focus on early and continuous monitoring of academic indicators such as FR and N-SR. While gender is generally not decisive, the specific interaction detected in MathE highlights the importance of considering it in targeted contexts.

Future research should aim to extend the temporal and institutional scope by incorporating data from additional universities, both national and international. It would also be valuable to explore dropout more deeply, using N-SR as an early warning sign of disengagement, and to distinguish between permanent dropout and redirection to other programs or degrees. Finally, future work could examine whether gender continues to be non-significant in later years and through degree completion, and whether, within certain performance ranges, it might act as a proxy for resilience or vulnerability in engineering compared to other fields.

APPENDIX

See Tables 7 and 8.

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