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Relevant factors in the decision to desert of engineering students in the context of emerging economies

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Introduction: Early dropout from engineering programs is a major concern for higher education institutions (HEIs) in emerging economies. Understanding the factors that influence students' decisions to abandon their studies is essential for designing effective retention strategies.

Methods: This study uses a quantitative approach through Partial Least Squares Structural Equation Modeling (PLS-SEM), based on the Spady model. A survey was conducted with 190 engineering students from a private university in Medellín, Colombia.

Results: The analysis revealed that academic and emotional support significantly influence students' decisions to continue their studies. Institutional commitment and structured support mechanisms provided by HEIs emerged as critical determinants of student retention.

Discussion: The findings underscore the importance of implementing university welfare strategies aimed at strengthening students' academic and emotional well-being. These strategies serve as key levers to reduce dropout rates and reinforce the role of HEIs in supporting engineering students throughout their educational trajectory.

KEYWORDS

student dropout, dropout, engineering students, emerging economy, Spady model

1 Introduction

The retention of students is a crucial concern for universities, as it is evaluated by government agencies and international organizations to ensure the academic quality of these institutions. Dropout rates have become a pervasive issue affecting a majority of higher education institutions (HEIs) worldwide (Alban and Mauricio, 2018).

Students may drop out of education for various reasons, such as academic challenges, social pressures, economic constraints, and psychological factors. This phenomenon has far-reaching implications, not only for the students themselves but also for their families and the HEIs they attend. Student attrition is a significant issue for HEIs due to the drain on resources it represents. In regions like Latin America, where resources may be limited, student attrition is particularly problematic. This situation intensifies inequalities and exacerbates the barriers that vulnerable students face (Vila et al., 2019). As Cerpa (2015) elucidates, one of the primary obstacles confronting the Sistema de Educación Superior Colombiano is the high rate of undergraduate academic dropouts. This challenge is particularly noteworthy given the recent surge in higher education enrollment in the country.

Garzón and Pérez (2012) propose that student attrition can be attributed to various factors, including financial costs, program types, students' biographical and social backgrounds, as well as the perceived value of education and educational qualifications. In response to these factors, Colombia has implemented the System for the Prevention of Student Attrition in Higher Education (SPADIES). SPADIES assesses and classifies the risk of student attrition at educational institutions (Suárez-Montes and Díaz-Subieta, 2015). This demonstrates the government's commitment to reducing higher education dropout rates.

Engineering programs have the highest rates of student attrition. The need for increased attention and the development of targeted strategies to reduce dropout rates among early-level students is emphasized by the most pronounced attrition during the initial semesters (Cerpa, 2015). According to the Ministerio de Educación Nacional – MEN (2022), the annual student attrition rate for university programs was 8.79% in 2018. Technological programs had a rate of 10.75%, and professional technical programs exhibited a rate as high as 17.41%. These figures have increased due to the global state of emergency caused by COVID-19 (Rincon et al., 2020).

Additionally, recent research shows that dropout rates in engineering programs are influenced not only by academic and economic factors but also by psychological pressure and a specific culture of stress within these fields (Mirabelli et al., 2025). This stressful environment, characterized by high demands and expectations, can negatively impact students' wellbeing and motivation, increasing their vulnerability to academic abandonment. Therefore, understanding the psychosocial dimension of the student experience in engineering is essential to developing comprehensive interventions that promote retention and academic success.

Furthermore, analyzing contextual and structural factors is crucial, especially in developing countries where resource limitations and unequal access to institutional support exacerbate the dropout problem (Kocsis and Molnár, 2025). In this regard, studies like this one are vital to provide local evidence that can inform educational policies tailored to the specific realities of each institution and region, thereby contributing to improved retention and graduation rates in high-demand and socially relevant programs such as engineering.

Therefore, it is crucial to identify the relevant factors that contribute to student attrition in engineering programs. This is essential for developing effective strategies to reduce the frequency of this issue in Colombia (Cerpa, 2015). With this objective in mind, this research aims to identify the most significant factors that influence the decision of engineering students to drop out at the Corporación Universitaria Americana - CUA on its Medellín campus in Colombia.

2 Theoretical framework

In higher education, attrition refers to a student's decision to withdraw from their academic program (Maldonado et al., 2021). There are five main approaches to analyzing student attrition, each offering explanatory variables to understand the underlying causes. These approaches include the psychological, economic, sociological, organizational, and interactional perspectives, as explained by Himmel (2002). These categories can be grouped into three overarching clusters: personal, family, and institutional characteristics (Donoso and Schiefelbein, 2007). Models have been developed to comprehensively elucidate student attrition as a multidimensional phenomenon.

The organizational category is closely related to the college or university. According to Díaz (2009), pre-university characteristics intersect in this category and significantly affect students' initial commitment to the institution and academic goals. Students' perceptions depend on their level of academic and social integration with the institution. In this ongoing process, the institution's commitment depends on a positive perception, which encourages the student to continue their educational journey within the program and institution (Donoso and Schiefelbein, 2007).

Interaction involves a student's constructive relationship with both peers and faculty, fostering opportunities for engagement that provide support and motivation. Within this framework of social integration, students reconsider the possibility of abandoning their academic pursuits. This interaction is closely linked to the concept of academic integration and is complemented by informal interpersonal relationships that help to cultivate academic confidence. As a result, their commitment to the institution is strengthened (Pineda-Báez and Ortíz, 2009).

The sociological literature offers a comprehensive framework for comprehending the attrition process (Maldonado et al., 2021). Significant factors have been identified within this category, including social integration, family environment, university integration, normative consistency, institutional commitment, and peer support (Jorquera et al., 2018). Furthermore, in addition to psychological factors, other external elements have been identified, such as academic and social integration, gender, socioeconomic status, program quality, and average academic performance for each semester (Díaz, 2009; Spady, 1971).

The turnover phenomenon has been studied through the psychological approach, which examines the personality traits of individuals. Scholars, such as Fishbein and Ajzen (1975), have presented a perspective rooted in beliefs and attitudes. Accordingly, factors such as perceived usefulness, perceived ease of use, subjective norms, and attitude help explain their influence on the intention to withdraw from an academic program (Ramírez-Correa and Grandón, 2018). In addition, Jorquera et al. (2018) identified additional factors such as achievement behavior, academic self-concept, perceived difficulty of study, and level of aspiration.

Attinasi (1989) expanded the model to enhance our understanding of pre- and post-enrollment attitudinal patterns and behaviors, allowing for a more comprehensive analysis of attrition in terms of students' evaluations of their post-enrollment college experience (Himmel, 2002). The study of attrition has continued to evolve. Ethington (1990) developed a more sophisticated framework that incorporated performance behaviors, such as persistence, choice, and achievement. Additionally, the framework included elements such as family support and encouragement, as well as values and expectations of success (Donoso and Schiefelbein, 2007).

The Spady model, developed by Spady (1971) (Figure 1), is one of the most widely accepted models for analyzing college student attrition. The researcher drew inspiration from Durkheim's study of the principles of suicide and identified parallels that could be applied to the phenomenon of dropping out. Both studies emphasize that the decision to drop out is not only influenced by individual factors but also involves

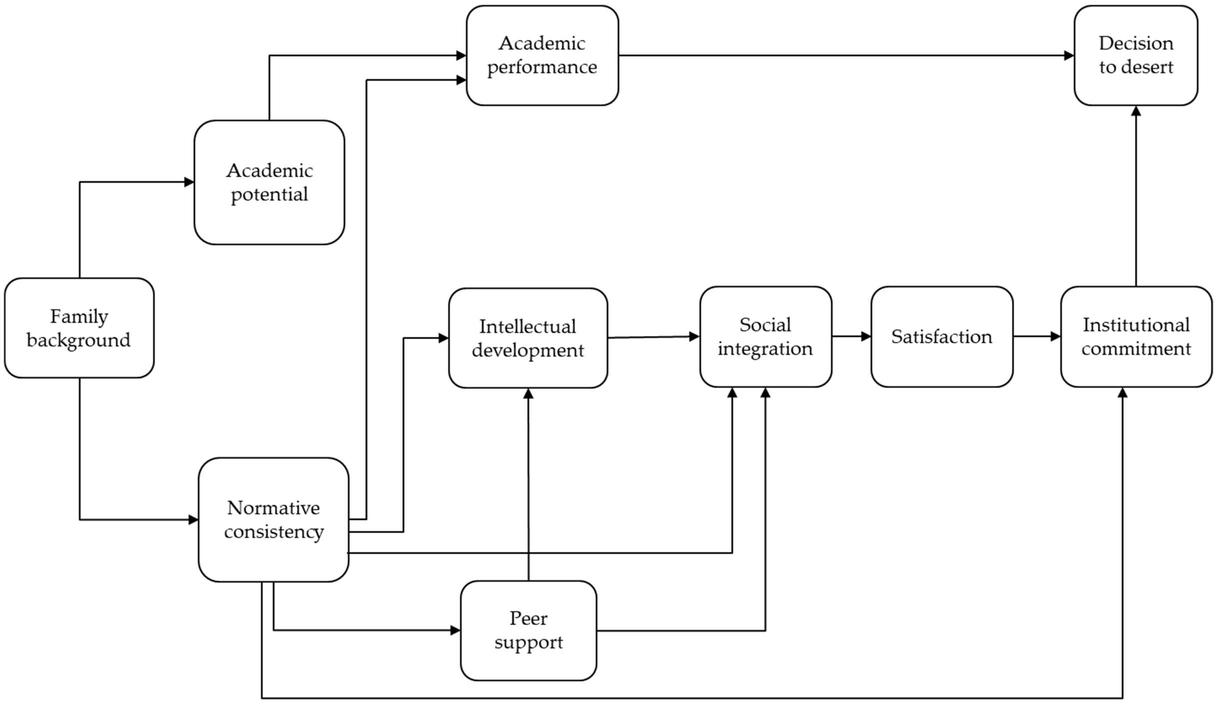

FIGURE 1
Spady model (Spady, 1971).

an individual's disengagement from their social system. Therefore, this phenomenon can be better understood as a result of the difficulties encountered when integrating into society (Vásquez and Miranda, 2019).

Although several models have been proposed to analyze student attrition-such as the model proposed by Tinto (1975, 1994), the model proposed by Bean (1980), as well as the model proposed by Pascarella and Terenzini (1980), the integrated model of Cabrera et al. (1993), and the retention formula of Seidman (2005)—this study adopts Spady's model (Spady, 1971) because of its emphasis on the interaction between academic, social, and personal factors. This model provides a fundamental structure particularly suited to the multidimensional context of attrition in engineering programs in emerging economies. However, future research could benefit from comparative analyses using more contemporary or integrative models.

2.1 Family background

According to Spady (1971), a student's decision to drop out of an academic program can be influenced by their family environment. The family environment can affect a student's social integration, relationships with the institution, peers, and teachers due to various influences, expectations, and demands. This cumulative effect ultimately leads to better integration into the university environment, which improves student retention (Himmel, 2002). The study identified predictors of student attrition mainly rooted in the early stages of students' university life, typically within the first 2 years (Björklund and Salvanes, 2011). Therefore, the following research hypothesis is formulated:

> *H1*: The academic potential of an individual is directly influenced by their family background.

> *H2*: Normative consistency is also directly affected by family background.

2.2 Academic potential

Academic potential refers to a college student's abilities and expected future performance that has not yet been demonstrated or anticipated. This concept illustrates the extent to which students believe they possess qualities that will enable them to develop skills and abilities in the academic field in the future (Akin and Akin, 2016). According to Mori Sánchez (2012), as students progress in their academic programs, the potential or shortcomings of their study plan become more apparent. As a result, students evaluate learning spaces more rigorously, especially due to the increased access they have in the labor market. This may have an impact on students' academic performance. Therefore, the following hypothesis is proposed:

> *H3*: Academic potential has a direct effect on academic performance.

2.3 Normative consistency

In this context, normative consistency refers to the motivation behind students' choice of a topic (Georg, 2009). It has been noted that this regulation involves coherence and compliance with social norms. Students' participation involves alignment with the social norm that is considered compatible with their motivations (Borden, 1988). Therefore, in the context of the Spady model, it refers to the level of compatibility between students' dispositions, interests, attitudes, and expectations and the behaviors, expectations, and demands they may encounter through interactions with various individuals in the university environment (Borden, 1987). The model proposes that normative consistency has an impact on academic performance, social integration, intellectual development, institutional commitment, and the student's integration with peers. As a result, the following research hypotheses are suggested:

> *H4*: Normative consistency has a direct effect on academic achievement.
>
> *H5*: Normative consistency has a direct effect on intellectual development.
>
> *H6*: Normative consistency has a direct effect on social integration.
>
> *H7*: Normative consistency has a direct effect on peer support.
>
> *H8*: Normative consistency has a direct effect on institutional commitment.

2.4 Peer support

According to the study conducted by Valencia-Arias et al. (2023), peer support assesses students' satisfaction with teachers' teaching methods. As outlined by John et al. (2018), peer support involves providing understanding and care to someone in an empathetic manner through the exchange of emotional and psychological experiences. It serves as a system for respectfully giving and receiving help through mutual agreement. In this way, students can establish relationships, nodes, and interactions-whether cognitive, didactic, or social-especially when teachers are not always adequately prepared (Estrada-Molina and Fuentes-Cancell, 2022). According to the Spady model, peer support has a significant impact on academic achievement, intellectual development, and social integration (Hadjar et al., 2023). Therefore, the following hypotheses are proposed:

> *H9*: Peer support has a direct effect on academic achievement.
>
> *H10*: Peer support has a direct effect on intellectual development.
>
> *H11*: Peer support has a direct impact on social integration

2.5 Intellectual development

Intellectual development is a by-product of educational outcomes (Carmo Nicoletti, 2019). Chalela-Naffah et al. (2020) suggest that the effectiveness of higher education institutions can be reflected in intellectual development. This is demonstrated through changes in institutional demands, curriculum flexibility, and academic program credit structure. Intellectual development involves problem-solving, informed decision-making, and understanding complex concepts (Martinez Ruiz et al., 2023). According to Spady's abandonment process model, intellectual development is directly related to social integration (Black, 2023). Based on this correlation, we propose the following hypothesis:

> *H12*: Intellectual development has a direct impact on social integration.

2.6 Academic performance

Academic performance refers to the evaluation of university students' achievements throughout their academic program (Castrillón et al., 2020). Research indicates that academic performance is a crucial predictor of dropout rates (Martínez-Navarro et al., 2021). Therefore, institutions can proactively identify students at risk of dropping out by consistently monitoring their academic performance and implementing early interventions (Ortiz-Lozano et al., 2023). For engineering students, there is evidence that academic performance has a positive effect on their intent to persist, especially during their first year of study (Marschall et al., 2023). Therefore, we propose the following research hypothesis based on this body of evidence.

> *H13*: Academic performance has a direct effect on the decision to desert.

2.7 Social integration

Beyond individual pre-enrollment and background characteristics, students' experiences within higher education institutions are crucial in predicting their decision to drop out. Social integration encompasses the relationships between students and teachers, as well as interactions among students. High social integration is contingent on quality and, consequently, satisfaction (Piepenburg and Beckmann, 2022). Consequently, research emphasizes the significance of promoting academic and social integration as a preventive measure against dropout (Franz and Paetsch, 2023). Studies have consistently shown a significant relationship between social integration and university student satisfaction (Myrtveit et al., 2017). Therefore, we propose the following research hypothesis:

> *H14*: Social integration has a direct effect on satisfaction.

2.8 Satisfaction

Student satisfaction is a crucial factor in determining the success and stability of academic institutions. According to Beck and Milligan (2014), students who are loyal and satisfied tend to achieve higher grades, better test scores, and have lower dropout rates than their less committed peers, which positively impacts institutional commitment. In this context, student institutional commitment is related to overall student satisfaction, sense of belonging, perceptions of educational quality, and willingness to return to the institution (Strauss and Volkwein, 2004). The research hypothesis proposed is as follows:

> *H15*: Satisfaction has a direct effect on institutional commitment.

2.9 Institutional commitment

Based on the research conducted by Lizarte Simón and Gijón Puerta (2022), a student's commitment to both the institution and their chosen academic path significantly influences their decision to persist to graduation. The theoretical framework suggests that students have varying expectations and commitments when it comes to the university environment. Institutional commitment, in particular, refers to the commitment to continue studying at a specific university (Schuster and King, 2022). Once enrolled, students' academic commitment is likely to change as they gain experience in both the academic and social aspects of the institution. Research has shown that higher levels of institutional engagement are associated with lower attrition rates compared to less engaged students (Beck and Milligan, 2014). Therefore, we propose the following research hypothesis:

> *H16*: Institutional commitment has a direct effect on the decision to leave.

2.10 Decision to desert

According to Spady (1971) the decision to desert is a social process, where the decision is the result of the interaction between academic/social integration and personal conditions. In addition, it is considered a dynamic process of institutional disengagement (Tinto, 1994). In this sense, the decision to desert is considered a predictor of the actual decision (Hadjar et al., 2023). According to Valencia-Arias et al. (2023) the decision to desert out is based on aspects such as family problems, lack of financial support, lack of vocational and professional guidance, differences in academic requirements between school and university, the number of credits needed to complete a degree, difficulty in paying tuition, difficulty in meeting additional costs, and psychological factors.

Alt text Figure 1. This figure depicts the model proposed by Spady in 1971. It provides a graphical visualization of the theoretical or conceptual framework that Spady developed in his research.

According to Spady, full integration necessitates meeting the demands of both the academic and social systems within higher education (Donoso and Schiefelbein, 2007). Studies have identified key factors that are now commonly used to describe and predict attrition in educational institutions (Maldonado et al., 2021).

3 Methodology

To achieve the research objective, we conducted a quantitative study with a correlational scope using a structural equation model. We administered a survey through Google Forms to students enrolled in the Systems Engineering and Industrial Engineering programs. A survey was conducted with 190 students, the majority of whom were enrolled in the Systems Engineering program (68%). The participants were predominantly male (76.5%), belonging to stratum 1 or 2 (53.5%), in their first five semesters (66.6%), and aged between 15 and 21 years (44.5%).

The proposed structural equation model is composed of 10 latent constructs derived from the model proposed by Spady (1971): Family Background, Normative Consistency, Social Integration, Satisfaction, Peer Support, Institutional Commitment, Intellectual Development, Academic Performance, Academic Potential, and Decision to Desert. Each of these constructs was operationalized by means of between 2 and 5 observable items, designed from the specialized literature and validated by experts. Table 1 presents the detailed correspondence between each construct and its observable indicators, together with the statements that were included in the data collection instrument.

The survey aimed to understand the reasons for dropping out by examining factors such as the secondary school attended, graduation age, marital status upon university entry, age of university entry, economic dependency, parental education level, and financial aid received. Table 2 provides additional socio-demographic information about the students.

Among the surveyed students, 83.2% reported receiving their secondary school diploma from a public school. Additionally, 61.3% of the students reported financial dependence on a family member or someone else. Upon entering university, the majority (80.6%) were single, and half of them (50.3%) had no financial dependents.

Regarding the age at which they received their secondary school diploma, 68.6% responded that they were between 17 and 19 years old. Similarly, when asked about their age upon entering university, the majority stated they were between 17 and 19 years old. This suggests that a significant portion of the surveyed students completed their secondary education and immediately began their professional education.

With regards to their parents' education, 54% reported that their fathers had completed primary or secondary education, and 61.3% reported the same for their mothers. When asked about scholarships and loans for professional education, 88% of respondents reported not receiving a scholarship, and 74.3% reported not taking out a loan.

This socio-demographic information establishes a profile for the average engineering student at the Medellín campus of the CUA. The profile aligns with that of a recently graduated young individual who is financially dependent on a family member and whose parents do not hold professional degrees.

4 Results

The Partial Least Squares Structural Equation Modeling (PLS-SEM) method was used to estimate the parameters of the proposed structural model. PLS-SEM is a variance-based technique widely used in the social sciences when the research objective is predictive and the theoretical model is complex or exploratory (Hair et al., 2011). This method allows the estimation of causal relationships between latent variables by maximizing the explained variance of the dependent constructs. Unlike the covariance-based SEM, PLS-SEM is particularly useful when the sample size is small, the data distribution is non-normal, or when the model includes numerous indicators and constructs (Hair et al., 2016).

The PLS-SEM approach consists of two submodels: the measurement model (external model), which assesses the relationships between the observed variables (indicators) and their corresponding latent constructs, and the structural model (internal model), which estimates the relationships between the latent variables. The estimation procedure is based on the partial least squares method, conceptually linked to principal component analysis (PCA). Key PLS-SEM results

TABLE 1 Study factors and indicators.

Factor	Indicator	
Family background	FB1	The support received from your family members would allow you to complete your university studies.
	FB2	Time-consuming personal or family obligations would cause you to put your career on hold.
	FB3	Parenthood may influence you to withdraw from your college career.
	FB4	Family problems (lack of family support, demand for more time from the student, pregnancy, need to care for children) are reasons for dropping out of college.
	FB5	The fact that their parents have completed university studies influences their decision to complete their studies.
Normative consistency	NC1	One reason I would finish my degree is that I find it interesting.
	NC2	One reason I would finish my degree is that I would have fun while doing it.
	NC3	I must feel comfortable as a college student to finish my degree.
	NC4	The degree must meet your expectations and be equal to what you expected it to be for me to complete it.
Social integration	SI1	Their affinity with the university environment and the people is a factor that motivates me to finish my higher education studies.
	SI2	The conflicts experienced with teachers and/or students are an important element at the moment of finishing higher education studies.
	SI3	The social adaptation with their classmates plays an important role in their permanence in the career.
Satisfaction	SE1	The price of the degree is too high compared to other institutions is a reason to drop out of college.
	SE2	Not having financial support for their studies is a reason for dropping out.
	SE3	Demotivation due to expectations of low income and unemployment in the future can be a reason for not continuing their studies in higher education.
Peer support	PS1	The lack of vocational and professional guidance from their teachers is a cause for dropping out of higher education.
	PS2	The relationship with the teachers is a motivating factor to finish their university studies.
	PS3	The teaching methodology of the tutors is one of the main motivators to continue with university studies.

(Continued)

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TABLE 1 (Continued)

Factor	Indicator	
Institutional commitment	IC1	Aspects such as the physical plant or location of the university may be factors that lead you to abandon your college career, even though you like it.
	IC2	Lack of knowledge of student benefits and college welfare is a factor in dropping out of college.
	IC3	Denial of a scholarship application by the university may cause you to drop out of higher education.
Intellectual development	ID1	The change in the demands of the school versus the university is a reason why he would not complete his degree.
	ID2	Do you consider that a rigid curriculum with little flexibility conditions your permanence in college?
	ID3	Do you consider that the number of credits it takes to complete a program is a cause for dropping out?
Academic performance	APR1	Psychological problems (depression, attention difficulties, etc.) could influence their academic performance and jeopardize their permanence in college.
	APR2	Emotional problems and family instability are important factors in their academic performance.
	APR3	Change of marital status may influence your academic performance and cause you to drop out of college.
Academic potential	APO1	Considers that the length of the curriculum is an important factor in increasing his academic potential.
	APO2	Considers that an optimal state of health would lead him to increase his capacity for understanding and would be a relevant factor in the completion of his studies.
	APO3	Considers that he/she could drop out due to a lack of self-discipline or perseverance in studying
Decision to desert	DD1	The difficulty in meeting tuition payments is considered to influence the decision to drop out of university studies.
	DD2	Considers that Difficulty in meeting additional career expenses influences the decision to drop out of university studies
	DD3	Considers that the difficulty in meeting the schedule influences the decision to drop out of university studies

Source: own elaboration based on Spady (1971).

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TABLE 2 Sample information.

Program	Percentage	Semester	Percentage
Systems engineering	68%	Between first and second	28.4%
Industrial engineering	32%	Between third and fourth	13.1%
Gender	Percentage	Between fifth and sixth	25.1%
Male	76.5%	Between seventh and eighth	19.3%
Female	23%	Between ninth and tenth	13.1%
Does not know/No response	0.5%	More than tenth	1%
Social stratum	Percentage	Age range	Percentage
Between 1 and 2	53.5%	Between 15 and 21 years	44.5%
Between 3 and 4	45.5%	Between 22 and 28 years	30.4%
Between 5 and 6	1%	Between 29 and 35 years	16.2%
Does not know/No response	0%	More than 35 years	8.9%
The type of school from which they obtained their secondary school diploma	Percentage	Financial dependence on family or another individual	Percentage
Private	16.8%	No, is independent	38.7%
Public	83.2%	Yes, is dependent	61.3%
Marital status at the time of university entry	Percentage	How many individuals are financially dependent on you?	Percentage
Single	80.6%	No one	50.30%
Married	4.7%	One	13.10%
Domestic partnership	13.1%	Two	22.50%
Prefer not to say	1.6%	Three or more	14.10%
Age at the completion of secondary school in years	Percentage	Age in years at the time of entering university	Percentage
14–16 years	27.8%	14–16 years	5.3%
17–19 years	68.6%	17–19 years	45.5%
20–22 years	2.6%	20–22 years	18.3%
More than 22 years	1%	23–25 years	9.4%
Does not know/No response	0%	26 or more years	21.5%
Educational level of the father	Percentage	Educational level of the mother	Percentage
None	5.2%	None	2.6%
Primary	23.6%	Primary	30.9%
Secondary	30.4%	Secondary	30.4%
Technical/Technology	13.6%	Technical/Technology	17.8%
Professional/University	15.2%	Professional/University	13.6%
Does not know/No response	12%	Does not know/No response	4.7%
Have you been granted a scholarship for your professional education?	Percentage	Have you taken out any loans for your professional education?	Percentage
Yes	12%	Yes	25.7%
No	88%	No	74.3%

include factor loadings, cross-loadings, composite reliability, Cronbach's alpha, average variance extracted (AVE), R^2 and Q^2 coefficients, and path coefficients, which are evaluated through bootstrap procedures to assess their statistical significance (Hair et al., 2017).

A Structural Equation Model was used to predict dropout behavior among engineering students through variance analysis, employing the PLS-SEM approach. This technique reflects both theoretical and empirical conditions in the realms of social and behavioral sciences (Martínez Ávila and Fierro Moreno, 2018). Zeng et al. (2021) emphasize that PLS-SEM is a causal modeling method that aims to maximize the explained variance of dependent latent constructs rather than constructing a theoretical covariance matrix. Therefore, the study assesses the convergent and discriminant validity of the measurement model, conducts hypothesis testing, and performs prediction analysis of the structural model.

4.1 Convergent validity

Model estimation is a crucial step in PLS-SEM. It involves determining an initial solution and, more importantly, identifying the dimension of the data, which is the most appropriate number of factors (Ferrando and Anguiano-Carrasco, 2010). This process is carried out through principal component analysis, where components are seen as a linear combination of the observed indicators or variables (Alaminos et al., 2015). Factor loadings are essential in principal component analysis as they serve as correlation coefficients between variables and factors. The analysis clusters variables into a few latent constructs. Variables with loadings higher than 0.4 are grouped under the same factor, while those with lower loadings should be considered for elimination (Balasundaram, 2009). Table 3 presents the observed indicators selected for the 10 constructs of the student dropout model. The analysis excluded items AF1, AF5, PA1, AP2, and CI.

In this study, the observed variables—or indicators—correspond to specific survey items designed to measure the latent constructs derived from the Spady model, such as family background, academic potential, normative consistency, peer support, academic performance, intellectual development, social integration, satisfaction, institutional commitment, and dropout decision. Each construct was operationalized using between 3 and 5 items based on previous literature and expert validation. These indicators were grouped under their respective constructs through principal component analysis

TABLE 3 Convergent validity.

Factor	Indicator	Factor loading	VIF	CA	CR	AVE
Family background	FB2	0.838	1.536	0.770	0.866	0.684
	FB3	0.789	1.540			
	FB4	0.852	1.678			
Academic potential	APO1	0.458	1.302	0.467	0.669	0.422
	APO2	0.536	1.316			
	APO3	0.876	1.016			
Normative consistency	NC1	0.825	2.289	0.819	0.878	0.643
	NC2	0.753	2.083			
	NC3	0.876	1.888			
	NC4	0.746	1.468			
Academic performance	APR1	0.902	2.194	0.817	0.891	0.733
	APR2	0.887	2.192			
	APR3	0.774	1.519			
Intellectual development	ID1	0.857	1.936	0.752	0.860	0.672
	ID2	0.731	1.254			
	ID3	0.865	1.981			
Peer support	PS1	0.819	1.162	0.544	0.814	0.687
	PS3	0.838	1.162			
Social integration	SI1	0.618	1.132	0.532	0.765	0.524
	SI2	0.705	1.265			
	SI3	0.832	1.410			
Satisfaction	SE1	0.846	1.571	0.793	0.878	0.706
	SE2	0.857	1.818			
	SE3	0.817	1.701			
Institucional commitment	IC1	0.807	1.316	0.658	0.850	0.740
	IC2	0.910	1.316			
Desicion to desert	DD1	0.872	2.759	0.830	0.899	0.749
	DD2	0.922	3.273			
	DD3	0.796	1.525			

Source: own elaboration based on SmartPLS 4. CL > 0.4; VIF < 5; CA > 0.7; CR > 0.7; AVE > 0.5.

(PCA), which identifies uncorrelated factors (i.e., the latent constructs) based on their linear combinations of observed variables.

The factor loadings, in this context, represent the correlation coefficients between each indicator and its associated construct. A threshold of 0.4 was used to retain the indicators, following standard recommendations. The elimination of indicators with loadings below this value was considered to improve the convergent validity of the model. Specifically, items FB1, F5, PS2, and IC were excluded based on this criterion, as detailed in Table 3.

Although some variables presented cross-loadings higher than 0.4 on more than one construct, the final grouping was based on content validity, expert judgment, and theoretical consistency with Spady's model. Thus, items AP1, AP2, and AP3, although with some loading on Family Background, were grouped under Academic Performance for conceptual consistency.

Convergent validity was assessed by calculating the AVE, a statistic that tests the true validity of the population model (Afthanorhan et al., 2020). The literature recommends that the AVE be above 0.5 (Amaro et al., 2015) In addition, we evaluated the variance inflation factor (VIF) to assess the formative collinearity of the indicators. Purwanto and Sudargini (2021) suggest that a VIF value of 5 or higher indicates a significant collinearity problem between formatively measured indicators.

They recommend a lower value, preferably below 3. To evaluate the internal consistency of the constructs, Cronbach's Alpha (CA) and Composite Reliability (CR) were used. Although CA is widely used for measuring reliability, researchers have increasingly turned to other reliability coefficients, such as CR, due to their higher scores (Fauzi, 2022). Hair et al. (2014) argue that CR is a more appropriate measure of internal consistency reliability than CA for two reasons. Firstly, unlike CA, CR does not assume that all indicator loadings are equal in the population, which aligns with the working principle of the PLS-SEM algorithm that prioritizes indicators based on their individual reliabilities during model estimation. Secondly, it is important to note that CA is sensitive to the number of items in the scale and may underestimate internal consistency reliability. However, by using CR, PLS-SEM can accommodate different indicator reliabilities, thus avoiding the underestimation associated with CA. It is generally accepted that both statistics should have a value of 0.7 or higher (Gutiérrez Rodríguez et al., 2020).

All constructs were considered to be reflexive, given that the observable items reflect the same latent phenomenon and are interchangeable. This reflexive nature is evidenced by factor loadings above 0.7 for most of the indicators, as well as adequate CR and AVE values, presented in Table 3. In addition, discriminant validity was assessed using the Fornell-Larcker criterion (Table 4).

4.2 Discriminant validity

To increase confidence in the interpretation of findings, it is crucial to evaluate discriminant validity. This validity indicates the absence of statistical correlations between test scores, which means that the tests do not measure the same processes. In other words, the correlation between indicators of one construct must be higher than the correlation between those indicators and the proposed measures for another construct (Afthanorhan et al., 2021).

Various methods exist for assessing inter-construct validity after analyzing the internal consistency (convergent validity) of the model. Discriminant validity is established when all correlations between indicators of different constructs, such as variables X and Y, are significant, and each of these correlations is higher than all correlations between indicators of both variables (Rönkkö and Cho, 2022).

The Fornell-Larcker criterion is a commonly used statistic for assessing discriminant validity. According to this criterion, a latent variable must capture more variance in its associated indicator variables than it shares with other constructs in the same model to establish discriminant validity (Fornell and Larcker, 1981). This is achieved by comparing the AVE with the squared correlations with other constructs in the model. The criterion being met is indicated by higher values for each construct, as stated by Henseler et al. (2015) and demonstrated in Table 4.

4.3 Hypothesis testing

This section evaluates the structural model through hypothesis testing. Table 5 and Figure 2 illustrate the relationship between the *p*-values. The p-value test establishes that $\beta > 0$ with a significance level of 0.05. This test is complemented by the T-value test, which is calculated as β/σ, with a threshold >1.96 (Kock, 2016). The Bootstrapping method is utilized for calculating hypotheses, as it is the most commonly used method for estimating the standard error in PLS SEM (Kock, 2014).

Additionally, the model's predictive capacity is evaluated using the coefficient of determination R^2. This assesses the model's fit in the composite scores sample of endogenous constructs by predicting individual case values in the total sample using model estimates (Hair Jr, 2021). According to the literature, values of 0.75 are considered substantial, 0.5 moderate, and 0.25 weak (Hair et al., 2019). These results are also presented in Figure 2.

Alt text Figure 2. This figure illustrates the hypothesis testing process as applied specifically to the 1971 Spady model. It provides a visual representation of how the hypotheses associated with this model were evaluated and tested.

The study results allow for the identification of validated hypotheses and those that are not. The strongest relationship is observed between academic potential and academic performance, as evidenced by the indicators used in the questionnaire, specifically, items related to students' perceptions of their self-discipline, perseverance, and ability to understand content when in optimal conditions. These results suggest that students who report stronger cognitive and motivational readiness are more likely to demonstrate consistent academic outcomes.

Similarly, the strong relationship identified between satisfaction and institutional commitment reflects questionnaire items addressing students' access to financial support, perceived return on investment, and expectations of future employment. When students report satisfaction with institutional services and prospects, they tend to express higher levels of institutional commitment. These interpretations are grounded in the constructs and indicators operationalized through the validated survey instrument.

Additionally, there is a strong correlation between peer support and intellectual development. Peer interaction in a collaborative environment stimulates the exchange of ideas and perspectives,

TABLE 4 Fornell-Larcker criterion.

	Academic performance	Academic potential	Decision to desert	Family background	Institutional commitment	Intellectual development	Normative consistency	Peer support	Satisfaction	Social integration
Academic performance	0.856									
Academic potential	0.622	0.649								
Decision to desert	0.541	0.555	0.865							
Family background	0.619	0.371	0.467	0.827						
Institutional commitment	0.565	0.464	0.492	0.512	0.860					
Intellectual development	0.656	0.555	0.457	0.573	0.677	0.820				
Normative consistency	0.148	0.317	0.276	0.017	0.228	0.104	0.802			
Peer support	0.426	0.471	0.419	0.331	0.410	0.388	0.422	0.829		
Satisfaction	0.474	0.467	0.673	0.456	0.468	0.395	0.228	0.363	0.840	
Social integration	0.511	0.483	0.403	0.369	0.524	0.540	0.411	0.452	0.348	0.724

promoting deeper learning through discussion and joint analysis of concepts. Peer interaction in a collaborative environment stimulates the exchange of ideas and perspectives, promoting deeper learning through discussion and joint analysis of concepts. This contributes to the construction of knowledge more comprehensively. Furthermore, a strong relationship exists between normative consistency and peer support. When normative consistency exists, students share similar expectations and values, creating an environment conducive to empathy, support, and mutual understanding.

The influence of family background on academic potential is highlighted, as it provides a supportive environment and resources that facilitate educational development. A home with a positive atmosphere toward learning, where the importance of education is encouraged, establishes a solid foundation for academic growth.

In terms of the factors that influence engineering students dropping out, there is a significant relationship between academic performance and the decision to leave. Positive performance is often associated with greater student retention, while poor academic performance can lead to frustration, lack of confidence, and demotivation, increasing the likelihood of a student considering dropping out. Institutional commitment also affects students' decisions to continue with higher education.

Regarding the model's predictive capacity, the constructs Decision to Desert, Academic Performance, and Social Integration exhibit the highest levels of explained variance, as reflected in their R^2 values (all above 0.45). Additionally, the Q^2 values for these constructs exceed the 0.35 threshold, indicating high predictive relevance according to established benchmarks (Hair et al., 2021). It is important to clarify that these thresholds (0.02 = small, 0.15 = medium, 0.35 = large) apply to Q^2, not R^2. While R^2 evaluates the amount of variance explained, Q^2 assesses the model's predictive accuracy through blindfolding. These metrics support the conclusion that the model has substantial predictive power for key outcomes, particularly in academic performance and Decision to Desert (see Appendix).

Although R^2 and Q^2 are commonly used in PLS-SEM to assess model fit and predictive relevance, recent literature has questioned their sufficiency as sole indicators. Authors such as Hair et al. (2021, 2016) suggest complementing them with alternative measures such as PLSpredict or predictive-oriented segmentation, especially in complex models.

5 Discussion

The findings of this study confirm that academic performance is a key determinant in the decision to desert engineering programs. This relationship is supported by the significant path coefficient between Academic Performance and decision to desert ($\beta = 0.386$, $p < 0.001$), as reported in Figure 2 and Table 5. In our model, academic performance is measured through indicators related to psychological and emotional factors affecting student achievement (Lázaro Alvarez et al., 2020). These results suggest that students who exhibit difficulties in maintaining academic performance, often due to psychological or emotional stressors, are more likely to consider dropping out. This supports prior literature, which emphasizes the importance of academic behavior, progression rate, and prior preparation in mathematics and logical reasoning (Bedregal-Alpaca et al., 2020).

TABLE 5 Hypothesis testing.

Hypothesis	Path value	*T*-value	*p*-value
Family Background → Academic Potential	0.371	5.180	0.000
Family Background → Normative Consistency	0.017	0.193	0.847
Academic Potential → Academic Performance	0.560	8.651	0.000
Normative Consistency → Academic Performance	−0.119	2.205	0.028
Normative Consistency → Intellectual Development	0.104	1.179	0.238
Normative Consistency → Social Integration	0.301	2.318	0.021
Normative Consistency → Peer Support	0.422	5.397	0.000
Normative Consistency → Institucional Commitment	0.128	1.772	0.077
Peer Support → Academic Performance	0.212	2.548	0.011
Peer Support → Intellectual Development	0.419	5.612	0.000
Peer Support → Social Integration	0.150	1.888	0.059
Intellectual Development → Social Integration	0.451	4.795	0.000
Academic Performance → Desicion to Desert	0.386	5.077	0.000
Social Integration → Satisfaction	0.348	4.437	0.000
Satisfaction → Institucional Commitment	0.439	6.569	0.000
Institucional Commitment → Desicion to Desert	0.274	3.515	0.000

Source: own elaboration based on SmartPLS 4. Path value > 0.005; T-value > 1.96; p-value < 0.05.

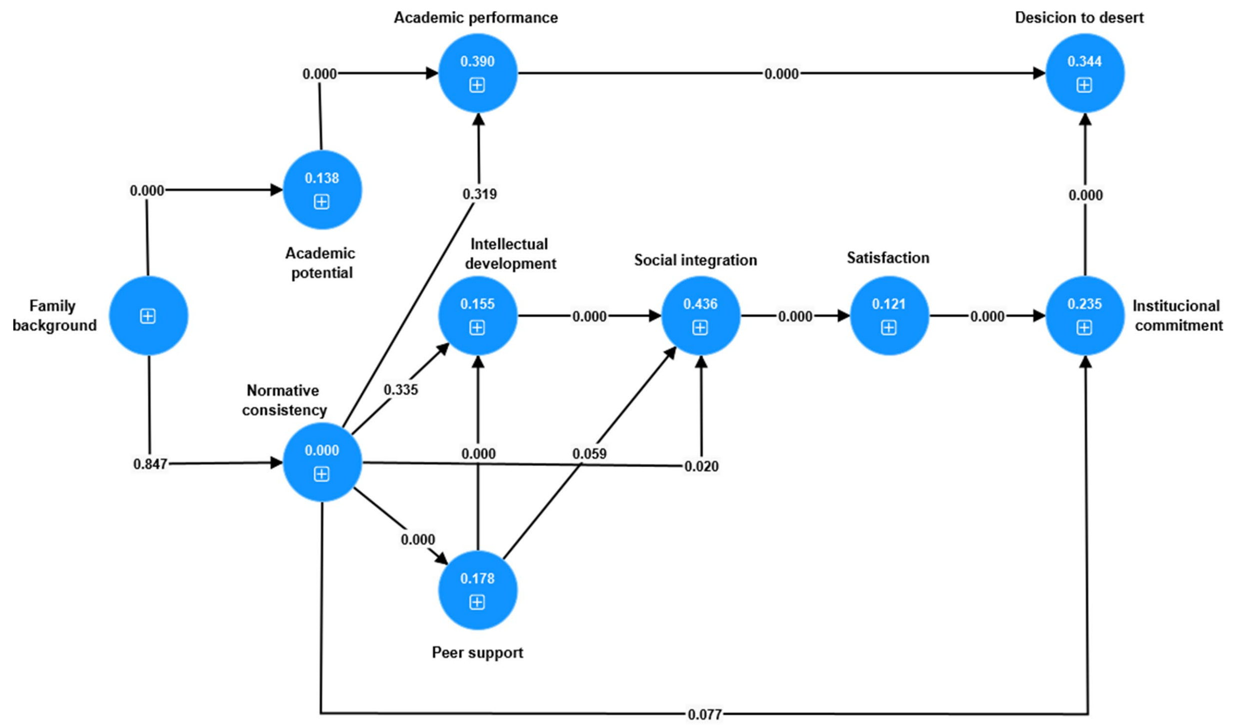

FIGURE 2
Hypothesis testing - Spady model (1971).

This study also identified Normative Consistency as a relevant construct influencing student retention. Normative consistency, defined as the alignment between students' motivations and their expectations of the program, showed direct effects on multiple constructs, including Social Integration and Peer Support. This relationship is supported by the positive and statistically significant path between Normative Consistency and Peer Support in the SEM model (see Figure 2). In our model, this construct captures indicators such as program interest, enjoyment, and perceived fit, highlighting that students who perceive coherence between their values and their academic journey are more likely to persist. These findings align with earlier studies that emphasize the role of student-program alignment in preventing dropout (Chalela-Naffah et al., 2020).

Although constructs such as Normative Consistency and Peer Support did not show significant direct effects on the Decision to Desert, the structural model reveals their indirect influence through mediating variables, including Social Integration, Intellectual Development, and Institutional Commitment. For instance, Normative Consistency enhances Peer Support and Social Integration, which in turn increase Institutional Commitment, ultimately reducing the likelihood of dropout. These indirect pathways underscore the importance of incorporating mediation analysis into dropout models, as recommended in the literature.

Peer Support emerged as a significant factor, particularly influencing Intellectual Development ($\beta = 0.419$, $p < 0.001$) and Social Integration ($\beta = 0.150$, $p = 0.059$). In our model, this construct refers specifically to the role of fellow students in shaping academic and emotional experiences (Pascua-Cantarero, 2016). Although previous research highlights the importance of professors in retention (Riveros Sanabria et al., 2018; Caicedo Chacón et al., 2019), our study focuses on the impact of peer relationships, indicating that collaboration, shared study strategies, and interpersonal bonds contribute meaningfully to intellectual growth and social belonging.

The relationship between Satisfaction and Institutional Commitment was also statistically significant ($\beta = 0.439$, $p < 0.001$). Satisfaction, as operationalized in our study, encompasses perceptions related to tuition affordability, access to financial aid, and academic program prospects. These elements were found to strongly influence institutional commitment, a construct that reflects students' loyalty and identification with the university. This connection supports findings in the Latin American context, where institutional commitment is frequently mediated by students' satisfaction with their educational experience (Murillo et al., 2018; Apaza and Huamán, 2012).

The constructs decision to desert, Academic Performance, and Social Integration exhibited the highest predictive capacity in our model, with R^2 values above 0.45, as shown in Figure 2 and Appendix. Additionally, Q^2 values surpassed the 0.35 threshold, indicating strong predictive relevance for these endogenous variables. It is important to note that Q^2 values above 0.35 suggest large predictive relevance, as established in the literature. These metrics reinforce the empirical robustness of the model.

Regarding the surveyed sample, the typical profile corresponds to a young male student from low-income households (stratum 1 or 2), recently graduated from a public high school, and dependent on family financial support. These characteristics reflect broader patterns in Colombian engineering education and contextualize the vulnerabilities identified in this research. The study contributes to the understanding of dropout risk among engineering students in private universities who often require additional academic support, especially in developing foundational competencies such as logical and mathematical reasoning (Hernández Betancur et al., 2016).

Although the model demonstrates strong predictive power, some constructs showed issues with convergent validity. In particular, Academic Potential exhibited an AVE below the 0.5 threshold, suggesting that some of its indicators may require refinement. Additionally, certain hypothesized paths, such as Normative Consistency → Institutional Commitment, while theoretically grounded, did not reach statistical significance ($p = 0.077$). These observations highlight areas for improvement in the model and indicate that future studies should consider updating the theoretical framework. While the Spady model provided a valuable structure for this analysis, its origin in the 1970s may limit its applicability to current educational contexts. More contemporary models could offer refined insights into the dropout phenomenon among engineering students.

It is important to note, however, that the model faces challenges related to convergent validity. Therefore, it is recommended to consider the application of more updated models. The Spady model, proposed in the 70s, may not fully capture the current situation. More recent models would likely be more aligned with the current dynamics and realities surrounding the dropout of engineering students. In addition, while the Spady model provided a valuable basis for this study, it did not include more recent or integrative models such as those developed by Tinto, Pascarella, Bean, Cabrera, or Seidman. These frameworks offer additional insights into student engagement, institutional adjustment, and persistence mechanisms. Future research could benefit from the application or comparison of these models to improve the theoretical soundness and relevance of dropout analyses in the current higher education landscape.

5.1 Limitations and future research agenda

This study provides valuable insights into the factors influencing engineering students' Decision to Desert, particularly within the context of a private university in an emerging economy. However, several limitations should be acknowledged. First, the cross-sectional design restricts the ability to assess the evolution of students' intentions or behaviors over time. Future studies would benefit from adopting longitudinal designs that can capture dynamic changes across the academic trajectory, particularly during critical transition points such as the first year or final semesters.

Second, the exclusive use of quantitative methods, though appropriate for testing causal relationships and validating the structural model, limits the interpretive depth regarding students' lived experiences. Incorporating qualitative components, such as in-depth interviews or focus groups, would provide richer contextual data and help uncover underlying motivations, expectations, and emotional responses related to academic persistence or dropout.

Third, the sample was drawn from a single institution and was composed primarily of students in Systems and Industrial Engineering. This may limit the generalizability of the findings to other types of engineering programs or institutional contexts. Comparative studies across public and private institutions, urban and rural settings, or different engineering disciplines would offer a broader and more nuanced understanding of dropout determinants.

Therefore, it is essential to acknowledge the limitations related to the study's sample size, as it consisted of only 190 participants, all of whom were from a private university in the city of Medellín. This restricts the possibility of generalizing the results to the population of engineering students in Colombia, particularly those enrolled in public universities, who may face different socioeconomic and institutional conditions. In this sense, it is recommended that future research include larger and more diverse samples, encompassing a broader population of universities and geographic regions, to enhance external validity.

This study focused on students currently enrolled in the Systems Engineering and Industrial Engineering programs. Students who had previously dropped out were not included, so the results focus on the identification of factors that predispose to dropout, rather than on their actual occurrence.

Finally, it should be recognized that while institutional commitment and academic performance are widely recognized as key determinants of student dropout, recent research suggests that psychological, socioeconomic, and family factors also play an important role (Gutiérrez-Monsalve et al., 2025). Beyond institutional and academic variables, the literature on student dropout increasingly points to the influence of mental health, economic hardship, job responsibilities, and family dynamics (Kocsis and Molnár, 2025). These factors interact with institutional elements and may intensify the risk of dropout, especially in students from vulnerable backgrounds. Therefore, while this study highlights institutional commitment and academic performance as central factors, the roles of unmeasured elements, such as financial pressure, emotional wellbeing, and family responsibilities, should not be ignored.

In addition, future research should consider the inclusion of socioeconomic and psychological variables not addressed in this model, such as financial stress, mental health conditions, external work commitments, family obligations, and academic motivation. These factors, often underexplored in structural models, may interact with institutional and academic variables in ways that either mitigate or exacerbate the risk of attrition. Their inclusion could enhance predictive power and provide a more holistic view of the dropout phenomenon, especially in settings marked by economic inequality and social vulnerability.

Finally, based on the study's findings, future research could also investigate the effectiveness of specific institutional interventions aimed at strengthening academic performance, peer support, and intellectual development—three key variables in the model. Experimental or quasi-experimental designs could be employed to evaluate the impact of academic mentoring programs, financial aid schemes, psychological support services, or peer-led learning communities on student retention and engagement.

By addressing these methodological and contextual limitations and expanding the scope of analysis, future studies can contribute to the development of more comprehensive and inclusive strategies for preventing dropout in engineering education, with implications for both institutional policy and national higher education planning in emerging economies.

6 Conclusion

This study aimed to identify the key factors associated with the decision to desert out in engineering students, based on a structural equation model applied to undergraduate students of Systems and Industrial Engineering at a private Colombian university. The model revealed that Academic Performance, Social Integration, and Academic Potential were the constructs with the highest predictive capacity to explain dropout intentions. These results are supported by significant path coefficients and confirm the crucial role of individual and institutional dimensions in student retention.

Empirical findings suggest that students with higher academic potential, reflected in indicators related to health, discipline, and motivation, are better prepared for academic performance and perseverance in their studies. At the same time, social integration, measured through the student's adaptation and sense of belonging, contributes positively to their continuity in the academic program.

Satisfaction with the academic experience was found to influence institutional commitment, particularly through concerns about tuition costs, financial aid, and future academic program expectations. Although other constructs, such as Peer Support and Normative Consistency, were not statistically significant in their direct trajectories, they could play an indirect role in shaping academic motivation and commitment, as evidenced by the observed indicators.

The model also highlighted the impact of psychological and emotional aspects, such as depression, family instability, and concentration difficulties, on academic performance, suggesting that school dropout depends not only on cognitive ability but also on the emotional and socioeconomic context of students.

Although this study does not propose formal intervention strategies, its results point to key areas where institutional efforts should focus: providing academic and emotional support, improving access to information on scholarships and financial aid, and adapting institutional policies to the realities of students from vulnerable backgrounds.

Finally, the model faced some challenges in terms of convergent validity on certain constructs, and its reliance on classical Spady theory may limit its ability to reflect the complexities of dropout in contemporary contexts. Future research should explore the application of more recent models and consider longitudinal approaches to better understand the dynamics of persistence and dropout.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by Ethics Committee of the Escolme University Institution. The studies were conducted in accordance with the local legislation and institutional requirements. The ethics committee/institutional review board waived the requirement of written informed consent for participation from the participants or the participants' legal guardians/next of kin because Consent was obtained from participants by agreeing to participate anonymously in the survey.

Author contributions

EM: Writing – original draft, Writing – review & editing. PR-C: Writing – original draft, Writing – review & editing. EA-C: Writing – original draft, Writing – review & editing. AV-A: Writing – original draft, Writing – review & editing. GM: Writing – original draft, Writing – review & editing. GS: Writing – original draft, Writing – review & editing. JJ: Writing – original draft, Writing – review & editing. MV: Writing – original draft, Writing – review & editing.

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Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2025.1582586/full#supplementary-material

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