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Predictors of University Attrition: Looking for an Equitable and Sustainable Higher Education

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Abstract: The failure and dropout of university studies are issues that worry all nations due to the personal, social, and economic costs that this they entail. Because the dropout phenomenon is complex and involves numerous factors, to reverse it would involve a comprehensive approach through interventions aimed at the factors identified as key in the decision to drop out. Therefore, the main objective of this work is to determine the profile of students who enter the EPN (STEM higher-education institution) to analyze the characteristics that differentiate students who drop out early in their career and those who stay in school. A sample of 624 students who accessed the EPN leveling course (a compulsory course at the beginning of their studies) participated in the study. A total of 26.6% of the participants were women. A total of 50.7% of the participants passed the course. Data referring to social, economic, and academic variables were analyzed. Comparison techniques, as well as artificial neural networks, were used to compare characteristic profiles of students who passed the leveling course and those who dropped out. The results showed significant differences between the profiles of the students who passed and those who dropped out with regard to the variables related to previous academic performance and motivational and attributional aspects. The artificial neural networks corroborated the importance of these variables in predicting dropout. In this research, the key variables predicting whether a student continues or leaves higher education are revealed, allowing the identification of students at possible risk of dropping out and thus promoting initiatives to provide adequate academic support and improve student retention.

Keywords: dropout; academic motivation; causal attributions; academic achievement; higher education

Citation: Vidal, J.; Gilar-Corbi, R.; Pozo-Rico, T.; Castejón, J.-L.; Sánchez-Almeida, T. Predictors of University Attrition: Looking for an Equitable and Sustainable Higher Education. *Sustainability* **2022**, *14*, 10994. https://doi.org/10.3390/su141710994

Academic Editors: Jordi Colomer Feliu, Jesús Granados-Sanchez, Linda Hagedorn and Marc A. Rosen

Received: 4 April 2022
Accepted: 23 August 2022
Published: 2 September 2022

1. Introduction

Failure and dropout of university students are issues that concern all nations due to the personal, social, and economic costs that they entail. Dropout is a global issue and generates numerous consequences for the student, as well as for the institution and the state. Because the dropout phenomenon is complex and involves numerous factors, reversing this problem requires a comprehensive approach, involving interventions focusing on the key factors identified as affecting the decision to drop out. In this study, an attempt was made to take a comprehensive approach to the problem, including both sociodemographic and psychoeducational variables, such as previous performance, emotional intelligence (EI), motivation and learning goals, and causal attributions, measured for university students. Therefore, the main objective of this work was to determine a profile of students who entered EPN (a STEM higher-education institution) to analyze the characteristics that can be used to differentiate students who drop out at the beginning of their university careers and those who remain in school.

2. Literature Review

The failure and abandonment of university studies are issues that concern all countries because of the personal, social, and economic costs they incur. In fact, the recent scientific literature [1–7] shows a committed and credible interest in fully addressing this need for educational intervention to provide the necessary resources, strategies, and methodologies to the educational scenarios of the 21st century, appealing to the quality of teaching in higher education and targeting the specific educational needs of university students, especially those who are at risk of social exclusion or have objective indicators of socioeconomic vulnerability.

At the European level, most countries take this issue seriously, as evidenced by the project HEDOCE (Higher-Education Dropout and Completion in Europe) published by the European Commission (2015) [8] that includes a synthesis of national policies designed to address this issue. Several studies conducted within the European framework related to failure [9] have shown that poor socioeconomic background is the dominant factor leading to desertion in students from minority groups, in addition to the lack of attention to the needs in the design and development of better educational programs [10,11].

In Spain, according to the U-Ranking Report (2019) of the BBVA Foundation (Fundación BBVA) [12], the percentage of students who do not complete university studies is 33% on average, being higher in technical and scientific degrees; this is a worrisome fact, given the need for graduates in science, technology, engineering, and mathematics (STEM), where dropout is approximately 40%, reaching 50% in engineering and architecture degrees from some universities. Although dropout occurs throughout the university career, it is concentrated in the first year of studies (20.4%); thus, any guidance or reinforcement efforts provided to these students are necessary at the beginning of their studies.

In Europe, some initiatives are aimed at analyzing European and national approaches to promote the recruitment of STEM professionals in relation to these needs of the labor market. The objective is to identify practices that help boost the supply of qualified STEM labor (Directorate General of Internal Policies of the Union, European Parliament, 2015) [11]. The European Commission's Horizon Europe (2020) program [13] subsidizes initiatives for enhancing the attractiveness of science education and scientific careers among young people in STEM (Horizon 2020 Work Program, 2014–2015) [14].

In Latin America and the Caribbean, there is also great concern about the failure and desertion of higher education. According to a 2017 World Bank report [15], only half of higher-education students manage to graduate. An example of this interest is the Latin American Congress on Dropout in Higher Education (Congreso Latinoamericano sobre el Abandono en la Educación Superior, CLABES), which has been held annually since 2011, with the main objective of bringing together teachers, education managers, and students from Latin American countries and Europe, concerned about the aspects related to academic dropout in higher education, as well as its causes and the possible initiatives that can be adopted to improve student retention [16].

2.1. Causes of Dropout

There are various causes of failure and desertion of university students; according to existing research, the main ones are as follows [12,17–19]: (a) deficiencies in the previous training of students; (b) inadequate design of study plans; (c) lack of accompaniment and support for students; (d) low quality of teaching; (e) few learning strategies or little student motivation; (f) an inadequate level of demand on the part of teachers; (g) the need to reconcile studies and work; (h) the poor social integration of students at the university. Improvement of these aspects should be based on dropout prevention and retention programs for the students.

As we have already pointed out, dropout is a global issue and generates numerous consequences for the student, as well as for the institution and the state. The Comprehensive University Dropout Management project "GUÍA" (Gestión Universitaria Integral del Abandono) consists of a network of university institutions formed with the intention of reducing dropout rates in higher education [20]. This project emphasizes the academic, social, and economic factors that lead to the decision to drop out by university students.

Social and/or cultural factors also influence dropout. The model implemented by Tinto [21,22] establishes that students, upon entering higher education, have their own characteristics (family, personal) that must fit with the reality of the institutional social system. His theory focuses on the effects of the organization of higher-education institutions on the individual, with student desertion being a reflection of the impact of the organization of higher education on socialization and student satisfaction. According to the theory of cultural capital, De Bourdieu [23], and the postulates of Tinto [21] in relation to the theory of social integration, cultural capital in students is represented by the cultural assets they apply to their development in higher education; on the other hand, the grade with which they enter the university and the average grades they maintain in the higher-education system are also important [24]. A good fit between the student's values and the norms of the university increases the student's sense of belonging the university, which in turn increases their academic motivation and academic success and decreases their intention to drop out [25,26]. It is in the early years where dropout rates are higher [27]. In turn, it has been identified that an early age of admission to the university, a low educational level of the parents, and gender constitute characteristics that imply risks of university dropout [28–30]. Regarding economic factors, dropout implies economic harm both for the state and for institutions, students, and their families. Public spending by each student [31] is also lost in the case of those who drop out.

In the Latin American environment, the number of studies on dropout has increased in recent years. Mellado et al. [32] conducted a review of scientific works related to dropout in Latin America and the Caribbean, reviewing 81 articles from 10 countries, managing to identify 111 related variables. They highlighted that all studies used the available data from the information systems of universities, whereas very few conduct additional surveys and none conducted surveys to identify the possible relationships between emotional intelligence, learning goals and causal attributions. In Ecuador, most studies carried out since 2018 have maintained the same models based on information from the academic platforms of universities and basic surveys on socio-economic and educational factors [33–38]. Regarding the EPN (Escuela Politécnica Nacional), two studies have been carried out on the subject of dropout. In [39] the grades obtained in the university entrance exam carried out by the government were analyzed together with data from the institutional information system to obtain factors related to dropout. Sandoval-Palis et al. [40] analyzed 11 socioeconomic variables obtained from a government information matrix and the grades obtained in the university entrance exam. The present study is the first of its kind in Latin America to exhibit the use of validated instruments to measure emotional intelligence, motivation, learning goals and causal attributions with the aim of relating them to the dropout of students in higher education.

2.2. Key Variables

Next, we analyze the relationship between dropout and the key variables integrated in this study: (1) previous performance; (2) emotional intelligence (EI); (3) motivation and learning goals; (4) causal attributions present in university students.

First, with respect to previous performance, it has been shown that well-prepared students are more likely to change careers than to drop out of school. In relation to academic factors, it is understood that previous academic performance directly affects the academic outcomes of students in two ways. On the one hand, there is a gap between the level of knowledge that students have when they enter the university and that which is required in the different disciplines they must study. On the other hand, there is a lack of mastery in the use of study and learning strategies that are required in a context of high academic demand [41].

In addition, the admission of correctly chosen students at the undergraduate level leads to a progressive reduction in dropout rates. Likewise, a more homogeneous group of peers in academic terms results in a greater tendency to stay in their initial career, while cohorts of students characterized by high competitiveness hinder the long-term permanence of students in university studies and facilitate the possibility of early dropout [42].

Second, several studies have shown the positive relationship linking emotional intelligence, achievement of academic performance, and lower rates of university dropout [43–46].

In addition, positive emotions embedded in learning processes are a predictor of effort, perseverance, and belief in one's own ability and in hard work being the main cause of achieving academic achievement [47–55]. In fact, it has been concluded that it is important to implement emotional education and mental health plans across all university studies as a good practice linked to the wellbeing of students, lower dropout rates, overcoming academic adversity, and perseverance in the achievement of high-performance goals and personal, academic and professional success, in general [56–58]. In this line, several studies have suggested specific programs to successfully train emotional intelligence in university students and demonstrate the multiple benefits that it entails [59–64].

Third, in terms of student motivation, it has been shown that there is a clear relationship between this variable and university dropout cross-culturally, obtaining the same clear positive tie between high motivation and a lower probability of university dropout in different countries and diverse cultural settings [65–73]. In fact, a correlation has been found between motivation and positive behavior of students, as well as favorable involvement in the learning process and academic achievement [7,46,74–81], in such a way that the most motivated students show less disruptive and/or challenging behavior, greater commitment to the learning process, and higher probabilities of achieving academic achievement. In the same way, recent studies have shown that the predictive value of motivation with respect to the probability of dropping out is clear, revealing that students with greater motivation are more resistant to the problem of dropping out, showing greater probabilities of completing the academic year [7,82,83].

Fourth, causal attributions play a determining role in academic achievement since they determine the ability of students to maintain the effort and persevere in their goals [84–91]. In this way, those students who have come to create an attributional style based on helplessness and characterized by the belief that their effort has little or no value for achieving positive academic outcomes are not proactive in the tasks, and the probabilities of dropping out are much higher [92–96], especially when the level of demand begins to increase given the natural evolution of the academic year. Some studies have suggested that attribution to controllable causes, such as attribution to effort, is strongly associated with academic performance [97,98]. The locus of control of causality also influences academic performance [97]; internal and controllable attributions, such as effort or self-regulation of learning, are related to higher academic performance [96,99,100].

These findings agree with the characteristics of those students who have causal attribution based on the belief that academic success depends on their effort and is, therefore, controllable and eligible for each individual [101–107]. In this way, highly motivated students, with an optimal level of self-efficacy, positive emotions based on the belief in their own ability, and an adaptive attributional pattern, consider that luck is not a particularly determining factor in their academic development and trust. Their attitude can make a difference and make it possible to achieve success [91,108–111]. For these reasons, they are capable of maintaining effort and perseverance until reaching their academic goals, radically decreasing the probability of falling into hopelessness embedded in university dropout.

2.3. Objective and Research Custions

Since the dropout phenomenon is complex and involves numerous factors, trying to reverse it would necessitate a comprehensive approach through interventions aimed at the factors identified as key in the decision to drop out. Therefore, the main objective of this work was to determine the profile of the students who enter the EPN (STEM higher-education institution) to analyze the characteristics that differentiate students who drop out at the beginning of their university careers and those who remain in school.

The primary research questions were as follows: Do more disadvantaged population segments have a greater probability of dropping out? Is gender related to dropout? Does lower previous academic performance increase the probability of dropping out? Do lower scores in emotional intelligence increase the probability of dropping out? Do attributions to external and uncontrollable causes increase the probability of dropping out? Do lower scores in achievement goals influence increasing the probability of dropping out? Do lower scores in motivation and self-regulated learning strategies influence increasing the probability of dropping out?

An attempt was made to take a comprehensive approach to the problem including both sociodemographic and psychoeducational variables. In this way, it was possible to propose the academic support most relevant allowing them to successfully complete higher education.

According to the existing literature, the variables considered as being able to differentiate among profiles include both sociodemographic and psychoeducational aspects.

The following hypotheses were considered in the study:

1. Students who belong to more disadvantaged population segments have a greater probability of dropping out [25,26];
2. Female students are less likely to drop out [28–30];
3. Students who have a lower previous academic performance have a greater probability of dropping out [112];
4. Students who have lower scores in emotional intelligence are more likely to drop out [113–115];
5. Students with attributions to external and uncontrollable causes have a greater probability of dropping out [96,99,100];
6. Students who present lower scores in achievement goals have a greater probability of dropping out [116,117];
7. Students who have lower scores in motivation and self-regulated learning strategies have a greater probability of dropping out [118,119].

3. Materials and Methods

3.1. Participants

In the EPN system, all students must take an academic leveling course that lasts for one semester. In this course, basic subjects are reviewed (the fundamentals of physics, chemistry, geometry and trigonometry, mathematics, and language and communication). In the present study, we initially considered 986 students belonging to a complete cohort who entered the leveling course. From this group, we selected those who passed the course (32.4%) and those who dropped out of the course (31.4%), giving a total of 629 students. Of this group, 26.6% were women and 73.4% were men. The remaining 36.2% of the students, who were not part of the study, were those who failed the course but did not drop out.

3.2. Instruments

3.2.1. Prior Academic Performance

In Ecuador, students who apply to a higher education institution must meet certain requirements. One of these is to take the National Exam of Educational Evaluation (Ser Bachiller), which is graded out of 1000 points. In the present study, the grade obtained in this exam was the first variable used to assess prior academic performance.

Sandoval et al. [120] developed an instrument composed of a mathematics section (55 items) and a language and communication section (25 items) with the objective of measuring students' initial basic competences in these areas. These two grades were used as the second and third variables to assess prior academic performance in the present study.

3.2.2. Goal Approach

The Academic Goals Questionnaire developed by Skaalvik (1997) [121] includes four sub-scales: (1) learning goals ("want to learn"), which refers to the intention of the student to compromise with the learning process, which is based on their intrinsic motivation; (2) performance-approach goals (wanting to show one's ability to others) which refers to the importance which the student places on displaying their knowledge in front of others; (3) performance avoidance goals (self-defeating, not wanting to be negatively judged by others) which refers to the inability of the student to assume risks in the learning process in order to avoid making mistakes in front of others, and (4) avoidance of academic work goals (doing tasks with the minimal amount of work possible), which refers to the students' approval of their subjects, and whether they exert the minimal effort in these subjects. It includes 22 Likert-type items, with five response options, using the following scoring method: 1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Usually; and 5 = Always. Sample items include "I prefer academic maters where you don't have to work too hard at home or in class"; "It is important for me to learn new things in class" or "In class I prefer to do as little as possible". The reliability index ranges between α = 0.85 (learning goals) and α = 0.89 performance-approach goals) [122].

3.2.3. Motivational and Self-Regulated Socio-Cognitive Skills

The Motivated Strategies Learning Questionnaire (MSLQ) [123] was employed. The instrument is composed of 44 Likert-type questions with seven response options, with 1 meaning "does not describe me at all" and 7 meaning "totally describes me". Sample items include "It is important for me to learn what is given in this course"; "I like what I am learning in this course", "I work hard to get good academic results, even when I don't like a course" and "I make summaries of materials to help me study".

The instrument contains two parts with different subscales for each one. The motivation part contains the following subscales: self-efficacy (how academically competent students feel), intrinsic motivation (level of students' personal commitment to academic obligations), and test anxiety (the level αof anxiety students experience in test situations in studies). The self-regulated learning strategies part includes the following subscales: metacognitive strategies (level of management and use of metacognitive strategies in their studies) and self-regulation (level of autonomy and self-discipline of students in their studies). The reliability indices are α = 0.75 (anxiety before evaluations), α = 0.89 (self-efficacy), α = 0.74 (self-regulation) and α = 0.83 (use of cognitive strategies) [123].

3.2.4. Emotional Intelligence

The Trait Meta-Mood Scale (TMMS), based on Salovey and Mayer's model of EI, is a self-reported measure composed of 24 items grouped into three factors—emotional attention (defined as the ability to pay attention to one's emotions), emotional understanding (defined as the ability to perceive, identify and understand emotions in oneself and others) and emotional regulation (defined as the ability to regulate effectively the moods and emotions in oneself and in other people)—which are valued on a five-point Likert scale, with (1) indicating "Completely disagree" and (5) indicating "Agree entirely" [124]. Sample items include "I pay a lot of attention to feelings", "I can understand my feelings" and "When I am angry I try to change my mood". The reliability of each factor is α = 0.90 for attention, α = 0.90 for clarity and α = 0.86 for repair [125].

3.2.5. Causal Attributions

The Multidimensional Causal Attributions scale [126] is a self-reported scale with 24 items, which are answered on a Likert-type scale (1–5), with (1) meaning "Completely disagree" and (5) meaning "Agree entirely". The scale allows one to obtain six indicators of causal attributions in the dimensions of internal/external, stable/unstable and controllable/uncontrollable and from the four attributional causes—ability, effort, luck/chance and the difficulty of the tasks. With the use of these indicators, six differential types of attributional styles or patterns can be obtained: F1: attribution of high academic performance to the ease of the materials; F2: attribution of academic performance to high academic ability; F3: attribution low academic performance to teachers; F4: attribution of academic performance to low academic ability; F5: attribution of low academic performance to low effort; F6: attribution of high academic performance to effort. Sample items include "Sometimes my success in exams depends on luck", "the most important reason for the good academic qualifications I get is my ability", I have the impression that some of the low grades I receive reflect the fact that some professors are excessively demanding with academic qualifications" and "Low academic qualifications tell me I didn't work hard enough". Regarding reliability, Cronbach's alpha of the total scale is 0.775.

3.2.6. Dropout

The analysis of dropout in universities is complex, not only because of the type of variables that influence it but also because various kinds of dropout have been conceptualized from different points of view [21]. In the present study, we used the definition of dropout proposed by Himmel [127]: the abandonment of a study program before graduation, when such withdrawal is for a period long enough to rule out the possibility of the student's return. Specifically, in this study, this measure involved assessing whether a student had dropped out of the academic leveling course or not".

3.3. Procedure

Secretaría de Educación Superior, Ciencia, Tecnología e Innovación (SENESCYT) is the government entity in charge of administering the entrance exam to public universities in Ecuador. According to the grade obtained, the student will be eligible for a group of careers in internally ranked universities, that is, if the student obtains a high score they can access better-quality universities and careers that are difficult to access, for example, software engineering at EPN (one of the best-ranked courses). Additionally, this organization performs complete surveys of the socio-demographic and economic characteristics of students. All this information is consolidated in an Excel table called Matriz de Tercer Nivel (MTN). This was the first input used for the research in this work, specifically, an MTN of 624 students enrolled in the leveling course of EPN.

In the second phase, we proceeded to administer an initial knowledge test in mathematics, language and communication. Prior to the beginning of this test, each student signed an informed consent form regarding his/her participation in the research. Each student was provided with a sheet of questions and an answer sheet which he/she would hand in at the end of the exam. The answer sheets were evaluated with the help of a high-speed scanner and software that allowed the automatic scoring of the answers.

In the last phase, a unified test including the Academic Goals Questionnaire, Motivated Strategies Learning Questionnaire, Trait Meta-Mood Scale, Multidimensional Causal Attributions scale and a questionnaire regarding general information about the student, with a total of 188 questions, was administered. Because some of the general student information questions required text-type answers, the questionnaire was developed in Google Forms to facilitate its analysis and it was carried out in the EPN computer labs.

This study was approved by the ethics committee of the institution responsible for the re-search (UA20150706). All participants provided written informed consent in accordance with the Declaration of Helsinki.

3.4. Data Analysis

A GLM (generalized linear model) was used to assess the differences between group profiles using a univariate split-plot approach, in which the measures of the dependent variables were treated as variables measured within the same subjects, and the groups (success/dropout) acted as variables between subjects. Gender, marital status and population segment were included as covariates. The variables related to prior academic performance, goal orientation, motivational and self-regulated socio-cognitive skills, emotional intelligence and causal attributions were included as independent intrasubject factors, and the variable of dropout (success/dropout) was included as a between-subject factor to analyze whether there was a significant difference between the groups. Box's M test and the Mauchly test were also performed.

Artificial neural networks were used to predict early dropout rates in EPN careers. The dependent variable was "success/dropout", and the factors considered were the variables that were significantly associated in the profile comparison analyses. First, using a random sampling process, the data were divided into training (70%) and test (30%) sets. Second, a gradient descent training algorithm was employed for modeling via an ANN. Once the maximum classification accuracy of the model was obtained, the neural network was evaluated, and the relative importance of each variable in the model was determined. The area under the curve (AUC) was used to evaluate the performance of the model. Artificial neural networks can establish a prediction model to analyze the relationships between variables using machine learning [128]. Neural networks are useful for predicting and classifying in several areas, including education, especially in relation to student performance and other aspects of learning [129–131]. Several works performed a comparison between ANN and statistical models (multiple regression, discriminant analysis, and logistic regression), from which it can be deduced that the success percentage of the ANN is superior to that of the three traditional methods. Regarding the predictive aspect, the ANN also appears to be more reliable than the commonly used multivariate methods [132–134].

All scores were transformed into z-scores. Statistical analyses were performed with SPSS V.24.0 (IBM, New York, NY, USA).

4. Results

The exploratory analysis of the data showed that all variables followed a normal distribution with values of asymmetry and kurtosis between 1.5 and −1.5.

4.1. Comparison of the Profile of Students Who Passed the Leveling Course (Mandatory in First Semester to Access University Studies) and Students Who Dropped Out

Table 1 shows the descriptive statistics of the study variables for each group (success/dropout).

Table 1. Descriptive statistics for each group (success/dropout).

Variable	Success (Non-Dropout) Mean (SD)	Dropouts Mean (SD)
Access grade	0.405 (0.935)	−0.361 (0.990)
Language test	0.168 (1.018)	−0.101 (0.988)
Mathematical test	0.750 (0.964)	−0.452 (0.853)
Tmms_Emotional_Attention	−0.044 (0.974)	0.062 (1.038)
Tmms_Emotional_Understanding	−0.082 (0.015)	0.005 (0.969)
Tmms_Emotional_Regulation	−0.082 (1.011)	0.034 (0.957)
Skaa_Learning_Goals	0.073 (0.975)	−0.067 (1.062)
Skaa_Performance-Approach Goals	0.003 (1.008)	0.019 (0.955)
Skaa_Performance Avoidance Goals	−0.116 (1.005)	0.111 (0.983)
Skaa_Avoidance_Academic_Work_Goals	−0.127 (0.968)	0.118 (1.024)
Mslq_Intrinsic_Motivation	0.067 (0.923)	−0.109 (1.050)
Mslq_Self-Efficacy	0.101 (0.964)	−0.074 (1.027)
Mslq_Test_Anxiety	−0.168 (0.989)	0.129 (1.004)
Mslq_Metacognitive_Strategies	0.007 (1.008)	−0.005 (1.033)
Mslq_Self-Regulation	−0.011 (0.967)	0.075 (0.941)
Eacm_Ease_High_Performance_Attribution	−0.099 (0.999)	0.104 (0.971)
Eacm_Capacity_High_Performance_Attribution	−0.063 (1.040)	−0.019 (0.980)
Eacm_Teachers_Low_Performance_Attribution	0.020 (1.011)	−0.028 (0.982)
Eacm_Low_Capacity_Low_Performance_Attribution	−0.054 (0.957)	0.029 (1.040)
Eacm_Low_Effort_Low_Performance_Attribution	−0.038 (1.019)	−0.001 (1.011)
Eacm_Effort_High_Performance_Attribution	−0.060 (0.947)	0.008 (0.997)

The GLM of repeated measures was used, including gender, marital status, and population segment as covariates, the variables related to prior academic performance, goal orientation, motivational and self-regulated socio-cognitive skills, emotional intelligence, and causal attributions as independent intrasubject factors, and the variable dropout (success/dropout) as a between-subject factor to analyze whether there was a significant difference between the groups. The results of Box's M test did not show homogeneity of the variance–covariance matrix (F = 1.21; df = 1,177,928.509; p = 0.01). The violation of this assumption has a minimum effect if the groups are approximately equal in size [135]. The Mauchly test was significant; hence, the tests of the intrasubject effects are provided with the corrected indices (lower limit, i.e., the strictest) (Table 2).

Table 2. Tests of within-subject effects.

Font	Type III	Degrees of Freedom	F	Significance	η^2 Partial	Observed Power
Within groups	32.01	1.000	1.90	0.16	0.003	0.280
Factor 1 × population segment	26.68	1.000	1.58	0.20	0.003	0.242
Factor 1 × gender	66.32	1.000	3.93	0.04	0.006	0.508
Factor 1 × marital status	48.61	1.000	2.88	0.09	0.005	0.396
Factor 1 × dropout	373.08	1.000	22.14	<0.001	0.035	0.997
Intra error	10,429.55	619.000				
Between groups	10.14	1	2.81	0.09	0.005	0.388
Population segment	1.87	1	0.52	0.47	0.001	0.111
Gender	0.001	1	0.00	0.98	0.000	0.050
Marital status	11.11	1	3.08	0.07	0.005	0.419
Inter error	2229.38	619				

Table 3 shows that the profile of the two groups was different, and that only the gender covariate was significant. The observed power was adequate; however, the effect size was small. The estimation of the parameters and the *t*-test to verify which variables were significantly different within the profile (Table 3) confirmed that there were statistically significant differences, obtaining higher scores for students who dropped out in the following variables: performance avoidance goals, avoidance of academic work goals, test anxiety, and facility high-performance attribution. In addition, in the form of higher scores for students who passed the course, significant differences were obtained in the following variables: access grade, language test, mathematical test, intrinsic motivation, and self-efficacy. Figure 1 shows a graphical representation of the profiles of both groups (dropout/pass) with the variables that were statistically significant in bold.

Table 3. Parameter estimates.

Variable	Parameter	B	Standard Error	*t*	Sig.	Confidence Interval 95%		η^2 Partial	Observed Power
						Lower Limit	Upper Limit		
Access grade	Intersection	−0.288	0.445	−0.648	0.518	−1.162	0.586	0.001	0.099
	Population segment	0.177	0.096	1.839	0.066	−0.012	0.365	0.005	0.451
	Gender	−0.008	0.087	−0.094	0.925	−0.179	0.163	0.000	0.051
	Marital status	−0.275	0.394	−0.699	0.485	−1.049	0.498	0.001	0.107
	Dropout = no	0.778	0.077	10.051	**<0.001**	0.626	0.930	0.140	10.000
Language test	Intersection	0.765	0.464	1.649	0.100	−0.146	1.676	0.004	0.377
	Population segment	−0.037	0.100	−0.375	0.708	−0.234	0.159	0.000	0.066
	Gender	−0.102	0.091	−1.127	0.260	−0.281	0.076	0.002	0.203
	Marital status	−0.636	0.411	−1.550	0.122	−1.443	0.170	0.004	0.340
	Dropout = no	0.264	0.081	3.269	**0.001**	0.105	0.422	0.017	0.904
Mathematical test	Intersection	−1.288	0.419	−3.076	0.002	−2.110	−0.466	0.015	0.867
	Population segment	−0.184	0.090	−2.037	**0.042**	−0.361	−0.007	0.007	0.529
	Gender	0.146	0.082	1.776	0.076	−0.015	0.307	0.005	0.426
	Marital status	0.803	0.370	2.167	**0.031**	0.075	1.530	0.008	0.581
	Dropout = no	1.196	0.073	16.433	**<0.001**	1.053	1.339	0.304	10.000
Tmms_Emotional _Attention	Intersection	0.747	0.464	1.610	0.108	−0.164	1.658	0.004	0.362
	Population segment	0.146	0.100	1.458	0.145	−0.051	0.343	0.003	0.308
	Gender	0.031	0.091	0.346	0.729	−0.147	0.210	0.000	0.064
	Marital status	−0.911	0.411	−2.219	**0.027**	−1.718	−0.105	0.008	0.601
	Dropout = no	−0.102	0.081	−1.270	0.205	−0.261	0.056	0.003	0.245

Table 3. *Cont.*

Variable	Parameter	B	Standard Error	t	Sig.	Confidence Interval 95%		η² Partial	Observed Power
Tmms_Emotional _Understanding	Intersection	−0.980	0.458	−2.140	0.033	−1.879	−0.080	0.007	0.570
	Population segment	−0.023	0.099	−0.237	0.812	−0.217	0.171	0.000	0.056
	Gender	0.179	0.090	1.993	**0.047**	0.003	0.355	0.006	0.512
	Marital status	0.698	0.405	1.721	0.086	−0.098	1.493	0.005	0.405
	Dropout = no	−0.086	0.080	−1.078	0.282	−0.242	0.071	0.002	0.190
Tmms_Emotional Regulation	Intersection	0.985	0.453	2.173	0.030	0.095	1.875	0.008	0.583
	Population segment	0.155	0.098	1.585	0.113	−0.037	0.347	0.004	0.353
	Gender	−0.023	0.089	−0.256	0.798	−0.197	0.152	0.000	0.058
	Marital status	−1.092	0.401	−2.723	**0.007**	−1.880	−0.304	0.012	0.776
	Dropout = no	−0.113	0.079	−1.437	0.151	−0.268	0.042	0.003	0.300
Skaa_Learning_Goals	Intersection	−0.190	0.469	−0.404	0.686	−1.112	0.732	0.000	0.069
	Population segment	−0.089	0.101	−0.880	0.379	−0.288	0.110	0.001	0.142
	Gender	−0.214	0.092	−2.331	**0.020**	−0.395	−0.034	0.009	0.644
	Marital status	0.598	0.415	1.440	0.150	−0.218	1.414	0.003	0.301
	Dropout = no	0.139	0.082	1.708	0.088	−0.021	0.300	0.005	0.400
Skaa_Performance-Approach Goals	Intersection	−0.606	0.453	−1.338	0.181	−1.496	0.283	0.003	0.267
	Population segment	0.126	0.098	1.289	0.198	−0.066	0.318	0.003	0.251
	Gender	0.209	0.089	2.350	**0.019**	0.034	0.383	0.009	0.650
	Marital status	0.108	0.401	0.269	0.788	−0.679	0.895	0.000	0.058
	Dropout = no	−0.007	0.079	−0.094	0.925	−0.162	0.147	0.000	0.051
Skaa_Performance Avoidance Goals	Intersection	1.035	0.458	2.261	0.024	0.136	1.935	0.008	0.617
	Population segment	0.141	0.099	1.432	0.153	−0.053	0.335	0.003	0.298
	Gender	−0.174	0.090	−1.940	0.053	−0.350	0.002	0.006	0.491
	Marital status	−0.790	0.405	−1.949	0.052	−1.585	0.006	0.006	0.494
	Dropout = no	−0.223	0.080	−2.805	**0.005**	−0.379	−0.067	0.013	0.800
Skaa_Avoidance_ Academic_Work_Goals	Intersection	0.547	0.460	1.188	0.235	−0.357	1.450	0.002	0.220
	Population segment	0.036	0.099	0.365	0.715	−0.159	0.231	0.000	0.065
	Gender	0.132	0.090	1.461	0.145	−0.045	0.309	0.003	0.308
	Marital status	−0.694	0.407	−1.704	0.089	−1.493	0.106	0.005	0.398
	Dropout = no	−0.249	0.080	−3.116	**0.002**	−0.406	−0.092	0.015	0.875
Mslq_Intrinsic_Motivation	Intersection	−0.365	0.458	−0.797	0.426	−1.263	0.534	0.001	0.125
	Population segment	−0.068	0.099	−0.691	0.490	−0.262	0.126	0.001	0.106
	Gender	−0.051	0.090	−0.567	0.571	−0.227	0.125	0.001	0.087
	Marital status	0.424	0.405	1.046	0.296	−0.372	1.219	0.002	0.181
	Dropout = no	0.176	0.080	2.207	**0.028**	0.019	0.332	0.008	0.596

Table 3. *Cont.*

Variable	Parameter	B	Standard Error	*t*	Sig.	Confidence Interval 95%		η^2 Partial	Observed Power
Mslq_Self-Efficacy	Intersection	0.455	0.460	0.990	0.323	−0.448	1.358	0.002	0.167
	Population segment	−0.228	0.099	−2.294	**0.022**	−0.422	−0.033	0.008	0.629
	Gender	−0.005	0.090	−0.050	0.960	−0.181	0.172	0.000	0.050
	Marital status	−0.237	0.407	−0.583	0.560	−1.036	0.562	0.001	0.090
	Dropout = no	0.158	0.080	1.982	**0.048**	0.001	0.315	0.006	0.508
Mslq_Test_Anxiety	Intersection	1.128	0.457	2.468	0.014	0.230	2.026	0.010	0.693
	Population segment	0.097	0.099	0.985	0.325	−0.097	0.291	0.002	0.166
	Gender	−0.285	0.090	−3.177	**0.002**	−0.461	−0.109	0.016	0.887
	Marital status	−0.620	0.405	−1.531	0.126	−1.414	0.175	0.004	0.333
	Dropout = no	−0.295	0.079	−3.713	**<0.001**	−0.451	−0.139	0.022	0.960
Mslq_Metacognitive_Strategies	Intersection	−0.148	0.470	−0.315	0.753	−1.070	0.775	0.000	0.061
	Population segment	0.100	0.101	0.983	0.326	−0.099	0.299	0.002	0.166
	Gender	−0.250	0.092	−2.716	**0.007**	−0.431	−0.069	0.012	0.774
	Marital status	0.448	0.416	1.078	0.282	−0.368	1.264	0.002	0.190
	Dropout = no	0.023	0.082	0.287	0.774	−0.137	0.184	0.000	0.059
Mslq_Self-Regulation	Intersection	0.446	0.441	1.011	0.312	−0.420	1.311	0.002	0.172
	Population segment	0.063	0.095	0.666	0.506	−0.123	0.250	0.001	0.102
	Gender	−0.190	0.086	−2.206	**0.028**	−0.360	−0.021	0.008	0.596
	Marital status	−0.118	0.390	−0.301	0.763	−0.883	0.648	0.000	0.060
	Dropout = no	−0.083	0.077	−1.077	0.282	−0.233	0.068	0.002	0.189
Eacm_Ease_High_Performance_Attribution	Intersection	0.672	0.451	1.491	0.137	−0.213	1.557	0.004	0.319
	Population segment	0.086	0.097	0.883	0.377	−0.105	0.277	0.001	0.143
	Gender	0.266	0.088	3.009	**0.003**	0.092	0.439	0.014	0.852
	Marital status	−1.123	0.399	−2.816	**0.005**	−1.906	−0.340	0.013	0.803
	Dropout = no	−0.206	0.078	−2.628	**0.009**	−0.360	−0.052	0.011	0.747
Eacm_Capacity_High_Performance_Attribution	Intersection	0.129	0.469	0.276	0.783	−0.792	1.050	0.000	0.059
	Population segment	−0.042	0.101	−0.416	0.677	−0.241	0.157	0.000	0.070
	Gender	0.018	0.092	0.197	0.844	−0.162	0.199	0.000	0.054
	Marital status	−0.127	0.415	−0.305	0.760	−0.942	0.688	0.000	0.061
	Dropout = no	−0.048	0.082	−0.591	0.555	−0.208	0.112	0.001	0.091
Eacm_Teachers_Low_Performance_Attribution	Intersection	0.727	0.457	1.591	0.112	−0.170	1.625	0.004	0.355
	Population segment	0.146	0.099	1.485	0.138	−0.047	0.340	0.004	0.317
	Gender	0.164	0.090	1.837	0.067	−0.011	0.340	0.005	0.450
	Marital status	−1.210	0.405	−2.991	**0.003**	−2.004	−0.416	0.014	0.848
	Dropout = no	0.050	0.079	0.633	0.527	−0.106	0.206	0.001	0.097

Table 3. *Cont.*

Variable	Parameter	B	Standard Error	*t*	Sig.	Confidence Interval 95%		η^2 Partial	Observed Power
Eacm_Low_Capacity_ Low _Performance_Attribution	Intersection	0.736	0.461	1.597	0.111	−0.169	1.641	0.004	0.358
	Population segment	−0.019	0.099	−0.191	0.849	−0.214	0.176	0.000	0.054
	Gender	0.115	0.090	1.271	0.204	−0.063	0.292	0.003	0.246
	Marital status	−0.873	0.408	−2.141	**0.033**	−1.674	−0.072	0.007	0.571
	Dropout = no	−0.091	0.080	−1.137	0.256	−0.248	0.066	0.002	0.206
Eacm_Low_Effort_Low _Performance_Attribution	Intersection	0.534	0.468	1.140	0.255	−0.386	1.453	0.002	0.207
	Population segment	−0.066	0.101	−0.650	0.516	−0.264	0.133	0.001	0.099
	Gender	0.170	0.092	1.854	0.064	−0.010	0.350	0.006	0.457
	Marital status	−0.741	0.414	−1.789	0.074	−1.555	0.072	0.005	0.431
	Dropout = no	−0.046	0.081	−0.569	0.570	−0.206	0.113	0.001	0.088
Eacm_Effort_High_ Performance_Attribution	Intersection	0.003	0.449	0.007	0.994	−0.879	0.886	0.000	0.050
	Population segment	0.109	0.097	1.129	0.259	−0.081	0.300	0.002	0.203
	Gender	−0.141	0.088	−1.607	0.109	−0.314	0.031	0.004	0.361
	Marital status	0.114	0.398	0.287	0.775	−0.667	0.895	0.000	0.059
	Dropout = no	−0.060	0.078	−0.773	0.440	−0.214	0.093	0.001	0.121

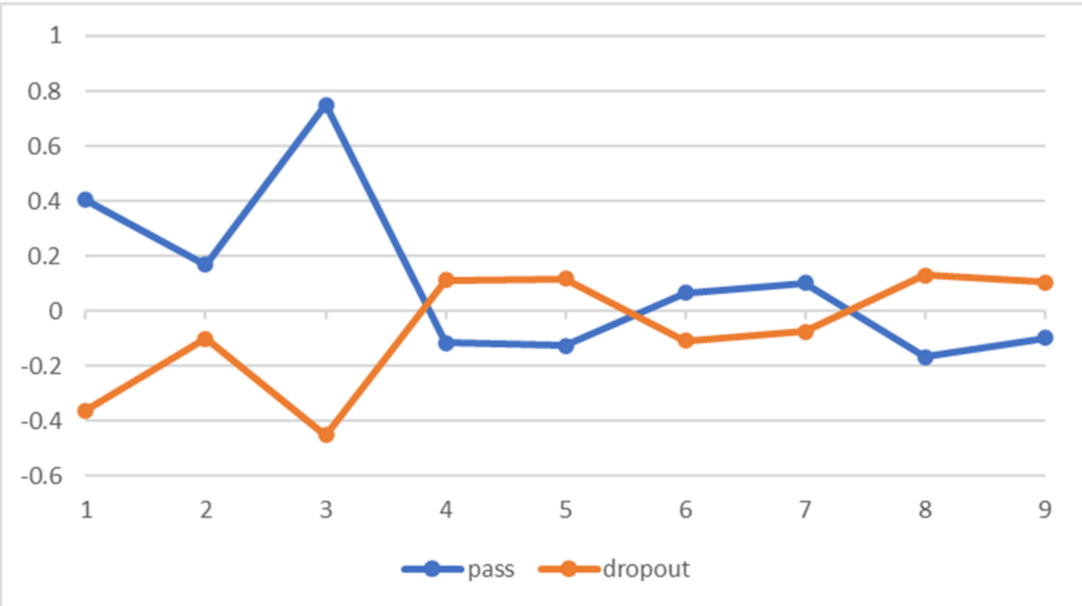

Figure 1. Graphical representation of the profiles of students who dropped out and the students who passed. Note: 1 = Access grade; 2 = Language test; 3 = Mathematical test; 4 = Performance avoidance goals; 5 = Avoidance academic work goals; 6 = Intrinsic motivation; 7 = Self-efficacy; 8 = Test anxiety; 9 = Ease high performance attribution.

In addition, the gender covariate was significant for the following variables: emotional understanding, performance-approach goals, and ease high-performance attribution, with men obtaining the highest scores. The variables learning goals, test anxiety, metacognitive strategies, and self-regulation scored highest in women. Figure 2 shows a graphical representation of the profiles of both groups (women/men) with the variables that were statistically significant.

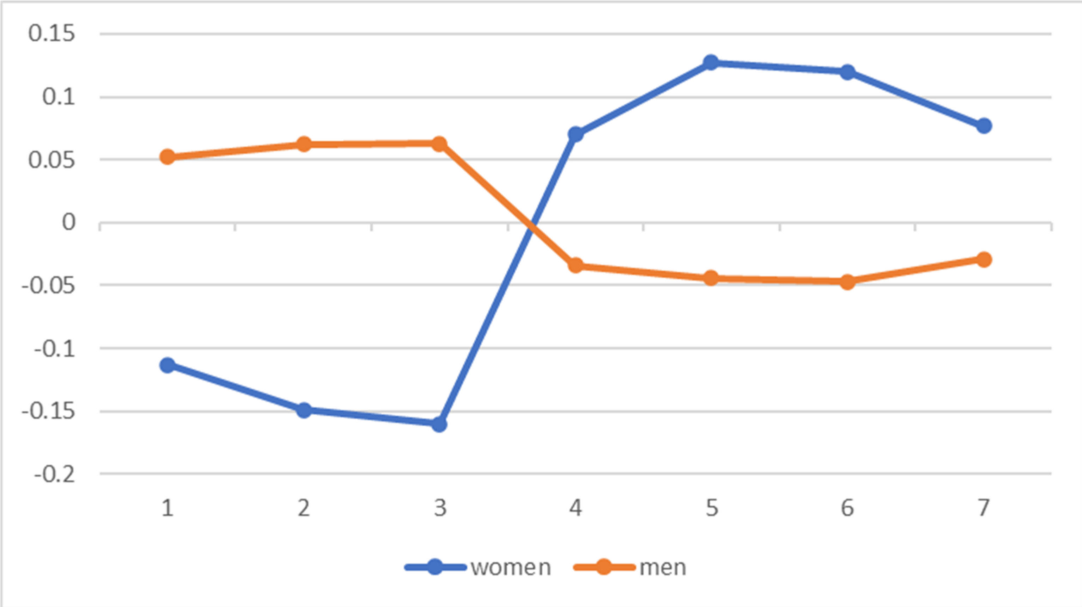

Figure 2. Graphical representation of the profiles of women and men. Note: 1 = Emotional understanding; 2 = Performance approach goals; 3 = Ease high performance attribution; 4 = Learning goals; 5 = Test anxiety; 6 = Metacognitive strategies; 7 = Self-regulation.

The population segment covariate was significant for the variables mathematical Test and self-efficacy, with the group of participants identified as a vulnerable population obtaining the lowest score in these variables. Figure 3 shows a graphical representation of the profiles of both groups (vulnerable population/general population) with the variables that were statistically significant.

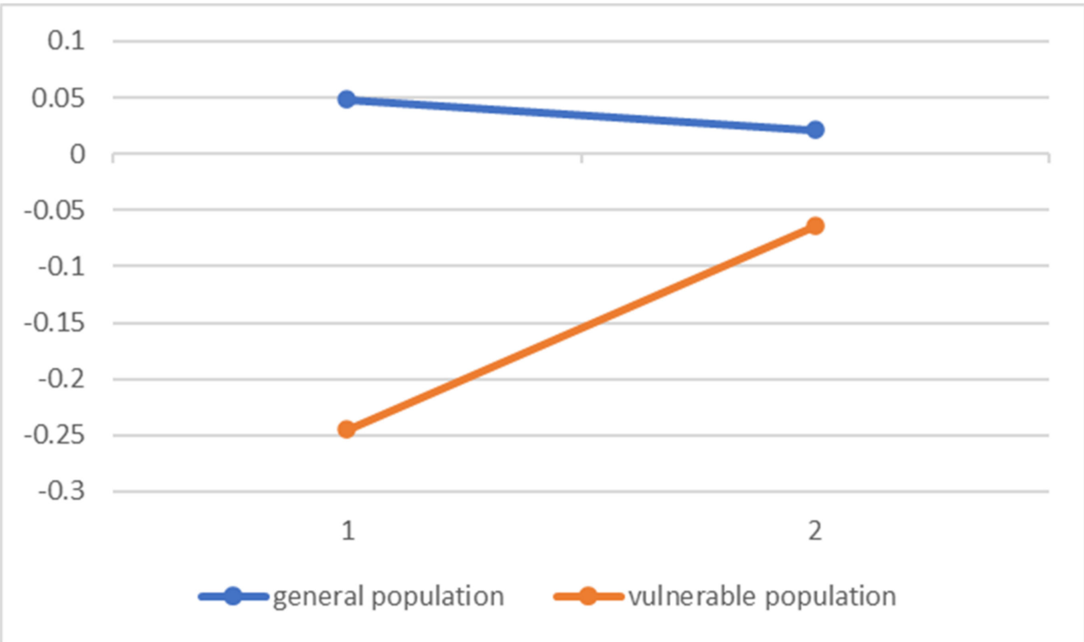

Figure 3. Graphical representation of the profiles of vulnerable population/general population. Note: 1 = Mathematical test; 2 = Self-efficacy.

The marital status covariate was significant for the variables emotional attention, emotional regulation, ease high-performance attribution, low capacity low-performance attribution, and teachers low-performance attribution, with the participants stating they were divorced scoring lowest in these variables. Figure 4 shows a graphical representation of the profiles of the three groups according to marital status (single/married/divorced) with the variables that were statistically significant.

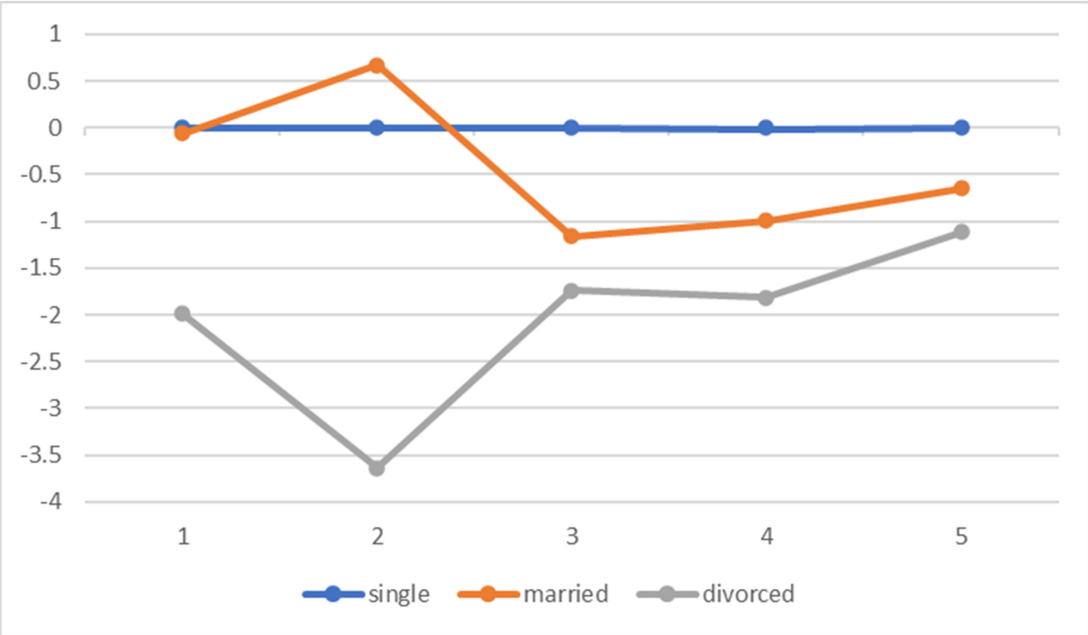

Figure 4. Graphical representation of the profiles of women and men. Note: 1 = Emotional attention; 2 = Emotional regulation; 3 = Ease high performance attribution; 4 = Teachers low performance attribution; 5 = Low capacity low performance.

4.2. Neural Network Analysis

Artificial neural networks (ANN) were used to predict the rate of early dropout in the EPN, taking into account the variables that were significant in the analysis of comparison of profiles between students who passed the leveling course and students who dropped out. These variables were access grade, language test, mathematical test, performance avoidance goals, avoidance of academic work goals, intrinsic motivation, self-efficacy, test anxiety, and ease high-performance attribution. The dependent variable was "success/dropout".

First, the data were divided into training (70%) and test (30%) sets using a random sampling process. Next, an ANN was modeled from the training dataset employing a gradient descent training algorithm. Once the maximum classification accuracy of the model was obtained, the neural network was evaluated, and the relative importance of each variable in the model was determined [136–138]. The performance of the model was evaluated using the area under the curve (AUC), which provides an aggregate measure of performance at all possible classification thresholds [139].

In the ANN model, all the variables were significant and classified from highest to lowest importance in the following order: mathematical test (100%), access grade (88.2%), performance avoidance goals (76%), intrinsic motivation (74.3%), self-efficacy (66.5%), avoidance of academic work goals (57.7%), language Test (54.8%), test anxiety (48.6%), and ease high-performance attribution (47.3%).

When analyzing the area under the curve, a value of 0.839 is found, indicating that the model had good discriminative capacity (Figure 5).

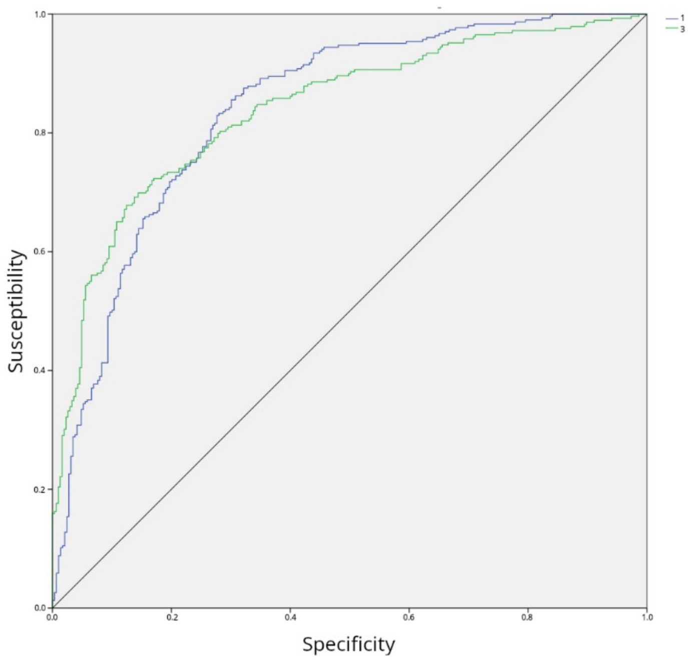

Figure 5. Graphical representation of the area under the curve (AUC) of the ANN model, where the dependent variable was dropout. Note: blue line 1 = no dropout; green line 3 = dropout.

5. Discussion

University dropout represents a problem that causes multiple effects for society. At the social level, it influences the increase in unemployment rates; at the institutional level, it acts to the detriment of efficiency and quality indicators; at the personal level, it limits the labor and social insertion of individuals [140].

Therefore, the main objective of this work was to identify the profile characteristics that differentiate students who drop out early in their academic career and those who continue studying. In this way, adequate academic support can be proposed that will allow them to successfully complete higher education.

According to the existing literature, the variables considered to analyze these differential characteristics included both sociodemographic and psychoeducational aspects. In the present work, we intended to analyze variables of both types in the same study, in order to propose a broad profile that includes both sociodemographic variables and psychoeducational variables, thus taking a more complete approach to the problem. This will allow a better understanding of early dropout at university, as well as a more complete approach in the proposal of solutions to reverse this dropout process.

A discussion of the results is carried out below on the basis of the hypotheses proposed.

Regarding the first hypothesis, "Students who belong to more disadvantaged population segments have a greater probability of dropping out", the population segment covariate was not significant in our data. To analyze this result, the geographical environment to which the university belongs, located in the country's capital and the second largest city in Ecuador, should be considered. In 2020, the dropout rate in higher education due to economic situations was 16.3% nationally but was higher in rural sectors (25.2%) [141]. Given that students from rural sectors are a minority in EPN, this may explain the lack of significance of this variable. Additionally, the model for accessing higher education in the country should be analyzed in depth, which is based on an entrance exam that favors the access of students from high-academic-level schools, both public and private, and that additionally have the economic solvency to pay for a preparation course aimed at passing this exam. The entrance exam has been even defined more as an assessment of social inequality than of student learning [142], which is why the few students in these population segments that enter the institution, feeling privileged with access, redouble their efforts to obtain good academic outcomes. This finding is consistent with that obtained by other recent studies since it has been shown that the persistence and university dropout of university students depends on a combination of individual, institutional, and economic factors, whose effects on the decision to drop out are mediated by the student's ability to successfully integrate into the academic system [1]. In addition, beyond the situation of vulnerability or social exclusion present in university students, other variables have been detected, such as motivation, which plays a key predictive role in the academic achievement of students [7,68,70,73,143], thus preventing dropout or failure and empowering the students to overcome difficulties, even when starting from disadvantaged social situations.

Regarding the second hypothesis, "Female students are less likely to drop out", the results did indicate that the gender covariate was significant in the comparison of profiles; however, the percentage of women in the sample who dropped out was the same as that of women who passed the leveling course. However, there were significant gender differences in the variables emotional understanding, performance-approach goals, and ease high-performance attribution, with men obtaining the highest scores. The variables learning goals, test anxiety, metacognitive strategies, women, and self-regulation obtained higher scores in women. In the case of the performance-approach goals component, it should be considered that, in a study conducted in another university in the same city, but with a sample featuring 61.67% women, a gender balance was obtained in the same component, possibly indicating that the gender distribution of the EPN students could be the differentiator in this result [144]. Analyzing the component ease high-performance attribution, the result indicated that, for male students who dropped out, the ease of the subjects was related to getting good grades; in other words, students with superficial approaches maintained that easiness of the subject is responsible for high performance. This is a type of external attribution in terms of the place of causality; it is stable in the stable–unstable dimension and is noncontrollable [126]. In the variables learning goals, test anxiety, metacognitive strategies, and self-regulation, women obtained higher scores. This result coincides with that of other studies, such as that of Valle et al. (2009) [122], who conducted a study with 632 university students, 70% of whom were women, obtaining a high score for the first variable referring to the learning goal. The variable test anxiety was analyzed in 323 students at a university in the United States, and a higher score was obtained in women. Additionally, the authors related this, together with cognitive strategies and self-regulation, to the problem of procrastination in higher-education students [145]. Other recent studies found differences in gender variables clearly related to dropout, such as previously acquired competencies or academic skills [7,42,146]. An interesting line of future research in this regard was considered in studies such as that of Vooren et al. (2022) [6], where female university students, despite showing lower dropout rates in the first year (specifically in STEM programs, as was the case of the present study), were less likely to finally graduate in comparison with men. However, if we evaluate work performance in the decade after graduation, women obtained an optimal level of performance, exactly the same as men. For these reasons, the aforementioned study concluded that females perform equally well in higher education in the long run [6].

Therefore, one of the added values provided by the present study is to understand how the variables integrated in our work regarding the management of test anxiety and the use of optimal cognitive strategies can be taught in the case of women to help them (the same as male students, but keeping in mind their own style of coping with learning) function better in careers of this field of knowledge, thus avoiding early dropout, persisting throughout the university career, and facilitating subsequent performance upon leaving the classroom, in the case of all students, regardless of gender.

Regarding the third hypothesis, "Students who have a lower previous academic performance have a greater probability of dropping out", the results confirmed it, since students who dropped out obtained significantly lower scores than students who passed the course in the previous performance variable (the university entrance grade), as well as the mathematical test and language test variables (performance tests at the beginning of higher education). In this sense, having a previous assessment, including the grade of a poorly designed entrance exam, allowed selecting students with a lower probability of dropping out. In some universities in which there was no entrance exam initially and then it was subsequently implemented, a significant decrease in dropout rate was identified [147]. In fact, in light of the results obtained, previous performance was the variable with the greatest predictive power of all those considered in our study. This evidence is in line with other studies showing that previous performance is a clear predictor of future performance [148–151].

Regarding the fourth hypothesis, "Students who have lower scores in emotional intelligence have a greater probability of dropping out", the results of the present investigation did not show significant differences in these variables between the groups. In a study that sought to characterize research on dropout intention in university students in the last 5 years, 15 quantitative empirical studies were reviewed, concluding that emotional intelligence is one of the variables least related to dropout intention [16]. This finding is not in line with what has frequently been evidenced in the scientific literature, since EI has been shown to be a key variable in the adaptation and prevention of university dropout [152–158]. It is possible that our study requires a deeper evaluation of the EI of students, considering different explanatory models for this variable (ability models, competence-based models, and mixed models) and perhaps including a more rigorous selection of measurement instruments. In this way, it would be possible to capture the differences that can be expected between an optimal level of EI and the decrease in dropout. In addition, a larger sample of participants included in the study would be another strategy to shed light on these results.

Regarding the fifth hypothesis, "Students with attributions to external and uncontrollable causes have a greater probability of dropping out", it should be noted that the results confirmed it, since students who dropped out scored significantly more, attributing high performance to the ease of tasks; in other words, according to them, it is the ease of the subjects that allows students to achieve good academic performance. This means that, in general, for those students whose academic performance depends on the ease of the subject, the performance of the students who obtain good grades is because the subject is easy. This is a type of external attribution in terms of the place of causality; it is stable in the stable–unstable dimension and is noncontrollable in the control–no control dimension. In a study on causal attributions in 787 university students in the Dominican Republic, it was observed that external causal attributions (to subjects, teachers, and luck) were those with a greater discriminative power and predictive capacity for low academic performance [159]. This result is consistent with what has been evidenced in the previous literature since students who attribute academic success to factors such as luck or the ease of the task (instead of causes such as effort or perseverance) are immersed in an attitude of helplessness characterized by attributing optimal performance to external and uncontrollable causes and concluding that the possibility of achieving goals is not related to the individual's involvement or their perseverance, with which the risk of academic dropout is very high before this type of attribution [160–165].

Regarding the sixth hypothesis, "Students who have lower achievement goals scores have a greater probability of dropping out", the results indicated that students who dropped out scored higher in the variables performance avoidance goals; that is, their goal was to not be judged negatively by others and avoidance of academic work, and to complete the tasks using minimal effort. However, no significant differences in the performance-approach goals factor were found between the students who dropped out and those who passed the course. This result coincides with that of a study in a United States university which showed that students who had good academic outcomes scored lowest in the variable performance avoidance goals, while those with poor performance scored high, weakening their goals orientation [166]. Regarding academic problems and dropout derived from the goal of completing tasks using minimal effort during university studies, some studies even predicted future problems of burnout in the working environment [167].

Regarding the seventh hypothesis, "Students who have lower scores in motivation and self-regulated learning strategies have a greater probability of dropping out", the results indicated that students who dropped out obtained significantly lower scores in the factors of self-regulated learning strategies, intrinsic value, and self-efficacy, while they scored higher in the negative factor of the motivation section "test anxiety". This result indicated a strong relationship between motivation and self-regulated learning strategies, which has been found in other studies, such as those carried out in three Colombian universities [168]. These findings are consistent with previous studies since other studies also showed that students who dropped out during the beginning of the university career scored higher in performance avoidance and work avoidance goals, while those who were capable of achieving good academic performance showed high levels of self-regulated learning, self-efficacy, evaluation of the importance of the tasks by their own intrinsic value, and a greater resistance to procrastination of academic tasks [169–175]. In addition, anxiety about academic evaluation has been frequently associated with worse academic performance [176–178].

Lastly, the population segment covariate was significant for the variables mathematical test and self-efficacy, with the group of participants identified as the vulnerable population obtaining the lowest score in these variables, which is consistent with previous studies identifying vulnerability and social exclusion as academic risk factors for new university students [179–181].

On the other hand, the marital status covariate was significant for the variables emotional attention, emotional regulation, ease high-performance attribution, and teachers low-performance attribution, with participants who declared themselves divorced scoring lower in these variables, whereas married participants scored lower for the variable low capacity low-performance attribution. There are no previous studies showing similar results, and it is possible that a larger sample of participants may blur the results without indicating any significance along these lines.

Lastly, in the ANN model, all the variables were significant, being classified from highest to lowest importance in the following order: mathematical test (100%), access grade (88.2%), performance avoidance goals (self-defeating, not wanting to be judged negatively by others) (76%), intrinsic motivation (74.3%), self-efficacy (66.5%), avoidance of academic work goals perform tasks with minimal effort (57.7%), language test (54.8%), test anxiety (48.6%), and ease high-performance attribution (47.3%). These results are consistent with everything highlighted throughout the discussion, especially the evidence that previous performance is a strong predictor of future performance, which has been strongly supported in previous studies.

To address the need to improve the student retention rate in higher education, different institutions have developed actions to improve academic performance and reduce dropout rates, especially in those who come from vulnerable contexts. This requires a comprehensive approach to the problem that allows working on the content of complex subjects while providing the student with tools and learning strategies to obtain better academic outcomes [182].

Most of the systematic actions to prevent academic failure and dropping out from university studies have been developed in Anglo-Saxon countries [183,184], although the need to implement and evaluate programs of this type in the European [9] and Latin American [185] context is increasingly recognized.

The rigorous assessment of the effectiveness of programs for preventing university failure and dropout is promising. Already in the 1980s, meta-analysis results [186] showed a moderate and significant effect of these programs on the academic outcomes of disadvantaged students and those at risk of failing.

On the other hand, since the 1990s, the American educational administration has collected and systematized the results of intervention programs with disadvantaged students in higher education [187] and promoted the implementation of new programs [188,189].

More recently, in this same Anglo-Saxon environment, there has been a large amount of research on intervention programs with students at risk of academic failure and dropout. Thus, other studies [183] offered a compendium of effective practices to retain students in higher education in the United Kingdom. Robbins, Oh, Le, and Button [190] highlighted the importance of motivational and emotional aspects in these intervention programs.

Thomas [191] collected the most effective aspects within these intervention programs for retention and academic success.

Special importance and popularity are given to the so-called brief intervention programs due to their short duration and their positive effects on motivation, academic success, and continuity in the studies of students at risk [192–194].

New intervention programs designed to improve the affective and cognitive aspects, which aim to prevent failure and dropout, should be based on the previous outcomes of this type of program and should also take into account the research on the personal and educational factors that affect the success of university studies in general [195,196].

6. Conclusions

In conclusion, according to Cabrera et al., there is a general consensus in accepting that dropout rates are an indicator of a low quality of university education since it is understood that the university has not been able to implement the appropriate mechanisms for students to be able to achieve academic goals [197]. However, there are multiple factors involved in dropout that do not depend on the university, such as students' economic conditions, mental health, changes of interest and other factors. Understanding students' needs and monitoring any noticeable changes are critical in the process of reversing dropout. In addition, we suggest that the key moment to implement actions that prevent dropout is before enrolment so that students can make vocational decisions according to their true interests and with the optimal level of self-knowledge regarding their strengths. In the same way, throughout their university career, it is necessary to provide students with training strategies that respond to their real needs and/or the areas of improvement detected.

In the present study, both socioeconomic and psychoeducational aspects were identified as being involved in university dropout. Although some of these factors are not determined directly by the university, it is important that the university has tools to detect them and is thus able to undertake improvements or action programs to intervene in regard to the issues detected as relevant to student dropout, allowing the process to be reversed. For these reasons, the early identification of university dropout can provide great value in improving student success and institutional effectiveness. In this line, the present study demonstrates the importance of creating successful actions and key educational policies at the beginning of a student's university career, as well as ensuring favorable academic evolution throughout their studies, thus aspiring to continuously search for excellence in the provision of higher education.

Therefore, this study is a pioneering work in terms of exploring the effect of belonging to a more disadvantaged population, the influence of the gender, previous academic performance, scores in emotional intelligence, academic attributions (especially if these are to external and uncontrollable causes), scores in terms of achievement goals and motivation and self-regulated learning strategies—all of which are important key variables to predict dropout into the context of South American Higher Education.

In light of these findings, new and effective education policies could be developed to respond to the underlying mechanisms and thus to combat this very serious problem of dropout, especially in vulnerable socioeconomic contexts where the implementation of interventions and enhanced support could be determinants for higher educational-system-wide coherence.

In fact, the quality criteria used to assess services provided by the university could be strongly influenced by the impact of the variables included in this study. This is necessarily related to the important educational challenges amongst vulnerable students.

In line with the findings of this study, further research is necessary to understand the resources that most useful to students at a high level of social risk in on order to prevent dropout and to ensure the integration of such resources into university-level policies, as well as their implementation. Thus, there is an urgent need to apply new measures designed to provide support for disadvantaged groups of students across the key variables identified in the evidence provided in this study, such as the important effects of motivation and self-regulated learning, the empowerment of the emotional intelligence and the impact of adaptive academic attributions, because this could represent a useful strategy for promoting progression and academic achievement. Thus, this study could contribute to ensuring that the aims of higher education can be realized according to high quality standards and responding to the demands and needs of more vulnerable students.

Author Contributions: Conceptualization, J.V., T.P.-R. and R.G.-C.; methodology, J.-L.C.; validation, T.P.-R. and R.G.-C.; formal analysis, J.-L.C. and R.G.-C.; data curation, J.V. and R.G.-C.; writing—original draft preparation, R.G.-C., T.P.-R., J.-L.C., T.S.-A. and J.V.; writing—review and editing, R.G.-C., T.P.-R., J.V. and J.-L.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by National Secretariat of Higher Education, Science and Technology, (SENESCYT;PIC-18-INE-EPN-002).

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of University of Alicante (UA-2021-04-20, 30 April 2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data sets generated and analysed during this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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