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Academic Performance of First-Year Engineering Students: A Systematic Literature Review*

ANA APARICIO COLINO[1,3,**], JOSE LUIS ARROYO-BARRIGÜETE [2,3] and CARMEN SÁNCHEZ ÁVILA[1]
[1] Department of Applied Mathematics to ICTs, Universidad Politécnica de Madrid, Madrid, Spain.
E-mail: carmen.sanchez.avila@upm.es, ana.aparicio.colino@alumnos.upm.es
[2] Department of Quantitative Methods, Universidad Pontificia Comillas, Madrid, Spain. E-mail: jlarroyo@comillas.edu
[3] Santalucía Chair of Analytics for Education, Madrid, Spain.
These authors contributed equally to this work.

The academic performance of first-year engineering students is a critical topic, given its relevance for understanding and improving retention, identifying at-risk students and fostering success in engineering education. This study employs the PRISMA methodology to conduct a rigorous and systematic literature review of research on the academic performance of first-year engineering students published between 2014 and 2024. Through an exhaustive search and selection process, 36 articles were identified and analyzed.

The review shows that academic achievement is a multifaceted construct measured through a wide range of indicators, including first-year or semester grades, performance in key subjects such as mathematics or introductory engineering courses, retention and graduation rates, and students' self-reported outcomes. The lack of standardization in these metrics underscores the complexity of the field and complicates cross-study comparisons. Two main approaches to measuring performance in the first year emerge: overall course averages based on large, multi-subject datasets, and subject-specific assessments that enable more controlled analyses.

Across studies, cognitive factors such as high school grade point average, university entrance scores and prior mathematics preparation consistently appear as strong predictors of first-year performance. Mathematics plays a central role as both a foundational knowledge base and a powerful predictor of subsequent success. At the same time, non-cognitive variables, including self-efficacy and motivation, also show robust associations with achievement. Finally, the review highlights the diversity of analytical strategies, from classical statistical models to machine learning techniques, and points to the value of mixed methodological approaches for capturing the complex interaction between cognitive, non-cognitive and contextual factors shaping first-year engineering performance.

Keywords: first-year engineering students; academic performance; PRISMA methodology; educational interventions; higher education; student success

1. Introduction

The transition from secondary to tertiary education represents a pivotal phase in students' academic and personal development. This transition, which marks the entrance into universities, engineering schools, and other post-secondary institutions, is typified by an increase in autonomy, the complexity of academic content, and the necessity to adopt new study strategies. This phenomenon varies not only by discipline, from medicine [1] to the exact sciences [2], to the arts and humanities [3], but also by country and cultural context. For instance, Japanese students in Tokyo who pursue their studies in English confront the challenge of navigating a language barrier [4], whereas in Africa, those from rural backgrounds must grapple with cultural and educational discrepancies that influence their integration [5]. In Spain, it has been demonstrated that students in the second year of baccalaureate experience considerable pressure and anxiety in anticipation of their imminent transition to university, reflecting the profound emotional impact that this transition can have on students [6]. Globally, this transition is often accompanied by discontinuities that impact the teaching-learning processes. In response, universities and colleges have implemented various initiatives to facilitate it, such as introductory courses and mentoring programs [7] or initiatives that provide academic support to prepare high school students for entry into higher education, thus improving their success and retention rates [8]. These interventions seek to improve students' chances of academic success by helping them adapt to the demands of higher education.

Considering these considerations, it is crucial to acknowledge that certain academic disciplines, such as engineering, inherently pose unique challenges that can exacerbate the challenges associated with transitioning to the university environment. The engineering curriculum is distinguished by its emphasis on mathematics and the sciences, coupled

** Corresponding author.

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with a rigorous academic environment. This can contribute to a higher attrition rate, particularly in the initial year. It is, therefore, essential to analyze and develop specific strategies that address the needs of engineering students in order to facilitate their adaptation and ensure their academic success during this transitionary period [9]. In this context, the initial year of university assumes particular significance, as performance during this period establishes the foundation for long-term success. A strong performance in the first year not only bolsters the student's confidence but also facilitates integration into the university environment. Conversely, poor performance can lead to demotivation and, eventually, to dropping out of university. This period is critical for many students, and it is, therefore, essential to study the factors that influence performance and to analyze the educational interventions and experimental methodologies that have been implemented to assess the impact.

This review examines studies on academic performance in the first year of engineering in diverse countries. It assesses methodologies for measuring academic performance, identifies key factors influencing it, and reviews analytical and statistical methods employed. Additionally, it analyzes educational interventions implemented in different contexts. The most effective practices are identified, and research gaps are highlighted, pointing to directions for future research.

2. Methods

This study follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [10]. The use of PRISMA for systematic reviews is essential to standardize and improve their quality, ensure transparency, reduce bias, and increase reproducibility through thorough documentation of methods and selection criteria, making it easier for other researchers to replicate the study [11].

2.1 Search Strategies and Information Sources

The Web of Science (WOS), Scopus, and IEEE Xplore databases were searched because of their prestige, scope, and reliability within the academic and research community. These platforms provide access to high-quality, peer-reviewed research and are widely used to collect studies in various fields, such as education and engineering. In the case of WOS, it is a database known worldwide for its coverage of a wide range of disciplines and is used by universities and top research centers. Its focus on high-impact journals ensures that the articles indexed are of high relevance and quality in their respective fields [12]. SCOPUS is considered one of the most comprehensive bibliographic databases, covering a wide range of disciplines, including social sciences, engineering, and education. Its citation measurement system, such as Scopus CiteScore, is often used as a benchmark for assessing the impact of research [13]. IEEE Xplore is a specialized database in engineering, technology, and computer science, making it a key resource for research in technology education and studies involving technical or engineering applications in education [14].

The search string used was as follows: TITLE-ABS-KEY (academic performance OR academic achievement OR academic success OR performance indicators OR academic outcomes OR student success) AND TITLE-ABS-KEY (first-year engineering OR freshman engineering OR introductory engineering OR engineering undergraduates OR engineering freshmen) AND TITLE-ABS-KEY (higher education OR university OR college OR post-secondary education OR tertiary education) AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO(DOCTYPE, ar)) AND (LIMIT-TO(LANGUAGE, english)).

The terms academic performance, academic achievement, and academic success are often used in educational research to describe student success in terms of grades, academic goal attainment, and progression in their studies [15, 16]. The experience of first-year engineering students has been the subject of numerous studies due to the dropout rates and unique challenges these students face. Research has shown that the terms first-year engineering and freshman engineering are widely used in studies that focus on the early experiences of engineering students at universities [17]. The focus on the first years is due to their critical impact on the retention and long-term success of engineering students. Terms such as higher education, university, college, post-secondary education, and tertiary education are commonly used to describe the educational environment in which academic performance studies take place and are widely used in systematic reviews of higher education research [18].

2.2 Eligibility Criteria and Study Selection

In terms of form, the following initial inclusion criteria have been adopted:

(a) Articles only, excluding the so-called gray literature. The exclusion of grey literature from this systematic review is justified, in part, by the lack of peer review, which raises questions about the quality and reliability of the sources. This lack of standardization may introduce bias or hinder the objective assessment of evidence, which negatively affects the reliability of the review [19].

(b) The language was English, as it is internationally recognized as the main language in high-impact scientific publications, and several studies have shown that articles published in English tend to be more cited and visible internationally [20].
(c) Published between 2014 and 2024. The search was conducted in July 2024, so only studies published between 2014 and July 2024 were included. Restricting the search to publications after 2013 and before 2025 ensures the relevance and timeliness of the studies [21].

The initial inclusion criteria were applied to a corpus of 125 articles, which constituted the focus of the subsequent search. A total of 48 articles were identified in the WoS database, 72 in Scopus, and 5 in the IEEE Xplore database. A total of 39 duplicates were identified, resulting in an initial sample size of 86. A preliminary examination of the articles yielded by the initial search was conducted, in which the titles and abstracts were reviewed. One article was excluded because it was not written in English [22], while another was not located [23]. This initial screening resulted in a total of 84 articles, which were then independently assessed by the authors to ascertain their alignment with the inclusion criteria. Of the 84 articles, 36 were found to fully meet the aforementioned criteria.

To ensure a rigorous reduction of biases, the articles underwent a two-step review process with a deliberate time interval between each review. One of the authors conducted a thorough, detailed evaluation of the articles, while a second author performed an independent, partial review to cross-check and validate the findings. This dual-review approach, combined with the temporal separation, helped mitigate potential bias by allowing for fresh perspectives and ensuring consistency and accuracy in the evaluation process.

The principal criteria for the inclusion of articles in the main content were as follows:

(a) *First-year students:* Studies that are specifically focused on first-year engineering students. Studies that cover students from all courses interchangeably [24–30] and [31] and studies that analyze the behavior of second-year students are also excluded. Third- and fourth-year students [32] or studies such as [33], conducted in the second year (fourth semester), or [34], which focus exclusively on the fourth year, are excluded.
(b) *Academic performance is measured by grades.* The articles included in this review should focus on factors that directly impact academic performance, specifically measured through grades. Some studies examine factors that, although do not directly measure grades [35], are nevertheless believed to influence academic performance. These variables contribute to a comprehensive understanding of educational success and personal development; thus, they are referenced as supplementary indicators in the literature, although they are not the primary focus of this study. For example, studies such as [36] and [37] are not included in this analysis as they assess skill development, such as collaboration and learning. Other studies exclude student success indicators such as retention or graduation rates [38–41], credits completed [42], or pass rates [43–46]. Furthermore, studies that rely on subjective perceptions or self-assessments of students [47–49], as well as those that utilize specific applications in an educational setting [50], fail to provide accurate data on final grades. Furthermore, studies that examine non-cognitive dependent variables, such as resilience, self-efficacy, motivation, social and academic support, and perceived sexism, have been excluded from this analysis [51]. Similarly, research exploring aspects such as sense of belonging [52], and studies addressing issues such as growth mindset versus fixed mindset [53], self-regulation, and volition [54] are excluded. In a similar vein, studies have been excluded that assess academic well-being [55, 56] life satisfaction [57], or mental distress [58]. Additionally, studies addressing topics such as engineering students' understanding of metaphors, preference for social networks like Facebook®[59], utilization of tools like Blackboard®[60], perceptions of career choice [61], approaches to learning [62], and experience with stereotypes [63] have been excluded. Additionally, studies assessing the sustainability of engineering campuses [64] and those designing instruments to measure affective characteristics of first-year students have been excluded [65]. While these studies are indirectly related to academic performance and their findings are highly relevant, they do not conclusively demonstrate the relevance of this relationship through final grades, which is the subject of this review.
(c) *Grades during the first year of study:* Academic performance is a broad concept that can be measured in a variety of ways, depending on the focus of the study. In this study we include two types of performance measures, both focused on grades. On the one hand, there is performance measured as the average of grades at the end of the first or second semester or at the end of the first full year. On the other, there is performance assessed within a particular

subject or a specific course corresponding to the first-year engineering curriculum. Studies that evaluate performance through grade point average at the end of the degree [66, 67] or grades obtained in subsequent courses [68, 69] have been excluded. Also outside the scope of this review are studies that measure the academic performance of the through pass rates or proprietary measures such as [70] that use cumulative study efficiency, which is the ratio of the number of credits earned to the total number of credits in which the student was enrolled. As can be seen in Fig. 1, which summarizes the search process in a PRISMA flowchart [71], of the 84 initial articles, 36 were finally selected, as 32 were excluded because they did not measure academic achievement through grades. In addition, 11 were excluded because they did not focus exclusively on first-year students, and 5 were excluded because they assessed performance in years other than the first year.

2.3 Data Collection Process

This article reviews studies that focus on the academic performance of first-year engineering students, as assessed by the grades earned by students during the first year. The review was organized into two categories, which are presented Table 1. The first category groups research that uses weighted first-year grades as the main measure of performance, focusing on identifying factors that influence academic performance in that year. The second category groups studies that analyze performance in specific subjects and evaluate the effectiveness of pedagogical methods and other interventions on academic outcomes. The tables summarize key data from each of the studies reviewed, including year of publication, country and university, objective of the study, sample analyzed, tests and variables considered, methods used, numerical results, and main findings. This organization facilitates a systematic comparison of the studies, making it possible to identify patterns and draw conclusions about the factors that affect the academic performance of first-year engineering students, either at a general level or in specific subjects. In total, 36 studies were reviewed: 16 on overall performance and 20 on subject-specific performance.

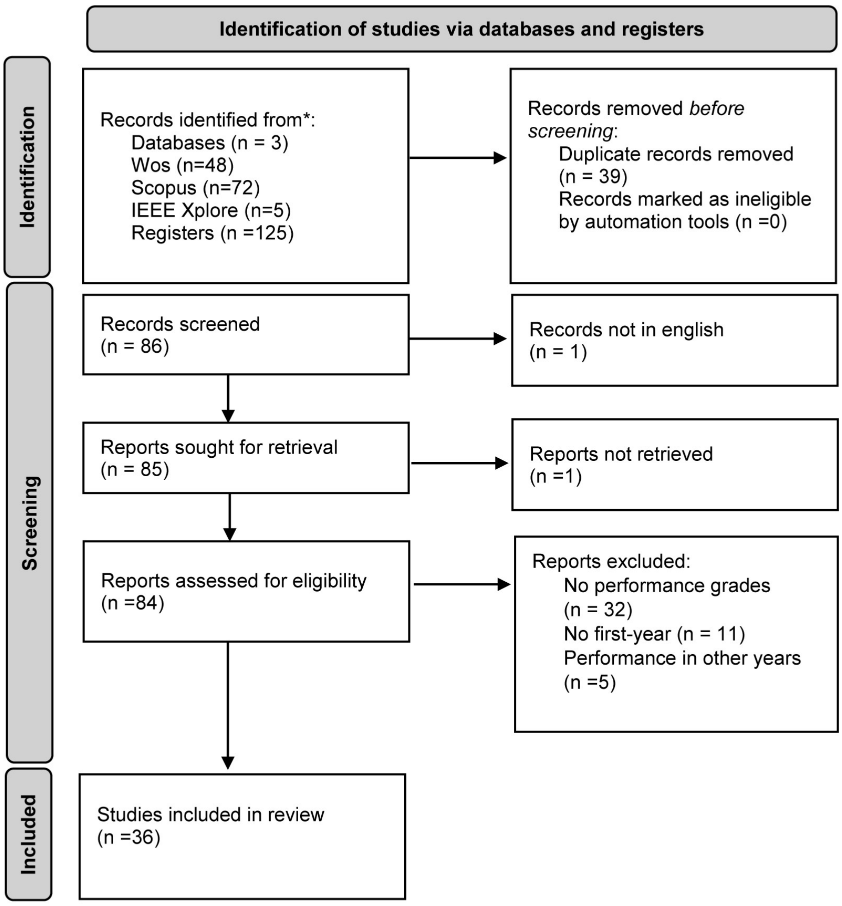

Fig. 1 PRISMA Flow Chart.

3. Results

3.1 Approaches to Performance Measurement

The results of the literature review are presented below, organized according to the structure mentioned earlier:

Performance as Measured by First-Year GPA (Grade Point Average): Studies of the academic performance of engineering students have shown that grade point averages, such as GPA, are an objective indicator of academic performance, particularly in the first year of study. In particular, research highlights that first-year GPA has a strong relationship with future academic performance, reinforcing its role as a reliable predictor of later academic success [72]. In addition, other studies confirm that GPA is an important predictor of academic performance and is used to identify at-risk students and guide early educational interventions [73]. The articles in this first group focus mainly on analyzing the characteristics that influence academic performance, using different data sources to extract independent variables, such as previous grades, standardized tests, and administrative data.

Performance measured by grades in specific subjects: Performance in specific first-year subjects, such as introductory courses, mathematics, or physics, helps provide a clear picture of students' performance during their first year. The performance in these key subjects serves as a predictive indicator of success in the program and is associated with improved overall performance in engineering. This relationship facilitates the early identification of students at risk of dropping out [74, 75]. The analysis of these subjects in the literature seeks both to identify factors that influence academic performance and to evaluate the effectiveness of different pedagogical methodologies and experiments conducted. The specific context of each subject allows the implementation of educational interventions and the measurement of their impact through questionnaires and performance assessments before and after their implementation. This controlled environment facilitates access to relevant data and limits the results to the interventions carried out.

Table 1 summarizes the classification of the selected studies, including the number of studies addressed and the corresponding references, in addition to a brief description detailing how performance was measured.

3.2 Variables affecting Academic Performance

The following identifies the factors that influence the academic performance of first-year engineering students, divided into two categories: cognitive and non-cognitive.

3.2.1 Cognitive Factors in Engineering Academic Performance

Academic performance in engineering programs during the first year of study is strongly influenced by a variety of cognitive factors. These factors relate primarily to students' prior skills and their academic preparation before entering college:

HSGPA: HSGPA (High School Grade Point Average) is one of the most consistent and reliable cognitive factors for predicting academic success in the first year of engineering. According to [104], it is one of the best predictors of first-year academic performance, although its effectiveness may vary depending on the student's home institution. A study with a sample of 4,689 students [86] confirmed that a low HSGPA is a significant predictor of low

Table 1. Classification of studies

Performance Measurement		Count	Reference	Description
Performance during the first year or in semesters		6	[76], [77], [78], [79], [80], [81]	First year
		7	[82], [83], [84], [85], [86], [87], [88]	First semester
		2	[89], [90]	First and second semester
Performance in specific courses	Introductory engineering courses	8	[91], [92], [93], [94], [95]	Introductory engineering course
			[96]	Engineering Skills and Ethics
			[97]	Engineering Science
			[98]	Problem Solving Skills
	Mathematics	8	[99], [100], [101], [102], [103]	Engineering Mathematics Course
			[104], [105], [106]	Calculus
	Physics	1	[107]	Engineering physics
	Digital Circuits	1	[108] [109]	Inverted digital circuits Digital circuits
	Design	1	[110]	Graphic expression course
	Mechanics	1	[111]	Mechanics of materials

performance in the first semester of engineering, and was able to identify 78% of students at risk of low performance using predictive models. Likewise, [78] highlights that HSGPA is the most representative variable in explaining academic performance, outperforming many other variables evaluated. In this context, the study [102] is particularly relevant, concluding that the difficulties in mathematics faced by engineering students could be related to secondary education, where procedural rather than conceptual understanding is prioritized.

College entrance score and standardized tests: The college entrance score is the score that combines high school grades and the results of an entrance exam and is used to evaluate the academic level of students and determine their admission to college. The study [77] highlights the importance of the college entrance score as a critical cognitive factor. This indicator was found to explain 35% of the variance in the first-year GPA of students from different engineering fields (electrical engineering, industrial electronics and automation, mechanics, industrial chemistry, and industrial technologies), suggesting that better academic preparation before entering university translates into better academic performance. Standardized tests, such as the SAT (Scholastic Assessment Test) in [104] and [88] and the ACT (American College Testing) in [86], in the United States, are tests that assess skills in key areas (mathematics, reading, writing). Both serve as predictors of academic performance in higher education. In the Philippines, study [79] found a significant correlation between CET (College Entrance Test) scores and academic performance in engineering programs. Finally, [110] highlights that CET scores are the best predictor of performance in the subject of Graphical Expression in Engineering, reinforcing the idea that previous academic performance plays a critical role in career success.

Cognitive knowledge in fundamental areas: Early performance also plays a fundamental role in academic success. Some studies [81] investigated the relationship between cognitive skills in fundamental areas such as mathematics, physics, chemistry or science, and academic success in engineering students compared to other areas. Their study showed significant correlations between the results of these tests and academic achievement. Other cognitive factors, such as intermediate performance in specific courses during the semester (attendance, test scores, and quizzes), also play a critical role in predicting academic performance [94]. Other examples are the results of [110] that underline the importance of a solid foundation in Technical Drawing and spatial skills for success in Graphic Expression subjects in first year of engineering degrees.

Early performance: In [102] a high correlation was found between students' initial mathematics performance and their final performance in an introductory mathematics course, suggesting that early performance is a key predictor of success in engineering mathematics courses.

3.2.2 Non-cognitive Factors Related to Academic Achievement

Non-cognitive factors are essential for academic performance, as they influence educational success beyond intellectual abilities. These include psychological, socioeconomic, demographic, behavioral, and institutional aspects. The interaction of these elements provides a comprehensive view of students' academic performance.

3.2.2.1. Psychological

The Psychological category in the context of studies on the academic performance of first-year engineering students encompasses a wide range of variables related to psychological and emotional aspects that may influence academic performance. Reference is made below to the factors found in the review conducted:

Motivation: Lack of motivation is one of the main reasons why engineering students drop out of their studies. In [90], the changes in the motivation of engineering students over six months were studied by analyzing amotivation, extrinsic and intrinsic motivation, and their relationship with academic performance. Extrinsic motivation was found to be positively correlated with performance in the first semester, while intrinsic motivation was found to be related to performance in the second semester. Although the overall level of motivation remained constant, an increase in extrinsic motivation was observed, driven by the desire to obtain a stable and well-paid career. This suggests that as students progress in their education, they adopt a more pragmatic approach to their studies.

Self-efficacy: For first-year engineering students, self-efficacy – or confidence in their ability to overcome academic challenges - is key to their adjustment and success. Those with high self-efficacy tend to persevere longer, cope more effectively with failure, and seek practical solutions, all of which positively impact their academic performance [102] and [76]. In addition, emotional intelligence strengthens this relationship and acts as a positive mediator of academic performance [84]. Self-efficacy is also associated with greater student engagement, which contributes to academic success by encouraging active participation in learning activities [85].

Growth mindset: The growth mindset in first-year engineering students involves the belief that skills in areas such as mathematics and physics can improve through effort and continuous learning. Students with this mindset perceive academic challenges as opportunities for development, rather than as indicators of talent or failure. In [80], the impact of growth mindset on the academic performance of these students is analyzed along with other variables such as perceived stress, resilience, and student engagement. Although this mindset was initially expected to positively predict GPA at the end of the first year, the results did not confirm this. However, the authors caution that the relationship between growth mindset and academic performance is complex. In contrast, the study [88] found that a positive appraisal of effort positively impacts performance during the first semester, whereas beliefs about intelligence did not show a significant effect on grades. This suggests that, by supporting beliefs in the importance of effort, engineering educators can contribute to students' academic success.

Perceived stress: Perceived stress arises when students feel that external demands exceed their resources. Among first-year engineering students, it often stems from academic pressure, adapting to the university environment, and family expectations. Without coping strategies, prolonged stress can lead to burnout, marked by fatigue, demotivation, and poor academic performance, ultimately affecting their well-being and future careers. Some studies, such as that conducted by [82], have explored the relationship between stress, burnout, and academic performance in engineering students. Their findings indicate that, in contrast to what has been observed in health science students, there is no direct relationship between these variables and academic performance in engineering. Nevertheless, the findings of [80] indicate that perceived stress serves as a substantial negative predictor of academic performance among first-year engineering students. As perceived stress levels increase, cumulative GPAs tend to decline. These conditions impede their capacity to concentrate and maintain motivation. Furthermore, data from [80] indicate that this negative impact is even greater in highly committed students, suggesting that high stress, especially, affects those who are more dedicated. Another relevant factor is test anxiety, which has been found to significantly decrease first-year GPA [87]. These findings suggest that, although stress and burnout do not impact academic performance in the same way in all fields, in first-year engineering students they do have a noticeable negative effect, particularly on anxiety management and emotional exhaustion.

Resilience: The capacity to withstand and recover from adversity is defined as resilience. Resilience in first-year engineering students can be defined as the capacity to adapt and recover in the context of academic challenges, including stress and heavy workloads. Students who demonstrate resilience tend to perceive obstacles as potential learning opportunities, which enables them to sustain motivation and maintain a stable academic performance. In [80], resilience was not identified as a direct predictor of cumulative GPA. However, it was observed to mitigate the adverse effects of stress. Students with high resilience did not exhibit a significant correlation between their stress level and academic performance. It can be concluded that resilience is a pivotal factor in attenuating the impact of stress. It is imperative to implement educational programs that fortify this skill, assisting students in managing pressure and enhancing their academic performance.

Beliefs and attitudes toward mathematics: Beliefs and attitudes toward mathematics in first-year engineering students refer to how they perceive their ability to learn mathematics, their level of confidence, and the value they place on this subject. These beliefs influence their motivation, effort, and performance in mathematics, a fundamental subject in engineering. Students who view mathematics from a formalistic perspective, i.e., as a set of abstract rules and procedures, have more difficulty relating mathematical concepts to engineering problem solving. This contributes to a lack of motivation and negative attitudes towards the subject, which in turn decreases their performance [102]. A study at Qatar University [76] highlighted that confidence in mathematics and science is the most important non-cognitive factor in predicting the academic performance of first-year engineering students.

Commitment, teamwork, and Big Five personality traits [112]: Commitment and focus on teamwork are significant predictors of academic performance, while personality traits have a less significant impact. In [83] it is found that teamwork competencies are better predictors of academic performance than personality traits. Regarding commitment, in [76] it was found that commitment to the university and social involvement are related to performance. In [80] it was found that although student engagement was not identified as a direct predictor of GPA, the relationship between stress and GPA was intensified in students with higher levels of engagement. This is understandable, as more engaged students tend to experience stress more intensely, which may negatively influence their academic performance. Along these lines, in [87] it was shown that conscientiousness was one of the few traits with a significant positive impact on academic performance, implying that students who prove to be more organized, responsible, and disciplined tend to get better grades. These students plan their assignments better, manage their time efficiently, and are consistent in their approach to studying. Conscientiousness enables them to establish and follow more effective work routines, which reduces the negative impact of stress and promotes better performance in their subjects.

3.2.2.2. Socioeconomic

Family socioeconomic level: The family socioeconomic level is identified as a factor that moderately influences academic performance, particularly in students facing resource constraints in rural areas or low-income families. This can result in lower performance and an increased risk of dropout [99]. Furthermore, in contexts where resources are limited, such as rural areas, socioeconomic constraints often affect performance. Many students in these contexts face challenges related to resource availability and other family issues, which can lead to low achievement.

Parental education: A student's academic development in their first year of engineering studies may be influenced by their parents' level of education. Parents with higher levels of education may be able to provide a supportive environment and high expectations, which can positively impact a student's motivation and performance. Students whose parents are engineers may have been exposed to engineering subjects from an early age, and those with highly educated parents may have greater financial resources to support their education [100]. However, this factor is not the only determinant of success, as aspects such as personal effort and educational environment are also critical [78].

3.2.2.3. Demographics

Gender: Gender can influence students' experience in the first year of engineering, as historically there has been an underrepresentation of women in the field. This can create additional challenges, such as perceived gender stereotypes and lack of role models. However, most of the studies reviewed did not find that it had a significant impact on the academic performance of engineering students. Studies such as the University of Valencia [77] or the Polytechnic University of Cartagena [110], ETH Zurich [78], the American University in Cairo [100], concluded that gender does not influence academic success. [107] investigated gender differences in motivation, procrastination, and academic performance in a Physics course for first year engineering students at the University of Monterrey, Mexico finding that women had higher intrinsic motivation and obtained better grades in the course than men, who showed higher levels of procrastination. In conclusion, although gender does not appear to significantly influence academic performance in most studies, contextual and psychological factors may modulate its impact.

Age: Regarding age, all the studies reviewed concluded that it does not have a significant impact on the academic performance of engineering students. Studies conducted at ETH Zurich [78], the University of Valencia [77] and Cartagena [110] in Spain and the American University in Cairo [100] agreed that age does not influence students' academic success.

First-generation student: First-generation students face additional challenges of not having a family referent in academics, which can create academic and emotional barriers. However, many develop resilience and motivation to overcome these difficulties. Thus, in Spain, a study from the University of Valencia [77] found that being a first-generation student does not significantly impact academic performance or retention in engineering.

3.2.2.4. Behavioral

Learning orientations: Learning orientations reflect the attitudes and strategies students adopt to interact with academic content and process information. They are divided into three main types: the deep learning orientation, which involves active understanding and is associated with better academic performance; the surface orientation, focused on memorization without comprehension and related to worse results; and the strategic orientation, which balances time management and planning to optimize performance. In [89], it was observed that students with an understanding orientation achieved better grades, while those with a reproduction orientation obtained lower scores, reflecting a superficial approach. Furthermore, in [81], negative correlations between surface orientations and academic performance were identified, highlighting the importance of deep learning in scientific areas.

Study habits: Study habits are crucial for academic success in engineering. In [100] investigates how an organized approach and techniques such as planning and continuous review are key predictors of performance in first-year engineering students in Egypt. Time management and planning are highlighted as essential factors, supported by statistical analysis and testimonials from students, who emphasize the importance of organization and distribution of tasks into small goals to achieve high academic performance. Study [97] examined the relationship between engineering students' use of study strategies and their academic performance in an introductory engineering course. A significant positive correlation was found between self-study strategies and performance on *problem sets* [113], indicating that students who focus on self-study tend to perform better on these exercises. Furthermore, problem set performance acted as a key mediator between study strategies and final course grades, showing a significant indirect effect. However, in [104] it was found that the factors WM (study methods), TA (attitude towards teachers) and EA (attitude towards the educational system), obtained from the SSHA (Survey of Study Habits and Attitudes) test [114], were not significant in the analysis of academic performance.

Social networking: Social networking for first-year engineering students is an effective tool to promote collaboration and shared learning. Through online groups and platforms, students can share resources, engage in academic discussions, resolve questions together, and establish connections with peers and professors. These networks also facilitate access to broader engineering communities, offering opportunities for mentoring, events and projects. However, the use of social networks must be carefully managed to avoid distractions and maintain a balance with academic responsibilities. Research [78] explores how social networks develop among unfamiliar students and the impact of this integration on their academic performance, showing that those who actively participate in social networks tend to get better grades. Thus, group study not only fosters knowledge sharing, but also contributes positively to the academic performance of engineering students, highlighting the value of social ties in the educational context.

Circadian preference (morning/afternoon) and class attendance: Circadian preference and regular attendance are essential for academic performance in the first year of engineering, especially in active learning courses. According to [98], where students tend to miss more morning classes, there is a negative impact on their performance because active learning requires constant participation in hands-on and collaborative activities. Lack of attendance not only affects the absent student, who misses crucial interaction and feedback opportunities, but also impairs the group dynamics, reducing the effectiveness of this pedagogical approach in the understanding of complex technical concepts.

3.2.2.5. Institutional

Institutional factors are key elements that shape the educational environment and have a significant impact on students' academic performance, particularly in demanding disciplines such as engineering. Although individual factors are often the most prominent in the educational literature, factors at the institutional level also play a crucial role in student success.

Curriculum, Teaching Competencies and Academic Services: The curriculum in the first year of engineering focuses on technical fundamentals, teaching competencies ensure clarity in teaching, and academic services provide crucial support for academic success. Some studies mention that several institutional factors, including curriculum design, teachers' pedagogical and scientific competencies, [100] and academic support services [110], influence the academic performance of first-year engineering students. However, in their quantitative results, only study habits and prior knowledge were shown to be significant predictors of academic success.

Class composition: The study [96] highlights that peer ability is crucial in individual performance: the presence of high ability students improves grades and retention, while the presence of low ability students may reduce these results.

As shown in the categorization in Table *2*, both cognitive factors, as well as non-cognitive factors, influence the academic success of first-year engineering students, although not all to the same extent and their impact depends on the context in which the studies are carried out.

3.3 Educational Interventions and Experiments Performed

The articles reviewed evaluate the impact of various educational interventions on the academic performance of engineering students, organized into four categories: (1) integration of technological tools, (2) innovative pedagogical methods, (3) reflection and self-regulation approaches, and (4) strategies to improve mathematical and problem-solving skills. Each intervention, evaluated in controlled studies, seeks to optimize instruction and prepare students for the challenges of engineering. The following are the interventions grouped by approach and methodology.

Table 2. Variables related to performance in the first year of engineering

Category	Subcategory	Features
Cognitive	Academics	HSGPA, college entrance scores, standardized test scores, performance in specific courses, knowledge in fundamental areas (mathematics, physics, chemistry, technical drawing), early performance.
Non cognitive	Phychologicals	Beliefs about effort, motivation, perceived stress, resilience, commitment, teamwork, and Big Five personality traits, growth mindset, attitudes toward mathematics, self-efficacy, and collaboration.
	Socioeconomics	Family income, parents' educational level.
	Demographics	Age, gender, being a first-generation student.
	Institutionals	Curriculum, teaching competencies and academic services, class composition.
	Behavioural	Learning orientations, study habits, integration in social networks, class attendance.

Use of technology and educational tools: The use of technology in engineering has been shown to improve both academic performance and perceptions of learning. It has been shown that the inclusion of iPads for three years in an introductory course improved test scores and increased positive assessment of learning [95] and the implementation of 3D printers in introductory courses at the University of Texas at El Paso also significantly increased performance and perceptions of the educational value of technology [92, 93]. The use of WhatsApp for team communication and online meeting platforms to coordinate discussions in a calculus course with a collaborative learning approach enabled greater interaction among students and facilitated collaborative learning, resulting in improved academic performance, interest, and satisfaction compared to traditional methods [101].

Innovative learning methods: Innovative learning methods such as the flipped classroom -an approach in which students study material independently before class, using face-to-face time for interactive activities and application of concepts-have been shown to improve performance and understanding in engineering. In [109], a digital circuits course at Central Michigan University showed that the inverted model increased both performance and perceived learning. Similarly, a study noted improvements in performance and efficiency in covering content [108]. However, this inverted model used in a mechanics course only showed significant improvement in midterm grades, with no noticeable difference in the final grade in [111]. This finding suggests that, although innovative methods such as the inverted classroom have significant potential, their implementation must be carefully tailored to the characteristics of the course and students in order to maximize their impact on learning.

Focus on reflection and metacognition: The focus on reflection and metacognition has emerged as a key strategy to improve learning in engineering and mathematics. Prompts are tools that encourage critical reflection and can be generic or specific, the latter being aligned with the course objectives. It has been concluded that specific prompts are more effective for the academic performance of engineering students [91], highlighting the importance of their alignment with learning objectives in first-year courses. Regarding the reflective approach, undergraduate mathematics students' awareness of changes in abstraction levels and their relationship to academic success has been investigated. Results indicate that students who better recognize these changes tend to perform better in their courses [103].

Mathematics and problem-solving courses: Mathematics is essential in the education of engineering students but often presents challenges that can affect their performance. Various educational interventions have been implemented to address these difficulties, focusing on improving problem-solving skills through collaborative and hands-on methods [101]. The study [105] presented an Engineering Mathematics course taught by engineers, which focused on essential mathematical topics for early engineering courses. The results showed that students in this course overcame mathematical challenges better, achieving better results than those in a traditional calculus course. In [106], a modeling-based mathematics course within a summer bridge program was analyzed, which helped students close the knowledge gap with respect to their peers. The results showed that this specific approach to mathematics learning improved both performance in fundamental courses such as Calculus and understanding of key concepts. In addition, the location of these courses within the academic calendar was shown to be a key factor in improving academic performance in these students.

3.4 Statistical Methods and Analytical Techniques

Most of the reviewed studies use descriptive statistical methods, such as calculating the mean and standard deviation, to summarize and describe the

Table 3. Quantitative statistical methods and analytical techniques

Category	Count	Method	Ref
Correlation Tests	18	Pearson/Spearman	[77], [79], [81–85], [90], [94], [97], [99], [100], [102], [104–105], [107], [110]
		Network Autocorrelation Models	[78]
ANOVA and related	15	ANOVA	[84–85], [87–88] [89], [98], [100], [102], [105–106], [108]
		ANCOVA	[91] , [106]
		MANOVA	[88], [109]
Main comparison	5	T-test	[83], [86], [101], [106]
Group comparison	7	Kruskal–Wallis Test	[82], [104], [107]
		Mann-Whitney Test	[82], [97], [81]
		Wilcoxon Test	[90]
Regression Analysis	19	Mediation Analysis	[97]
		LASSO and Ridge Regression	[76]
		Linear Regression	[78], [83], [80], [86–88], [100], [110–111]
		Logistic Regression	[104], [96], [94], [110]
		Hierarchical Multiple Regression	[98], [87], [88], [111]
Multivariate Analysis	5	Hierarchical Cluster Analysis	[89]
		Sequence Clustering Analysis	[89]
		Exploratory Factor Analysis	[102]
		Hidden Markov Model (HMM)	[89]
		Stochastic Actor-Oriented Models (SAOMs)	[78]
Structural Equation Modeling (SEM)	2	Path Analysis	[77]
		SEM with Bootstrap	[84]
Data Mining and Machine Learning Technique	10	Classification and Regression Trees	[86], [94], [99]
		Naive Bayesian Classification (NBC)	[94]
		Support Vector Machine (SVM)	[94]
		Neural Networks	[94]
		Multivariate Adaptive Regression Spline (MARS)	[99]
		Kernel Ridge Regression (KRR)	[99]
		K-Nearest Neighbor (KNN)	[94], [99]

data. However, the analyses go beyond basic descriptive approaches, incorporating a variety of techniques. These range from correlation tests to more advanced methods, including machine learning models. Table 3 provides a detailed summary of the statistical and analytical methods used in the studies, organized by category. These methods include correlation analysis, hypothesis testing, nonparametric tests, regression techniques, multivariate analysis, structural equation modeling, hierarchical models, and data mining or machine learning approaches. This classification highlights the most used tools and their references in the literature. Additionally, some studies integrate qualitative methods, such as thematic content analysis [103] and [111], Likert-scale surveys to measure perceptions [92, 93] and [95] and interviews to gather in-depth perspectives [100] and [103].

4. Discussion

Academic achievement is a multifaceted concept that can be evaluated from different perspectives and by a wide variety of metrics. The first conclusion of this review is drawn from the exclusion of many articles due to the diversity in the ways of measuring academic success, which highlights the inherent complexity of this type of research. Measures of performance have been found with grades at the end of the first year [76, 78], or at the end of either semester [82–84], grades in some key subjects such as mathematics [99–101] or physics [107], or with grades in introductory engineering courses [91–93]. However performance is also measured through rates such as retention or graduation rate [38, 39] and [41], or with subjective metrics that capture student perceptions such as student satisfaction [47–49], among others. The lack of standardization in these metrics reflects the diversity of theoretical and methodological approaches present in the field. While some studies focus on short-term academic performance, such as test scores, others address medium- or long-term success such as [32] and [34], and can even be measured by post-education career achievements.

In this review, two approaches to measuring academic achievement in the first year of university are highlighted: the use of overall course averages and subject-specific assessment. Overall averages span multiple subjects and require large and diverse databases, which adds complexity to the analysis. In contrast, evaluating a single subject allows for a more manageable and controlled analysis focused on specific conditions. In both approaches, grades are the most objective and widely used measure for assessing academic performance in different educational contexts [72, 73].

This same variety in how academic performance is defined and measured also underpins several limitations of the present review, as it complicates comparability between studies. While some studies use overall averages, others focus on specific subjects and apply different methods within each approach. These differences generate variability in the results and make it difficult to draw consistent conclusions. The significant difficulties in accessing administrative data from institutions for data protection reasons must be taken into account, which makes performance more feasible to measure in a specific subject, where the informed consent of individual students can be requested. Similarly, there are differences in the predictors of academic performance, influenced by contextual and cultural variations. The lack of longitudinal studies limits our understanding of these factors over time, and cultural and socioeconomic differences restrict the generalization of findings, highlighting the need for context-specific research.

A common trend observed in the literature review is the influence of cognitive factors related to prior performance, such as university entrance score and standardized entrance exams. University entrance score emerges as a crucial cognitive factor for students' academic performance, especially in the first year of engineering [77], which is consistent with results observed for degrees in other branches than engineering [115]. As for standardized tests, the review of studies shows mixed results regarding their predictive ability for university performance. This is consistent with other studies prior to this review, such as [116] which indicates that factors such as student motivation can significantly influence the results of these tests, which can distort the conclusions about the learning obtained. Likewise, nuanced results along these lines are obtained in other contexts, such as in [117] who analyzed state tests in Russia and found that, although these tests successfully predict academic performance during the first university year, their predictive ability decreases in subsequent years.

The HSGPA has been shown to be a relevant indicator in a variety of contexts. This conclusion has been supported by findings in other disciplines, such as psychology [118]. Furthermore, there is evidence highlighting HSGPA as a reliable predictor not only during the first year of university studies, but also until the end of the degree [119]. A relevant study found that, despite variations in HSGPA among different schools, it remains a robust and consistent predictor of college completion, even outperforming ACT scores [120].

Multiple studies reviewed highlight that mathematics is crucial to the academic success of engineering students, both as an essential knowledge base and as a predictor of future performance. Cognitive skills in mathematics show a significant correlation with academic performance, outperforming other areas [81]. In addition, beliefs and attitudes toward mathematics, including confidence and perceived value, impact freshmen performance. Early mathematics performance correlates strongly with success in university courses, indicating that a strong mathematics foundation is a key predictor [102]. The ability to recognize changes in levels of mathematical abstraction is also associated with better outcomes [103]. Educational interventions such as collaborative courses and hands-on problem-solving methods [101] mathematics courses taught by engineers [105] and summer programs based on mathematical modeling [106] have been shown to close knowledge gaps and improve understanding, contributing to better overall performance. These results support the conclusion that strong mathematics preparation is critical for success in the early years of engineering studies [121].

On the other hand, non-cognitive psychological variables, such as self-efficacy and emotional intelligence, are also determinants of performance, which is consistent with studies in other branches [122] where self-efficacy is found to be a robust predictor compared to other factors, even after considering stress. Self-efficacy helps students to overcome difficulties and achieve better results, while motivation has a differential influence: extrinsic motivation is associated with performance in the first semester and intrinsic motivation in the second [90]. This is also consistent with studies from other fields [123] that found that both intrinsic and extrinsic motivation were significantly related to academic performance, with effort acting as a partial mediator between these variables and GPA. Some behavioral variables, such as orientation towards deep learning approach, have also been found to be relevant in affecting academic performance, which is also consistent with what has been found in other branches such as science and health [124].

In another line of analysis, it is evident that the presence of certain universities in the literature may reflect regional or institutional priorities in addressing the challenges faced by first-year engineering students. Institutions such as Purdue University and the University of Texas at El Paso, for example, not only contribute frequently but also tend to focus on innovative pedagogical practices and interventions tailored to their specific educational contexts. This suggests that while the distribution of studies is relatively broad, certain universities play a pivotal role in advancing research in this domain.

The literature reveals a variety of methods to analyze academic performance. Penalized regressions and hierarchical models excel in complex data; nonparametric techniques such as Kruskal-Wallis and Mann-Whitney U are useful for nonnormal data. Machine learning improves predictive accuracy for both performance [125], and retention [126], while correlation tests and ANOVA remain essential, especially in combination with advanced methods, thus offering a comprehensive view.

In conclusion, a mixed methodological approach is best suited for the analysis of academic performance in this educational field.

5. Future Research

For future research, it would be key to compare institutions both nationally and internationally, assessing how variations in educational systems affect the performance of engineering students. Factors such as curricular approaches, admissions policies, and teaching models require further analysis to understand their impact. Developing a standardized framework would enable accurate comparisons between institutions and countries, facilitating the identification of best practices and allowing institutions to adapt their educational strategies according to their needs. In addition, it is essential to assess the consistency of the findings over time to ensure that the conclusions are applicable in the long term and not influenced by external changes.

6. Conclusions

This systematic review shows that academic performance in the first year of engineering is a complex and methodologically diverse construct. The studies analyzed use multiple indicators – first-year or semester averages, grades in key subjects, retention or graduation rates, and even subjective measures of self-perceived performance – which makes it difficult to directly compare results and highlights the lack of standardization in the metrics used. Within this context, this study has focused on articles that measure performance using grades obtained during the first year, either through overall averages (course or semester GPA) or performance in specific subjects. These two approaches are confirmed as complementary: the first provides an overview of progress, while the second offers a more controlled and contextualized analysis.

In relation to the factors associated with performance, the results confirm the consistent weight of prior cognitive factors. HSGPA, university entrance exam scores, and standardized test results repeatedly appear as solid predictors of academic success in the first year of engineering, in line with what has been observed in other disciplinary fields. Early performance in fundamental subjects also reinforces the cumulative nature of learning. Within this set, mathematics emerges as a critical component of the engineering curriculum: it acts both as an essential knowledge base and as one of the most powerful predictors of subsequent performance. Its comprehension is conditioned by the level of prior knowledge and attitudes toward the subject, which directly influence the ability to solve complex problems. The studies reviewed show that active pedagogical approaches and the use of educational technologies can improve performance and conceptual understanding in this area, helping to reduce knowledge gaps in the first years of study.

The review also underscores the important role of non-cognitive factors in understanding academic performance. Psychological variables such as self-efficacy, motivation and certain study habits show consistent, significant associations with students' grades and are therefore key to a comprehensive picture of achievement. Self-efficacy emerges as a strong predictor, while motivation displays different patterns of influence across the first and second semesters.

In addition, factors such as perceived stress, resilience, learning approaches, participation in academic social networks and class attendance help refine this picture, reinforcing the idea that success in the first year cannot be attributed solely to prior academic preparation. By contrast, demographic variables like age and gender do not, in most studies, exhibit a clear and systematic effect on grade-based performance. Socioeconomic status remains a more contested factor, with its impact depending heavily on the educational context: in some cases, a higher socioeconomic background is linked to better access to resources, whereas well-designed institutional and policy measures can help to reduce or compensate for these disparities.

In terms of educational interventions, the studies reviewed indicate that certain pedagogical strategies can improve first-year performance when implemented in a manner consistent with the curriculum and student characteristics. The integration of digital technologies, active teaching-learning methods (such as the flipped classroom or collaborative learning), and approaches focused on reflection and metacognition are associated, taken together, with improvements in performance and perception of learning, although their effects are not uniform across all contexts or subjects. This suggests that the effectiveness of interventions depends both on their design and on their degree of adaptation to institutional conditions and the specific needs of the student body.

The review also highlights a wide diversity of methodologies in the analysis of academic performance, ranging from classical statistical techniques (correlations, mean comparisons, ANOVA, regressions) to hierarchical models, structural equations, and data mining and machine learning approaches. The use of mixed methodologies, which combine traditional statistics with advanced techniques and, in some cases, qualitative methods, is particularly suitable for capturing the complex interaction between cognitive and non-cognitive factors. This type of analysis allows patterns to be detected that would not be evident with conventional methods and offers new perspectives for the design of educational interventions and the formulation of policies aimed at improving performance.

Finally, the results underscore that the geographic and cultural context is a determining factor in the effectiveness of interventions and in the interpretation of findings. Differences in infrastructure, educational resources, and teaching practices require theoretical models and support strategies to be adapted to the specific context of each institution and country. In this regard, the need for flexible and adaptive approaches that integrate both students' prior abilities and their attitudes toward learning is highlighted to optimize the impact of actions aimed at improving academic performance in the first year of engineering.

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Ana Aparicio Colino received the degree in telecommunications engineering from the Universidad de Valladolid, Spain, in 2005. She is currently pursuing a PhD degree at the Universidad Politécnica de Madrid, in collaboration with Universidad Pontificia de Comillas, where she is a researcher at the Santalucía Chair of Analytics for Education. Her main field of study is academic performance and dropout in engineering degrees. Since 2006, she has held various engineering and management positions in a multinational energy company in Spain, with experience in smart grids, renewable energy, and portfolio management. Her interests include educational data analytics, predictive modeling, and digital and intercultural learning programs.

José Luis Arroyo-Barrigüete received PhD degrees in economics (2006), engineering (2007), and philological studies (2019), as well as degrees in statistics (2004) and industrial engineering (1999), from universities in Madrid and Seville, Spain. His research focuses on applying quantitative methods to education and business. He began his career in 2000, working for multinational firms such as Accenture, Abengoa, and Acciona. Since 2018, he has been a Full-Time Professor in the Department of Quantitative Methods at Universidad Pontificia Comillas. He is the author of numerous academic publications. Prof. Arroyo-Barrigüete leads the GIIDA Research Group on Teaching Innovation and Analytics and co-directs the Santalucía Chair of Analytics for Education.

Carmen Sánchez-Ávila has a PhD degree in Mathematics Sciences and is currently a Full Professor at the Universidad Politécnica de Madrid (UPM), Spain, where she teaches in the Department of Applied Mathematics to ICTs. She is also Director of the GB2S Research Group at the UPM's R&D+i Center for Energy Efficiency, Virtual Reality, Optical

Engineering and Biometry (CeDInt-UPM), which she helped found. She has led over 40 R&D projects and contracts in biometric authentication, smart mobility, and data analytics, and has authored over 60 JCR-indexed articles in journals such as IEEE Transactions on Industrial Electronics, Pattern Recognition and Plos One, among others. Her research interests include biometric security, deep learning and signal processing. She is a member of the AENOR technical committee on biometric standards, as well as the ELLIS Madrid unit for developing innovative methods of interpretable causal machine learning based on probability for dynamic scenarios and cross-cutting quantum technologies for intelligent systems. She also heads the MENTOR Educational Innovation Group and actively supports mentoring and outreach in engineering education.