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Understanding the dynamics of college transitions between courses: Uncertainty associated with the decision to drop out studies among first and second year students

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Abstract

University dropout is a phenomenon of growing interest due to its negative consequences. Various variables have been studied in order to understand why this problem occurs. Satisfaction with the degree choice, self-regulation strategies and engagement within the university are some of the variables that have been studied in order to understand why students decide to drop out university. In this sense, it is also important to consider uncertainty, which refers to the level of certainty that students have about these variables to understand the decisions to drop out. Therefore, the aim of this research is to analyse the uncertainty associated with the decision to drop out studies among first year and second-year students, based on these three variables using Multiple Criteria Decision-Making. We performed descriptive analyses and FTOPSIS method on a sample of 719 students from a university in the north of Spain. We saw a relationship between the three variables studied and the intention to persist, as well as being a first-year student. In conclusion, it is important to continue studying the variables that influence this phenomenon in greater depth. In addition, this type of analysis could help in future research to understand in greater depth the influence of other variables on dropout rates.

Keywords University dropout · Engagement · Self-regulation strategies · Satisfaction · Fuzzy · FTOPSIS

Introduction

The democratization of the access to higher education has allowed a greater and more varied number of students to enter the university, increasing the heterogeneity among students (Hadjar et al., 2022). Thus, the decision to continue their academic education by

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completing tertiary studies, a voluntary and individual decision of the student, is increasingly studied by different authors throughout the world (Behr et al., 2020; Fourie, 2018; Sandoval-Palis et al., 2020). This proliferation of research is produced by the concern that has created, among teachers and educational institutions, the high percentage of students who drop out their studies. This problem in the educational system has brought with it that the study of university dropout, as well as its causes and consequences, is a focus of attention not only in the university community, but also for the governments of the countries at an international level (Constante-Amores et al., 2021).

High university dropout rates can be observed in every country in the world. In Latin America and Caribbean countries, the rate can reach up to 54% (Ferreyra et al., 2017), in the United States the average university dropout rate is 40% (Hanson, 2021) and in Spain this rate stands at 33.2% (Ministry of Universities, 2021). These rates, moreover, are above the average dropout of the countries of the Organization for Economic Co-operation and Development (OECD), which is around 30% (Organisation for Economic Co-operation and Development, 2020).

In this sense, it becomes necessary to understand why students decide to drop out their studies in order to prevent their causes and reduce these high rates, not only in the national context, but also at a European level.

Theoretical framework

The study of university dropout has not been an easy task, going from a simple explanation, through one-dimensional models, to an increasingly complex explanation in which multiple factors are considered to understand this phenomenon. In fact, the first explanatory theories of dropout reveal the study of models that tried to explain this phenomenon through an abridgment of variables of a single type, that is, one-dimensional models. But since 1975, interactionist models appeared, which considered the study of university persistence as a phenomenon that takes place as a consequence of multiple variables of a diverse nature that interact with each other (Tinto, 1975). Currently, interactionist theories focused on the study of the intention to persist in university studies have been the most accepted (Kerby, 2015; Morelli et al., 2022; López-Aguilar et al., 2022).

Related to the interactionist theories of dropout, the concept of uncertainty in Multi-criteria Decision-Making analysis has gained greater relevance in the scientific field recently. This concept refers to the lack of knowledge or complete information about the outcomes and probabilities associated with the different available alternatives. In this context, decision makers face the difficulty of accurately predicting future outcomes, which may affect their ability to effectively evaluate and compare options (Jones & Smith, 2020). In this sense, and taking into account that there is a compendium of variables of different nature that interact with each other to give rise to students who decide to drop out their studies, this type of analysis allow us to give a much more accurate explanation of the uncertainty associated with these variables to make decisions.

In this case, the study of university dropout through interactionist models meant a change in the focus of study, thus observing which the variables that make the student persist are. Among these variables, we find that motivation is an essential condition for persistence (Tinto, 2015), that is, it is unlikely that the student will persist in the face of the obstacles that they may encounter in the university system if they are not motivated. Thus, a construct that is increasingly studied and investigated in the scientific literature and that is intrinsically related to motivation is engagement (Cho et al., 2022).

Engagement is understood as the set of manifestations of motivation for studies that arise from the satisfaction of the needs for competence, autonomy and relationship in the learning context (Fredricks et al., 2004). In fact, this variable is closely related to motivation, which is why there is usually some overlap between them in scientific research. In fact, some authors maintain that it should be understood as the behavioural manifestation of motivation, being this last one the antecedent and source of energy for engagement (Cho et al., 2022). The study of engagement presents its beginnings in the workplace. However, it has recently begun to be analysed in higher education, sometimes as one of the variables that can influence the intention to persist the studies (Gabi & Sharpe, 2021; Kwon & Jung, 2020).

Engagement can be defined as a positive mental state related to work or academic context. Thus, it is considered a persistent affective-cognitive state, which is not focused on a particular event. Engagement is made up of three dimensions: vigor, which is the willingness to dedicate effort to studies and persist in the face of difficulties; dedication, which is the feeling to be involved with studies and the feeling of enthusiasm, inspiration, pride, challenge and meaning; and absorption, which is the great state of concentration and immersion in the studies, in such a way that time passes quickly and there is discomfort at having to leave the tasks or studies (Schaufeli et al., 2001).

Another highly relevant variable also investigated in relation to engagement and dropping out of studies is the use of learning self-regulation strategies is especially important. Self-regulation of learning, like engagement, has not only been studied in relation to persistence in university studies, but also with academic performance, a variable traditionally studied in relation to the intention to drop out. For Wolters and Taylor (2012), the constructs of self-regulated learning and engagement are strongly related. In the first decade of the 21st century, studies on self-regulation strategies made a qualitative leap, concretizing its concept and extending their application. In this context, Zimmerman's socio-cognitive model (Zimmerman & Moylan, 2009) based on the phases of forethought, performance and self-reflection, was configured as a rigorous option for continuous improvement between the different sub-processes proposed.

Finally, affective-motivational variables have gained increasing relevance in recent years as one of the most relevant predictors in the study of the variables used to predict the intention to persist. In fact, this supposes a reinterpretation of the classic models of dropout or university persistence such as that of Tinto (1975) in which only psychosocial variables were taken into account. Although this model has been one of the most accepted, variables such as satisfaction with the studies completed or the fulfilment of previous expectations have recently become more relevant.

Next, the relationship found in this type of variables and university dropout in the current scientific literature is explained.

Literature review and hypothesis development

As previously mentioned, engagement has been one of the most recently studied variables in comprehensive models to prevent university drop out. Some studies such as the one carried out by López-Angulo et al. (2020), with students from a university in southern Chile, observed that the dimensions of vigor and dedication predict 30% of the variability of a model of permanence of students in the first year, while only dedication was a significant predictor of the intention to persist during the second academic year. In other words, it was observed that engagement, in the indicated dimensions, predicted the probability of permanence in studies in early academic stages. Along these same lines, the study carried out by López-Aguilar et al. (2021) with students from a university in the south of Spain, indicated that students with higher scores in the different structural dimensions of engagement (vigor, dedication and absorption) had higher grades in the subjects they were studying, that is, they obtained a better academic performance (a variable traditionally related to university dropout).

As can be seen, the scientific literature tells us that this is a very useful construct to explain the process of gradual disengagement that ultimately leads to dropping out of university (Hancock & Zubrick, 2015; Ramos et al., 2017; Rumberger & Lim, 2008). That the student is committed and involved with the challenges that the university system proposes is not a minor issue. After the implementation of a common education space (not only at European level, but as a global trend), the Teaching-Learning (T-L) process has been transforming, going from models in which instructional learning put the focus of this process in the teacher, to new models in which the student is taken as the centre of this process (Bernardo et al., 2019). This leads the student to participate in a much more proactive way in university life, for which it is necessary not only to be committed to the institution and to their own academic training process, but also to another skills and attitudes that allow them to put into practice autonomous and self-regulated learning (Tirado-Morueta & Aguaded-Gómez, 2014).

For this reason, in this new European Higher Education Area (EHEA), it is necessary for academic success that students become strongly involved with their studies and that they approach them as a challenge (Truta et al., 2018) so that their intention of persistence in the degree does not decline with the challenges that the university proposes. That is to say, students who show low involvement behaviours such as: delivering their academic tasks late, skipping classes, or attending classes without previously prepared material, will be those who are less likely to succeed in the current educational model and, finally, they will end up having a high probability of dropping out their studies (Shcheglova et al., 2020). This challenge becomes much more relevant in first-year students, who are the ones with the highest dropout rates nationwide. Then, we propose the following hypothesis:

H1: There is a greater intention to drop out in the first year of the degree.

Similarly, the study of self-regulated learning in relation to engagement has been increasing in the literature. According to Núñez et al. (2013) those students who receive instruction on self-regulation strategies have greater engagement and facilitate the achievement of better variable academic performance, as mentioned above, commonly related to dropping out of university studies. Regarding the relationship between academic performance and the use of self-regulation strategies, the results of previous research seem to indicate that there is a direct relationship between the use of these strategies and the increase in academic performance, especially in stages prior to university (stages in which this relationship has been most commonly observed).

According to a study carried out by Bareto-Trujillo and Álvarez-Bermúdez (2020) with a group of high school students belonging to the metropolitan area of Monterrey (Mexico), the results showed that the students used the metacognitive strategy more frequently and that this variable is the one that predicts academic performance the most. Along the same lines, Javaloyes and Nocito (2016) found similar results in their research with a group of first-year Business Management and Administration students, that is, the relationship between the use of self-regulation learning strategies and academic performance was statistically significant, in such a way that items referring to help-seeking, perseverance and self-efficacy showed a direct relationship with the increase in academic performance. Expanding on what was mentioned above, authors such as Belloc et al. (2011), Gaeta and Cavazos (2016) and García-Marcos et al. (2020) relate academic performance problems to inadequate study conditions, as well as time management problems (variables that have been investigated as part of the use of self-regulation learning strategies). However, studies that delve into the relationship between the use of these self-regulated learning strategies and the intention to persist in university studies are still necessary (Bernardo et al., 2019).

What has been analysed most frequently has been the relationship between academic performance and the intention to persist. In this sense, according to an investigation carried out by Casanova et al. (2021) with engineering students from a public university in the north of Portugal, it was observed that the reason why students dropped out was related not only to academic performance but also to vocational interest. Following the line of previous research, not only academic variables are relevant when predicting the intention to persist in the university.

Taking into account the affective-motivational variables, in different research works such as those by Straham and Credé (2015) with two groups of students of students from 300 public and private universities in the United States, it was observed that there was a strong relationship between intention to drop out the university studies and satisfaction with the degree completed. These results are confirmed by Castro-López et al. (2021), showing satisfaction with the degree´s choice studied as one of the best predictors of the intention to drop out. In turn, studies such as the one by García-Aretio (2019) or the one by Bernardo et al. (2018) observed that another variable that influences the prediction of university dropout is interest in academic content. Similarly, according to Feixas-Condom et al. (2015), the interest in the degree and the lack of liking for the contents studied are decisive in the expectation of dropout. Something similar occurs with academic expectations: in a study by Conde-Rodríguez et al. (2017), in which Spanish first-year students of degrees related to the legal-social and scientific-technological field of a university in Spain participated, it was observed that there is a relationship between problem-solving strategies, life goals and the academic expectations of first-year university students, these three variables being the key in their academic success and the prevention of dropping out of university studies. Therefore, taking into account the role of affective-motivational variables in the prevention of university dropout, it is hypothesized that:

H2: satisfaction with the degree is the variable with the greatest weight in decision-making to drop out the degree, especially in first-year students.

It is challenging to establish relationships among this diverse group of variables. Taking into consideration all of the above, as well as the theory of uncertainty associated with dropping out of university studies, conducting Multi-criteria Decision-Making analysis can assist researchers in gaining a more comprehensive understanding of the phenomenon. This is because it not only enables us to observe the variables that exert the most influence on the decision to drop out of university, but also provides insights into the criteria and options involved in making such a decision within a broad spectrum of possibilities.

For all these reasons, the aim of this research is to analyse the uncertainty associated with the decision to drop out studies among first-year and second-year students, based on engagement, satisfaction with studies and the use of self-regulation learning strategies.

Method

Sample

The study sample is made up of 719 students from a public university in the north of Spain, of whom 521 were first-year students and 198 second-year students. The students, in addition, were from different degrees, the main ones being: Degree in Psychology (40.4%), Degree in Teaching in Primary Education (24.5%), Degree in Teaching in Early Childhood Education (14.1%) and Degree in Business Administration and Management (7.2%), leaving the rest (13.8%) distributed in other degrees such as the Degree in Speech Therapy, the Degree in Social Work, the Degree in Accounting and Finance, the Degree in Economics and the Degree in Pedagogy. Of all of them, 78.3% were women, probably as a consequence of being traditionally feminized studies, with a mean age of 19.28 years (SD=3.368).

Instrument

The instrument used in this research consisted of two standardized questionnaires. First, the Early University Dropout Intentions Questionnaire (EUDIQ-R; Bernardo et al., 2022a). This questionnaire is composed by thirteen items grouped into three factors: satisfaction, social adaptation, and self-regulation strategies. In this study, we use two of the three factors defined after the Confirmatory Factor Analysis. The reliability results were high, above .80 (General scale α=.821; ω=.822).

The Satisfaction Factor is made up for four items collected on a five-point scale (1 = Strongly disagree to 5 = Strongly agree). Examples of the items include “I am satisfied with the degree” and “The degree meets the expectations I had about it”. The use of self-regulated learning strategies was made of six items given on a five-point scale (1 = Strongly disagree to 5 = Strongly agree). Examples of these items include “Before I start studying I set goals” and “I organize my study session according to difficulty”.

Engagement was measured with the 17 items of the Utrecht Work Engagement Scale (UWES-S; Schaufeli & Bakker, 2003), adapted to Spanish university students. The responses were collected on a six-point scale (1 = Never to 6 = Always). Some examples of items include "I forget everything that happens around me when I am absorbed in my studies", "I feel strong and vigorous when I am studying or going to class", and "I find it difficult to disengage from my studies".

Finally, the instrument also included a series of sociodemographic data were measured (sex, age, university and current degree, among others), as well as two items to measure the intention to drop out. In this sense, participants were asked if they had ever had the intention to drop out of their degree (i.e., change their university degree) or to leave the university completely (i.e., leave the university system permanently), for which dichotomous answers were given (1 = No, 2 = Yes).

Procedure

The research was approved by the Responsible Research and Innovation Subcommittee of the Research Ethics Committee of the University of Oviedo, allowing the processing of the necessary permits obtained for the study. After that, the recruitment of participants was randomized in an ex-post-facto study. Subsequently, the sample selection was carried out through a non-probabilistic and intentional procedure, which took as its starting point the accessibility of the collaborating teachers in the research. Furthermore, student participation was voluntary and anonymous. Finally, students completed the CARE questionnaire online during the first semester using Google Forms. Prior to completing the questionnaire, a text was included informing the students of the objective of the study and assuring them of the confidentiality of their data, compliance with data protection, as well as the usual ethical requirements.

Data analysis

We carried out data analysis using SPSS v.24 and MatLab 6.5, performing descriptive analysis (frequencies, percentages and median) and Multiple-criteria Decision-Making based on the FTOPSIS method.

MCDM

The multi-criteria decision-making theory approach has emerged as an outstanding approach to address real-time solutions to unpredictable conditions providing the best solution among the different alternatives (Stojcic et al., 2019). The most commonly used methods in MCDM are WSM (Weighted Sum Model), WPM the (Weighted Product Model), AHP (Analytic Hierarchy Process), COPRAS (Complex Proportional Assessment), PROMETHEE (Preference order organisation method for enrichment evaluation), ELECTRE (Elimination and Choice Method Expressing Reality), TOPSIS (Technique of Order of Preference by Similarity to Ideal Solution), Decision Making Trial and Evaluation Laboratory (DEMATEL) VIKOR (VlseKriterijuska optimizacija I komoromisno resenje), Weighted sum of products assessment (WASPAS), MAUT (Multi-attribute utility theory), MULTIMOORA (Multi-Objective Optimization on the basis of a Ratio Analysis), ORESTE (Organization, Arrangement and Synthesis of Relational Data), GLDS (Gained and Lost Dominance Score) and Multi-objective programming (Bidoux et al., 2019; Hafezalkotob et al., 2019; Castro-López et al., 2021).

Each method has its advantages and disadvantages, and its application fields. However, none of the methods dominates the other methods. It is possible to use more than one method to address the same multi-criteria decision problem and to provide more detailed information (Mulliner et al., 2016; Lee and Chang, 2018).

Multi-criteria decision making (MCDM) methods have been applied in different areas such as businesses, industries, manufacturing, banking, energy, sustainability, etc. (Hassan et al., 2018) and they are becoming the main tools to analyse MCDM problems (Siksnelyte-Butkiene et al., 2020).

However, such tools are relatively unexplored in higher education although studies are now beginning to appear that consider these multi-criteria decision support techniques in the university environment. Some studies, such as Hassan et al. (2018) or Kazancoglu and Ozkan-Ozen (2019), make a literature review on the use of the MCDM for higher education. Other authors analyse an MCDM problem using one of the above techniques. For example, Kazancoglu and Ozkan-Ozen (2019) use DEMATEL to construct and analyse a structural model involving cause-effect relationships between complex factors. Ayouni, et al. (2021) applied Fuzzy VIKOR to identify the framework criteria and select alternatives from three learning management systems adopted in Saudi Arabian universities.

Though, several studies combine two or more techniques to optimise results in MCDM. For example, Wu et al. (2012) combines the analytic hierarchy process (AHP) and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods to rank the performance of each private university with respect to the relative weight of each evaluation index. Shayganmehr, and Montazer (2020) determine indicators and indexes for the importance of e-services in Iranian University with Analytical Hierarchy Process (AHP) and PROMETHEE methods.

Nevertheless, to deal with the effects of uncertainty and fluctuations among experts' preferences, Zadeh (1965, 1973) developed a fuzzy set theory in which the qualitative aspects of decisions are represented by linguistic variables that can be expressed qualitatively by linguistic terms and quantitatively by a fuzzy set in the universe of discourse and the respective membership function (Azizi et al., 2015). Some authors include fuzzy version to the previous methods. For example, Kiani Mavi (2014) analyse the entrepreneurial orientation phenomenon or Chopra et al. (2021) to establish the ranking and classifying MOOC key acceptance factors in higher education both studies with FAHP and FTOPSIS techniques.

FTOPSIS method

Among the different multi-criteria decision-making methods that incorporate fuzzy variables, the FTOPSIS method developed by Hwang and Yoon (1981) is considered one of the most widely used (Yatsalo et al., 2020). Its importance lies in the fact that it allows optimising decision making to rank performance by similarity to the ideal solution (ranking method) as collaborative decision makers (Parida, 2020). According to this approach, the best alternative must have two characteristics: it must be the closest to the best positive ideal solution and the farthest from the best negative ideal solution (Chen et al., 2006). This technique consists of three steps (Castro-López, et al., 2021) (1) fuzzy variation matrix for each criterion; (2) normalise and compute the weigh normalised; (3) define fuzzy positive ideal solution (FPIS, A+) and negative (FNIS, A-); (4) determine the closeness coefficient for each alternative and establish the ranking between them.

Step 1. Determine the fuzzy valuation matrix for each criteria. For this purpose, Ci (i=1...n) are the evaluation criteria and Aj (j=1...m) are the solution alternatives to be rank ordered. The fuzzy decision-making matrix has the format presented in Eq. 1.

$$\left[\tilde{D}_x\right] = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_i \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \cdots & C_j & \cdots & C_n \end{array} \\ \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \ldots & \ldots & \ldots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \ldots & \ldots & \ldots & \tilde{x}_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \tilde{x}_{ij} & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \ldots & \ldots & \ldots & \tilde{x}_{mn} \end{pmatrix} \end{array} \quad (1)$$

Where $\tilde{x}_{ij}$ is defined as the fuzzy value assigned to criterion 'j' under alternative 'i' expressed as a triangular fuzzy number: $\tilde{x}_{ij} = \left(x_{ij1}, x_{ij2}, x_{ij3}\right)$.

Step 2. Normalise and compute the weigh normalised. For this measurement, a normalisation must be performed to measure the criteria in the interval [0. 1] according to Eq. 2.

$$\tilde{x}_{ij}^{*} = \frac{\tilde{x}_{ij}}{\max_j\left(x_{ij3}\right)} = \left(\frac{x_{ij1}}{\max_j\left(x_{ij3}\right)}.\frac{x_{ij2}}{\max_j\left(x_{ij3}\right)}.\frac{x_{ij3}}{\max_j\left(x_{ij3}\right)}\right) = \left(x_{ij1}^{*}.x_{ij2}^{*}.x_{ij3}^{*}\right) \tag{2}$$

The weights for each criterion will be given in the form of triangular numbers and those obtained with the AHP method will be considered. Afterwards, the normalised elements and the weighted decision matrix are then calculated by multiplying each element by its weighting weight, as indicated in Eq. 3:

$$\tilde{v}_{ij} = \tilde{W}_j * \tilde{x}_{ij}^{*} = \left(w_{j_1} * x_{ij1}^{*}, w_{j_2} * x_{ij2}^{*}, w_{j_3} * x_{ij3}^{*}\right) \mathrm{i} = 1, 2, \ldots \mathrm{m}; \mathrm{j} = 1, 2, \ldots \mathrm{n} \tag{3}$$

Step 3. Define fuzzy positive ideal solution (FPIS, A+) and negative (FNIS, A-). The fuzzy positive-ideal (FPIS, A$^+$) and the fuzzy negative-ideal solution (FNIS, A$^-$) where the nature of the criterion (benefit criterion "I'" or cost criterion "I”") will be considered to select the optimal fuzzy value among all the alternatives. Equations 4 and 5. Allow the identification of such positive and negative solutions.

$$A^{+} = \left\{\tilde{v}_1^{+}.\tilde{v}_2^{+}.\ldots.\tilde{v}_n^{+}\right\} = \left\{\left(\max v_{ij} \middle| i \in I'\right) \times \left(\min v_{ij} \middle| j \in I''\right)\right\} \; where \; i = 1, 2, \ldots, m \tag{4}$$

$$A^{-} = \left\{\tilde{v}_1^{-}.\tilde{v}_2^{-}.\ldots.\tilde{v}_n^{-}\right\} = \left\{\left(\max v_{ij} \middle| i \in I'\right) \times \left(\min v_{ij} \middle| j \in I''\right)\right\} \; where \; j = 1, 2, \ldots, n \tag{5}$$

Then, the benefit criteria (*I'*) and cost criteria (*I"*) is determine using Eqs. 6 and 7. In those cases, real numbers “1” and “0” are usually chosen -in their fuzzy representation- to express the components.

$$I' = \tilde{v}_j^{-} = (1, 1, 1); \tilde{v}_j^{+} = (0, 0, 0) \tag{6}$$

$$I\prime' = \tilde{v}_j^{+} = (1, 1, 1); \tilde{v}_j^{-} = (0, 0, 0) \tag{7}$$

Step 4. Calculate the distance of each alternative. To this end, the positive and negative distances to the ideal solution. For this end, Eqs. 8 and 9 allows the distance calculation for each alternative to the ideal solution.

$$D_i^{+} = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}.\tilde{v}_i^{+}\right) \mathrm{i} = 1, 2, 3 \ldots, \mathrm{m}; \mathrm{j} = 1, 2, \ldots, \mathrm{n} \tag{8}$$

$$D_i^{-} = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}.\tilde{v}_i^{-}\right) \mathrm{i} = 1, 2, 3 \ldots, \mathrm{m}; \mathrm{j} = 1, 2, \ldots, \mathrm{n} \tag{9}$$

Where $D\left(\tilde{v}_{ij}.\tilde{v}_j^{+}\right)$ is the distance between those fuzzy numbers.

Step 5. Calculate the closeness coefficient for each alternative “*i*” according to Eq. 10 that make it possible to classify and rank the alternatives.

Table 1 Aggregated results in terms of weights and consistence

	weighting values	Index	
C1: Satisfaction	0.137	CI	0.018
C2: Self-Regulation	0.780	RI	0.525
C3: Engagement	0.083	CR	0.034

Table 2 Unstandardized fuzzy matrix

	1st course			2nd course		
Satisfaction	6.50	7.64	9.02	6.17	7.35	8.69
Self-Regulation	6.13	7.23	8.55	6.00	7.12	8.41
Engagement	4.49	5.85	6.83	4.35	5.70	6.69

$$CC_i = \frac{D_j^-}{D_j^- + D_j^+} \quad i = 1, 2, \ldots, m \tag{10}$$

Results

To apply the AHP method was carried out through virtual interviews with 5 experts on early school leaving at university level. As a result, we have obtained the peer evaluation matrix of the 3 criteria that define dropout intention (C1: Satisfaction, C2: Self-Regulation; C3: Engagement). Then, each expert establishes importance weights for each criterion that, in his or her opinion, best defines the proposed higher education dropout model. The results are then aggregated in terms of weights and consistency coefficients for the proposed assessment model, as shown in Table 1 below.

As we can see in above, RI denotes the Random Index, and weights values considered to analyse the 3 criteria that define dropout intention are rational. It is due to the fact that consistency index (CI) and consistency ratio (CR) are below comparison matrix are below 0.1, therefore, the results are consistent (Chen & Huang, 2022). Therefore, these weighting values will be considered adequate for the FTOPSIS method.

To implement the FTOPSIS method, we have considered the results of the questionnaire carried out among students in the first years of higher education give an unstandardized assessment matrix shows in Table 2. It represents the data in triangulated vectors for each of the variables analysed for this multicriteria analysis that involve first and second-year courses but unstandardised.

Then, the weightings are then normalized in the fuzzy matrix, yielding the results in Table 3. It shows the data in triangulated vectors for each of the variables analysed in this multicriteria analysis for first and second-course once we normalise the results following the indications of Wang and Chin (2006).

Then, considering the weights assigned on each criterion, considering the results obtained in the previous AHP method, we construct the normalized-weighted fuzzy matrix in terms of triangulated vectors for each of the variables analyzed (Satisfaction, Self-regulation, Engagement) for each course as shown in Table 4.

Table 3 Normalized fuzzy matrix

	1st course			2nd course		
Satisfaction	0.72	0.85	1.00	0.68	0.82	0.96
Self-regulation	0.68	0.80	0.95	0.67	0.79	0.93
Engagement	0.50	0.65	0.76	0.48	0.63	0.74

Table 4 Normalized fuzzy matrix

	1st course			2nd course		
Satisfaction	0.08	0.10	0.18	0.08	0.09	0.18
Self-regulation	0.56	0.63	0.69	0.55	0.62	0.68
Engagement	0.03	0.06	0.07	0.03	0.06	0.07

Table 5 Ranking of the intention to drop out arranged by course

Course	D_i^+	D_i^-	CC_i	Ranking
1st course	3.31	1.30	0.282	1
2nd course	3.33	1.27	0.276	2

Furthermore, we calculated the distances of each criterion to the fuzzy ideal scores and the closeness coefficient of each course, taking into account the distance to the ideal solution (positive and negative) of each alternative (first-course and second-course). Finally, the results obtained are illustrated in Table 5.

As can be seen in the table above, the closeness coefficient for each alternative (CCi) is higher in the first year than in the second year. Therefore, it is the first-year students who consider dropping out of their studies in Higher Education more than those in the second year where the closeness coefficient values are lower.

Discussion

The democratization of access to higher education has allowed access to the university for a larger and more diverse number of students and, although most students manage to overcome challenges and to adapt to the demands of the university system (which requires highly committed and autonomous students), some of them experience more difficulties, even deciding to drop out their studies permanently. For this reason, the aim of this research was to analyse the uncertainty associated with the intention to drop out of studies among first and second year students, based on engagement, satisfaction with studies and the use of self-regulation learning strategies. Therefore, this study proposed two hypotheses: there is a greater intention to drop out in the first year of the degree and satisfaction with the degree is the variable with the greatest weight in decision-making to drop out the degree, especially in first-year students.

As can be seen in the results´ section, the students in the first course show a greater intention to drop out than those who are in the second year, taking into account satisfaction with the studies, the use of self-regulation learning strategies and engagement, confirming the first hypothesis of this research. These results, moreover, are in line with those already observed in previous research, as presented below.

In this research, the influence of engagement, satisfaction with studies and the use of self-regulation strategies on the intention to drop out of first-year students has been observed. More specifically, satisfaction with the course also proved to be the variable with the greatest weight when deciding to drop out the studies, confirming the second hypothesis of this research.

This is the case of the studies by Mostert and Pienaar (2020) who, taking into account the variables analysed in this research, observed that those first-year students who experienced exhaustion (one of the dimensions of burnout, a construct that is contrary to engagement), were less satisfied with their studies. When another of the dimensions (cynicism) was analysed, it did not serve to predict satisfaction with studies as expected, but it did predict students' intention to drop out. Satisfaction and commitment to studies seem to be two variables related in the research, since low levels of engagement can reduce levels of satisfaction with the degree, and may result in dropping out of studies, either permanently or due to change degree. The students who have low engagement scores are also less satisfied with the degree and, therefore, are more likely to drop out of their university studies (Moore & Loosemore, 2014). In addition, related to the above, for first-year university students, social support is essential as a protective factor against satisfaction with career and university, as well as for university dropout (Akanni & Oduaran, 2018; Mason & Nel, 2011).

Continuing with studies that have focused on the analysis of variables such as engagement and its influence on university dropout in first-year students, the contributions of Fourie (2018) are relevant. This author observed that being committed to the institution during this first course is directly related to the intention to persist. These results are, in turn, in line with those provided by Thomas (2012). Therefore, and above all as a result of these new challenges in tertiary education in which students pursue their studies in a more autonomous and self-regulated way, commitment to the degree becomes essential to be able to promote successfully.

Similarly, studies on satisfaction with studies are necessary, a variable related to commitment to the degree (Mostert & Pienaar, 2020). Thus, another of the variables studied in this research was first and second year students' satisfaction with their studies, a variable traditionally studied in relation to university dropout. As can be seen, this is another of the variables with the greatest influence on the decision to drop out, as observed in research such as that by Scheunemann et al. (2021) in which higher satisfaction with studies was found to be significantly associated with higher subsequent dropout intentions, possibly due to unfulfilled expectations.

Finally, the influence of the use of self-regulated learning strategies was the one that had the greatest weight in the decision to drop out. The transition from High School to university constitutes a critical stage, since there is a break between a highly structured and controlled educational cycle and the independent, autonomous and self-regulated learning of higher education that requires of students highly committed to their university studies (Beaumont et al., 2016; Dörrenbächer & Perels, 2016; Sáez et al., 2018). For this reason, this is one of the variables of great interest when investigating university dropout, since this transition from one T-L model to another can be considered one of the variables that has the greatest weight when deciding whether to persist or not. However, this has been one of the variables that has shown more variability of results in its relationship with university dropout.

On the one hand, there are studies that have reported the lack of a direct relationship between this variable and the intention to drop out during the first year of studies (Bernardo et al., 2022b). On the other hand, authors such as Jiménez-Rodríguez et al. (2021) have observed that metacognition, a cognitive component of self-regulation, is an explanatory variable of academic performance and the intention to persist in the degree. Indirectly, it was also observed that the use of self-regulated learning strategies was related to the intention to drop out (that is, the higher the self-regulated learning, the lower the intention to drop out) when students had high levels of social support (Morelli et al., 2022). What has been observed in recent research is the importance of this variable during university teaching, as well as the need to train students in the use of these strategies so that they are able to adapt to the new training requirements in higher education.

Additionally, more research has attempted to analyse university dropout in first-year students than in later years. This is so because the highest university dropout rates occur in this first year, as evidenced by official data from the Ministry of Universities (2022): taking exclusively the definitive dropout from the university institution, disregarding those students who change degree, it has been observed that more than 6% of the students who enter at university dropped out after the first year, 3% after the second year and 2% after the third year. Thus, after the first year and as the student persist at the university, the chances of dropping out decrease, counting, after the third year, with a retention rate of more than 98%. This also occurs in the United States, with first-year students having the highest dropout rate (around 25%), decreasing in subsequent courses (Hanson, 2021). The primary factor contributing to this phenomenon relates to one of the variables investigated in this study: satisfaction with the course. Generally, numerous students embarking on new academic paths may perceive a misalignment between their initial expectations and the actual fulfilment of their chosen field, leading them to discontinue their studies within the first year. However, students who pass this first period are more likely to continue in the degree until they graduate that is to say, improving their trajectories, as can be seen in this research. Therefore, it is not surprising that university dropout has been analysed more frequently in first-year students than in other university courses.

In short, it seems important to expose what could be the institutional measures for the prevention of university dropout, especially focusing on those courses in which it is more likely to occur, for example, during the first year. These measures can range from the classroom to the broader institutional context, and can focus both on the student and on university teaching staff and services. Some actions may include tutoring programs (Fourie, 2018; Ponce et al., 2018), as well as training actions aimed at improving study and learning skills (Rosário et al., 2019). Academic guidance could also be included for first-time students in order to facilitate contact to offer them re-entry alternatives and help them outline their academic-professional expectations (Seco et al., 2016). With all this, it seems important to consider that the intervention should preferably be carried out in the classroom context, especially in the first year, due to the initial lack of knowledge on campus, support services and other non-formal environments for learning and skills development (Álvarez-Pérez & López-Aguilar, 2017).

Limitations

This study has several limitations. On the one hand, the sample acquisition was restricted, as the range of academic disciplines in which the students were enrolled during the research was relatively limited. Although the sample size was deemed sufficient, future investigations should encompass a broader array of degree programs and branches of knowledge, such as engineering or architecture, where the phenomenon of student dropout has received less attention.

On the other hand, the variety of variables taken into consideration in this study is also very limited. It seems important for future research to include a broader range of factors that can shed light on why students contemplate dropping out their higher education studies, such as academic performance, self-efficacy, attributions, or other relevant personal characteristics. Furthermore, it is essential for future studies to adopt comprehensive models, which not only examine the interaction of these variables with the phenomenon but also explore their mutual interaction.

Moreover, in future research, the intention to drop out from studies could be assessed more comprehensively by employing a questionnaire or standardized test. This approach would enable a more nuanced examination of the significance of this variable, moving beyond its binary classification and allowing for a more detailed analysis. However, it would be interesting for future researches to not only consider the intention to drop out, but also whose students finally commit the dropout behaviour.

Conclusions

In conclusion, it is essential to take actions that serve to prevent or alleviate the phenomenon of university dropout, both in the academic and professional spheres. In this way, not only institutional measures should be promoted in order to encourage academic success and permanence in the university, but also the variables that have been less studied should be analysed in depth in order to know their consequences. Thus, it will be possible to guarantee, to a greater extent, the permanence of first-year students until the end of their higher studies.

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Declarations

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