Evaluating Critical Success Factors in the Permanence in Higher Education using Multi-Criteria Decision-Making

University dropout is a phenomenon of growing interest due to the high financial costs that it involves for both families and states. Various variables have been studied in order to understand why this problem occurs. Satisfaction with the degree choice, study self-regulation and social adaptation within the university are some of the variables that are most important when studying the dropout intention. However, studying these variables is not an easy task and Fuzzy Inference Systems have helped by reducing the subjectivity of language. Therefore, the objective of this research is to adapt Fuzzy Inference Systems to improve knowledge about the intention to remain at university. We performed descriptive analyses, a classification tree and Multiple-criteria Decision-Making based on Analytic Hierarchy Process (AHP) and Fuzzy Inference Systems (FIS) on a sample of 1,912 students from different universities in Spain. We saw a relationship between the three variables studied and the intention to remain. In conclusion, there is no single variable for understanding the phenomenon of university dropout, but several variables that interact within a holistic model.

Keywords: self-regulation; university dropout; permanence; AHP; fuzzy inference systems.

1. Introduction

In recent years there has been an increase of the number of studies related to university dropout in response to the negative consequences it can have which affect the student, the family, the educational community, and society in general (Cervero et al., 2017). The complex impacts it may have on young people include difficulties involved in entering the labour market and in future career development, which could contribute to a deterioration in the quality of life (Cabrera, 2015).

The university dropout rate in Spain is still very high (around 30%), a much higher proportion the 16% European average (Bernardo et al., 2020). According to Colás (2015), this represents an economic cost to the country of more than 1,500 million euros per year.

Studying why this occurs means identifying and analysing the variables that could explain the phenomenon. Nowadays, different models have emerged based on specific factors within the educational process. Psychological, academic, sociological, economic and organizational variables are some of the most commonly-studied variable types (Viale, 2014).

Nevertheless, research based on a single specific factor has been overtaken by interactionist models (Tinto, 1975; Ulriksen et al., 2010) which are focused on the relationship of each of the aforementioned variables in order to weigh their importance in the decision to remain or dropout. For this reason, and although there has been special interest in observing the influence of academic and social variables, these are part of a holistic model that cannot be explained by considering their elements separately. In Spain, a higher progress has been made in the first line, trying to determine which variables influence the dropout intention and to what extent, as in the case of satisfaction (Bethencourt, 2008), self-regulation (García-Ros & Pérez-González, 2011) and academic and social adaptation (Bernardo et al, 2016), with fewer studies drawing up complex models which show the relationship between the study variables considered and which go beyond the national level (Díaz, Pérez, Bernardo, Cervero & González-Pienda, 2020).

2. Theoretical framework

Among the academic variables, satisfaction with the choice of degree and fulfilment of prior expectations have become highly important in predicting permanence at university. Studies such Diniz et al. (2016) found that the mismatch between what students expected to find and what they actually found when doing their degree contributed to the decision to dropout (Räisänen et al., 2018; Rodríguez-Muñiz et al. 2019). Equally important are studies of young people's vocations and the relationship with the likelihood of continuing at university or not (Almeida et al., 2012; Casanova et al., 2018). Belloc (2011) observed that both the lack of a vocation and low satisfaction with the current degree negatively influenced academic performance during the first year, one of variables most strongly related to student permanence at university (Esteban et al., 2017).

In this regard, time management, effort regulation and metacognitive self-regulation are some of the most influential constructs in students' academic performance in Higher Education (Broc, 2011). Several studies have shown that the students who are less likely to drop out of university are those who have a strategic approach to the demands of self-regulated learning (Stefanou et al., 2013; Broadbent & Poon, 2015; Cabrera, 2015).

However, as previously mentioned, academic variables are not the only ones that have received particular attention in studies of university dropout: social variables have also become particularly important recently. Building support networks, teacher relationships with students, and participation in institutional groups are some of the most important (Willcoxson, 2010; Gilardi & Guglielmetti, 2011), with social adaptation being one of the central elements to ensure commitment to the academic institution (Tinto, 1975).

Many authors have considered social adaptation within higher education to be an especially important variable in predicting the quality of students' academic transition and as a protective factor against university dropout (Tinto, 2005; Xuereb, 2014; Viale, 2014; Cervero et al., 2017).

However, the real world is subject to uncertainty and vagueness. Human acts and behaviours can hardly be described in an exact or precise way. That is why reality should not be studied in absolute terms with deterministic or probabilistic techniques that, in the search for precision, try to modify the real world to fit rigid, static mathematical models, losing valuable information along the way (Prieto et al., 2020). The application of models based on fuzzy logic makes it possible to manage the uncertainty associated with human actions and behaviour more effectively. This is because they process linguistic concepts typical of natural language, much closer to real descriptions of problems and their solutions.

The objective of this study is to adapt fuzzy inference systems to improve knowledge about the intention to drop out or remain on a university course by being able to include the associated uncertainty in the decision making about staying or dropping out.

3. Materials and methods

To achieve the objective, the research took place in 3 stages. In the first stage, we performed qualitative and quantitative studies. The sample for this study comprised 1,921 students aged between 17 and 55 years old (M = 19.81; SD = 3.501) from three Spanish universities: the first university provided 59.6% of the sample, the second 17.4% and the third 23%. Almost a third, 571 (29.7%), were men and 1350 (70.3%) were women. The students we interviewed were taking various degrees in different knowledge branches at their universities: 51 (2.66%) were studying science, 718 (37.38%) health sciences, 1077 (56.06%) social and legal sciences, 11 (0.57%) engineering and architecture, and 64 (3.33%) arts and humanities. Finally, in regard to the description of the sample, it should be mentioned that the majority are new students (89.3%) while the remaining 10.7% are distributed among second (5%), third (3.6%) and fourth (2.1%) years.

Following this, we performed the appropriate analyses to create a classification tree that would allow us to find a predictive model producing the variables subsequently used in the following stages. In the design of this tree, we used the Chi-square Automatic Interaction Detector (CHAID) growth method, seeking the strongest interaction between the selected variables and the dependent variable of interest: the intention of dropping out from university.

Subsequently, we used the AHP methodology, as it is capable of solving complex decision-making problems, and makes it possible to establish the weights of the attributes that influence the intention to leave the university on the basis of pair comparisons.

Finally, through fuzzy inference systems, we added the uncertainty associated with multi-criteria decision processes, and with it, achieved better optimization of the results. This analysis produced a series of inference maps, allowing us to intuitively estimate dropout intention based on the assessment of the input variables. In the following sub-sections, each of the indicated phases is described in detail.

3.1. Instrument

We prepared an ad hoc questionnaire to analyse students' intentions of dropping out (Bernardo et al., 2019). It was composed of 66 items, organized in an initial block of personal and sociodemographic data, and 8 additional blocks.

The initial block included items such as sex, age, grant availability, parental qualification, etc. designed with dichotomous, multiple and simple choice modes. The remaining blocks used a five-point Likert-type response scale corresponding to: 1) Strongly disagree; 2) Disagree; 3) Neither agree nor disagree; 4) Agree and 5) Completely agree. An exception was the first subsection of the self-regulation block, which used the scale: 1- Never, 2- Daily, 3- Weekly, 4- Monthly and 5- Long-term.

The 8 blocks making up the questionnaire are: reason for choosing the degree (with 13 items, such as: the degree was exclusively my choice, I chose this degree thinking about job opportunities, etc.), prior knowledge (with 4 items, such as: I think that my study techniques are appropriate, I feel that my previous high school knowledge is sufficient to face this first year, etc.), economic variables (with 2 items: it is a great effort for my family to pay for my studies and obtaining a grant is what allows me to pay for my degree), current situation (with 11 items, such as: I am up to date with my subjects, a lot of effort is required to study this degree. etc.), interest in the degree (with 5 items, such as: I try to get the best possible grade, I am frequently distracted during classes, etc.), integration (with 6 items, such as: when I have a question I ask the teacher, my level of adaptation in the academic field is satisfactory, etc.), institutional variables (with 3 items, such as: I would recommend this institution to other students, I am aware of the existence of mechanisms for guidance and student orientation in my university, etc.), and self-regulation (with one section on the time frame of application of strategies, with 2 items: I plan my study and evaluate my learning; and a second with 7 items, such as: before starting the study session I set myself a goal for it, actively participate in my study and learning because deep understanding is important for my intellectual growth, etc.).

However, aspects related to academic performance (Belloc et al., 2011; Esteban, et al., 2017) and social adaptation (Gilardi and Guglielmetti, 2011) seem to have a greater weight in predicting dropout behaviours, the factors of social adaptation and self-regulation, which are closely related to academic performance, have been used to perform the analyses, as well as different variables related to the fulfilment expectations, satisfaction and interest in the studies.

On the other hand, the dropout intention variable was dichotomized in order to present the results in a simple and intuitive way, for which the values 1 to 3 of the dropout intention were integrated into the value 0 (no dropout intention), while the values 4 and 5 of the original variable were grouped into the value 1 (dropout intention).

3.2. Data collection

We asked teachers to collaborate. Following that, the students (preferably first and second year) completed the questionnaire online using Google Forms. We included text informing the students of the study objective and assuring them of the confidentiality and protection of their data, according to the usual ethical requirements.

3.3. Statistical Analysis

We carried out data analysis using SPSS v.24 and MatLab 6.5, performing descriptive analysis (frequencies, percentages and median), classification trees, and Multiple-criteria Decision-Making based on AHP and Fuzzy Inference Systems (FIS).

Before executing the decision tree, we dichotomized the response of the dependent variable. The responses "strongly disagree" and "disagree" were replaced with 0 as the only negative value and the responses "neither agree nor disagree", "agree" and "strongly agree" were replaced with 1 as the only positive value.

3.4. Classification tree

The classification tree is a predictive and classification technique typical of data mining, which creates a classification model based on flow charts that make it possible to explain the behaviour with respect to a certain decision and to reduce the number of independent variables (Berlanga, Rubio & Vilà, 2013).

3.5. Analytic Hierarchy Process (AHP)

The AHP methodology developed by Saaty (1980) allows for multi-criteria assessments of decision making based on comparisons of relative importance of each factor involved in making the decision (Saaty, 1996). Subsequently, this information will be used as input data in the fuzzy inference system in order to include the uncertainty and ambiguity of human judgment in making decisions about whether or not to drop out of a university course.

The AHP method is widely used in a variety of fields including manufacturing, energy, banking, the environment, marketing, and education because it is easy to apply and produces excellent results (Mastrocinquea et al., 2020). The AHP method consists of four phases (Yu et al., 2011), illustrated in Figure 1.

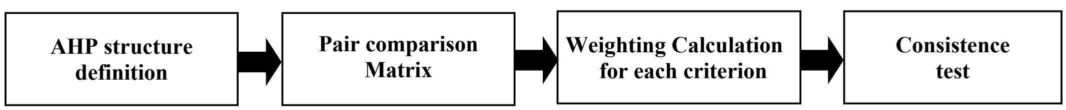

Figure 1. Phases method AHP (Source: Adapted from Yu et al., 2011).

In the first phase, the structure of the problem to be solved must be defined along with what objectives will be sought. This method has the advantage of allowing a hierarchical criterion structure, which provides better user focus by assigning weights to the criteria and sub-criteria. Each element in the hierarchy can be broken down into explanatory elements, and as many as necessary should be used (Luthra et al., 2016). In other words, AHP consists of structuring the decisional problem into different hierarchical levels such as a main goal, main dimensions, sub-criteria and alternatives (Erdogan et al., 2017).

To illustrate, Figure 2 shows a three-level AHP decision tree. The first level establishes the objective or goal to be achieved. The second level establishes the criteria to be followed to carry out the evaluation, and the third level establishes the different alternatives or sub-criteria.

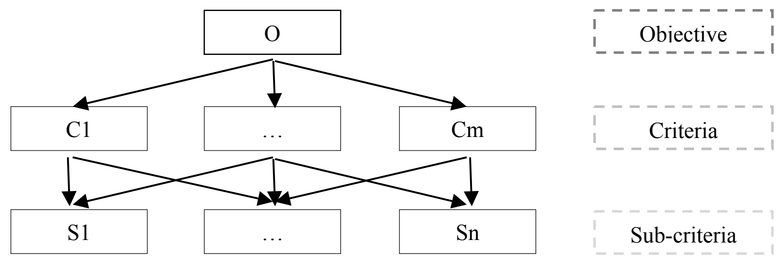

Figure 2. Structure AHP (Al-Husain & Khorramshahgol, 2020).

In the second phase, priorities are established between the various elements of the hierarchy, allowing the decision-maker to assess their importance through peer review. In these evaluations, crisp ratings are eliminated allowing the evaluator to provide a relative verbal assessment, more assimilable to natural language.

One of the strengths of this method is the possibility of quantitatively evaluating the criteria and sub-criteria on the same preference scale. This evaluation can be numerical, verbal (Table 1) or graphical. The use of verbal responses is intuitively more appealing, easier to use and more relatable to everyday life than numerical responses (Mastrocinquea et al., 2020). Saaty (1980) proposed a relationship between linguistic and numerical values (from 1 to 9). A standardized comparison on nine levels is shown in Table 1.

Table 1. Standard comparison scale in nine levels.

Definition	Value
Equally important	1
Weak importance	3
Essential importance	5
Demonstrated importance	7
Extreme importance	9
Intermediate values	2, 4, 6, 8

Source: Adapted from Saaty (1980).

Once the relationship between the numerical and linguistic values is established, matrices are constructed to allow pair-wise comparison, as indicated in equations 1 and 2.

$$A = [a_{ij}] = \begin{bmatrix} 1 & a_{12} & a_{13} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & a_{23} & \cdots & a_{2n} \\ \frac{1}{a_{13}} & \frac{1}{a_{23}} & 1 & \cdots & a_{3n} \\ \cdots & \cdots & \frac{1}{a_{3n}} & \cdots & \cdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & & \cdots & 1 \end{bmatrix} \tag{1}$$

$$a_{ij}^{*} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{2}$$

Where a_{ij} are the elements of the pair-wise comparison matrix (i, j= 1, 2, 3, …n)

Then, once the pair-wise comparison matrices are established, the weights of the criteria and sub-criteria are calculated for each level of assessment. Equation 3 will be used for analysis.

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}^{*}}{n} \tag{3}$$

Where w_i is the weight, a_{ij} are the elements of the pair-wise comparison matrix, and n is the number of criteria or sub-criteria in the pair-wise comparison matrix.

In the fourth and final phase, the consistency of the priorities set out above is evaluated. To determine this consistency, Saaty defines the so-called consistency ratio for each of the matrices established in the previous phase. The consistency ratio (CR) is used to directly estimate the consistency of the comparison pairs and is expressed as illustrated in Equation 4:

$$CR = \frac{CI}{RI} \tag{4}$$

Where CI is the consistency coefficient and RI is the random index, which indicates the consistency of a random matrix (Table 2).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{5}$$

Where λ_{max} is the maximum self-value and n is the dimension of the decision matrix.

Once the consistency is calculated, the weights are obtained, which represent the relative importance of each criterion. To do this, the method of the self-values described in the following expression is used.

$$A\,w = \lambda_{max}\,w \quad (6)$$

Where A represents the comparison matrix, w the autovector or preference vector, and λmax the autovalue.

The consistency ratio indicates whether the comparisons made are acceptable or not and need to be reviewed (Luthra et al., 2016; Erdogan et al., 2017, Büyüközkan et al., 2020). For his analysis Saaty (1980) established a relationship between consistency ratios and the number of criteria used to analyse each subsystem as illustrated in Table 2.

Table 2. Consistency ratio.

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Source: Saaty (1980).

Once the weights are calculated and the consistency of the assessments confirmed, they will be used to design a fuzzy inference system for determining the dropout rate.

3.6. Multiple-criteria Decision-Making based on Fuzzy Inference Systems

The use of decision support tools aims to achieve more consistent results by implementing expert knowledge in decision making. Such decisions are subject to subjective assessments, uncertain, and therefore difficult to describe precisely and rigorously. Fuzzy Inference Systems can be useful in managing the uncertainty associated with multi-criteria decision processes by being able to process the subjectivity inherent in the definition of any evaluation model.

These systems take place in five phases: (1) Fuzzification of the entries, (2) Applying fuzzy operators to the antecedents, (3) Implication method, (4) Aggregation of consequences, and (5) Defuzzification (Ross 2004).

Fuzzy inference systems allow us to include both qualitative and quantitative information by defining the linguistic labels that describe the input and output variables of the valuation system. For the knowledge base definition, techniques such as the Delphi method, group dynamics and in-depth interviews are usually used in order to capture the knowledge of an expert team related to the problem to be addressed. Thus, after agreeing on the typology of the labels to be used (triangular, trapezoidal, etc.) and the specific partitions of the variables, the linguistic rules that govern each proposed decision system must be determined (e.g.: IF *Var1* is LOW AND *Var2* is MEDIUM THEN *Var3* is MEDIUM). These rules will allow the five-phase inference process described above to be triggered for any given value of input.

For partitioning the variables, a 2-tuple based linguistic representation model can be used (Wang and Wang, 2020) that allows its systematic design by means of fuzzy numbers. Based on a scale of previously defined linguistic preferences, an expert team will agree on the priorities to be given to each potential assignable label in any variable of the model.

Once the input and output variable partitions are defined, the rule base for any decision subsystem in the proposed model must be defined. To this end, the option chosen in this study consists of weighting the fuzzy labels assigned to each input variable of a subsystem with the weights obtained locally for them via the AHP methodology. This way a weighted fuzzy output value will be obtained for each rule, which does not have to coincide with any of the labels assignable to the output variable according to its agreed partition. Thus, in each rule we will calculate the distance between the entry variables and the potential labels assignable to the output variable according to its partition. The distance used in this case, considering trapezoidal fuzzy numbers, as indicated in Equation 6.

$$Dj = D([a_o.b_o.c_o.d_o] - [a^j.b^j.c^j.d^j]) = \sqrt{P_a(a_o - a^j)^2 + P_b(b_o - b^j)^2 + P_c(c_o - c^j)^2 + P_d(d_o - d^j)^2} \quad (6)$$

Where $[a_o,b_o,c_o,d_o]$ represents the weighted fuzzy output of the rule whose output is to be estimated, $[a^j,b^j,c^j,d^j]$ the fuzzy j-th label of the output variable partition and Pa, Pb, Pc and Pd the priorities given to the vertices of the fuzzy trapezes considered (where Pa+Pb+Pc+Pd=1). Finally, the label of the partition at which the previous distance is minimal is chosen as the output label of the rule.

In this study, the inference process was implemented using *Matlab's Fuzzy Logic Toolbox*, allowing us to obtain a university dropout assessment according to the values assigned to the input variables in a simple and intuitive way through inference maps. In these maps, the evaluation of an output variable can be analyzed according to any value of the input variables in the system (in case there are three or more input variables, the map reflects only two of them for constant values of the rest).

4. Results

4.1. Classification tree

Considering the above, we validate a model (Table 3) by using classification tree analysis to allow us determining the most influential variables.

Table 3. Model classification table.

	Risk
Estimate	.166
Standard error	.008

The analysis shows a 94.3% chance of success in the permanence option, considering this as the opposite of dropout intention. This means a high predictive value for the selected variables as a result of the classification tree (see Figure 3).

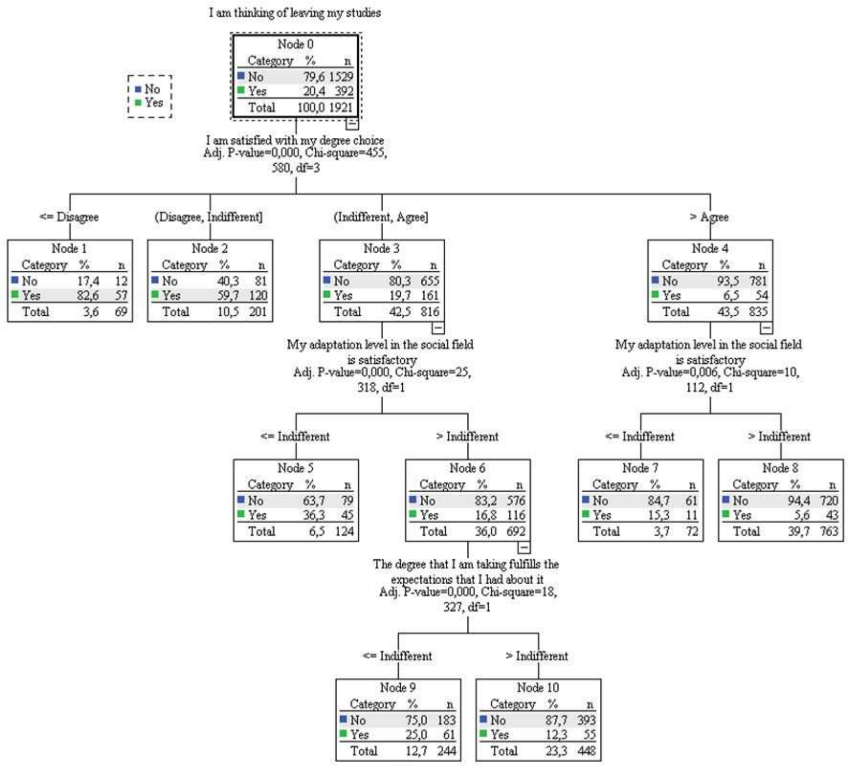

Figure 3. Classification tree relating to the intention of dropping out from university.

As the tree shows, the variable that best predicts dropout intention is satisfaction with the choice of degree ($\chi 2$ = 467,567; p <.001; df = 3). If the evaluation of this variable (SA3) is positive (> 4), 93.1% of the students are classified as having "no dropout intention", which falls to 15.9% in the case of those students who disagree or totally disagree with the item.

However, at a second level, there are three variables that seem to function as modulating elements. On the one hand, active participation in the learning process for a deep understanding of the contents (SR4) ($\chi 2$ = 6.603; p = .041; df = 1) compensates to some extent for dissatisfaction with the choice of degree, since among those who score this variable negatively (values 2 or 3), and self-regulation positively (> 3), there is still a lower probability of dropout (46.2%).

On the other hand, among those who value satisfaction with their choice of degree more positively ($\geq$3) there are two variables of influence. The first is satisfactory adaptation in the social arena (AD3) ($\chi 2$ = 21,260; p <.001; df = 1): Those who are relatively satisfied with their choice of degree (values 3 or 4) and at the same time score social adaptation as adequate (> 3) tend not to consider dropping out (81.4%). The second is the fulfilment of expectations regarding their current degree (SA1) ($\chi2$ = 9,608; p = .008; df = 1): Those who report high satisfaction with their choice of degree (> 4) as well as their fulfilment of prior expectations (> 3) are less likely to be considering dropping out (94%).

Something similar occurs at a third level with the variable "my current degree fulfils the expectations I had for it" (SA1) ($\chi2$ = 23.079; p <.001; df = 1), the tree classified those who positively scored this item mostly (86.6%) in the no intention to drop out group (> 3), and all of those who also reported appropriate social adaptation (a > 3) and were satisfied with their degree choice (3-4).

As a result of the analysis of the classification tree, we established that the model that best predicts dropout intention was composed of the variables SA3, SR4, AD3 and SA1 (Figure 4).

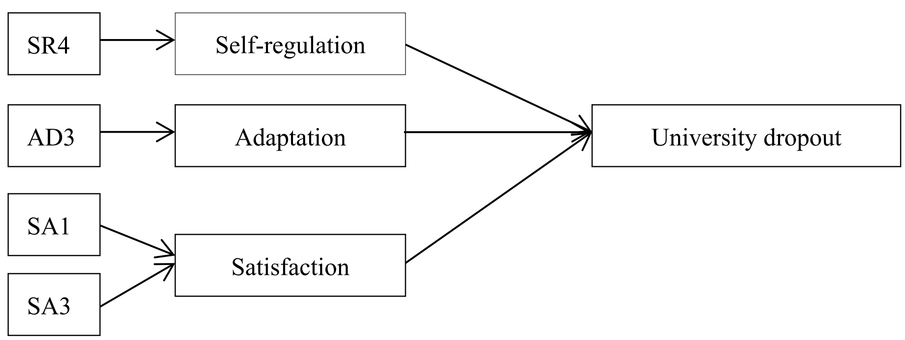

Figure 4. Evaluation model.

4.2. Analytic Hierarchy Process (AHP)

Commonly the application of the AHP method is often combined with the Delphi method for participatory decision-making processes to build consensus (Le Pira et al., 2017; Mastrocinquea et al., 2020). In this case, six university experts in dropout intention participated. Each expert made a comparison between different criteria that define each variable. In this case, the pair-wise comparison matrix has the following dimensions: self-regulation (6x6), satisfaction (4x4), adaptation (3x3) and dropout intention (3x3). As an example, Figure 5 shows the overall assessment matrices for each of the criteria defining each subsystem in the assessment model.

SELF-REGULATION

	C1	C2	C3	C4	C5	C6
C1	1	0.248	0.169	0.452	0.383	0.757
C2	4.036	1	0.661	1.665	0.605	1.864
C3	5.904	1.513	1	2.376	0.953	4.079
C4	2.211	0.600	0.421	1	0.794	2.376
C5	2.608	1.653	0.421	1.260	1	3.141
C6	1.322	0.536	0.245	0.421	0.318	1

SATISFACTION

	C1	C2	C3	C4
C1	1	0.566	0.318	0.504
C2	1.766	1	0.707	0.661
C3	3.141	1.414	1	0.750
C4	1.985	1.513	1.334	1

ADAPTATION

	C1	C2	C3
C1	1	1.513	1.849
C2	0.661	1	1.348
C3	0.541	0.742	1

DROPOUT INTENTION

	C1	C2	C3
C1	1	1.513	1.849
C2	0.661	1	1.348
C3	0.541	0.742	1

Figure 5. Example of global comparison matrices.

Subsequently, using the method described in the methodology (section 3), the weights of the criteria were calculated for each expert and at an aggregate level (Table 3), together with their corresponding consistency analyses (Table 4). To aggregate the individual priorities into the group priorities we can use the geometric weighted method (WGMM) (Ssebuggwawo et al., 2009), where $w^{[k]}$ is the weighting that aggregates the weights of each evaluation subsystem considered. This is calculated as follows in Equation (6).

$$w^{[k]} = \left(w_1^{[k]}.w_2^{[k]}...w_n^{[k]}\right) \quad (6)$$

Where: $w_i^{[k]} > 0.\ \sum_{i=1}^{n} w_i^{[k]} = 1$ is the priority weight vector of the k-th actor responsible for decision making.

Then, through Equations 7 and 8, the aggregate priority vector is calculated for each of the assessment subsystems that define the proposed model.

$$w_i^{[G]} = \prod_{k=1}^{r} \left(w_i^{[k]}\right)^{\beta_k} \quad (7)$$

Where: $w_i^{[k]} = \left(\prod_{j=1}^{n} a_{ij}^{[k]}\right)^{1/n}.\ i \in \{1, n\}$ (8)

Equations 7 and 8 give the priorities of individual decision makers, being $w^{[k]}$. k ϵ {1, n}.

Finally, once the individual aggregation vectors are calculated, the group aggregation vector is calculated from Equation 9.

$$w^{[G]} = \left(w_i^{[G]}\right).\ \ i \in \ \{1,n\} \tag{9}$$

Table 4 shows the weights for the criteria according to the individual expert ratings and their aggregation.

Table 4. Results weights of each criterion

	Self-Regulation						Satisfaction				Adaptation			DropOut Intention		
	C1	C2	C3	C4	C5	C6	C1	C2	C3	C4	C1	C2	C3	SR	SA	AD
Exp.1	0.144	0.317	0.336	0.077	0.068	0.058	0.282	0.179	0.439	0099	0.539	0.164	0.297	0.110	0.581	0.309
Exp. 2	0.126	0.316	0.316	0.104	0.087	0.050	0.381	0.108	0.342	0.169	0.548	0.211	0.241	0.101	0.433	0.466
Exp. 3	0.042	0.060	0.384	0.103	0.217	0.193	0.060	0.111	0.278	0.551	0.568	0.334	0.098	0.557	0.123	0.320
Exp. 4	0.035	0.193	0.276	0.109	0.288	0.099	0.040	0.368	0.202	0.389	0.333	0.333	0.333	0.297	0.164	0.539
Exp. 5	0.040	0.143	0.123	0.351	0.199	0.144	0.102	0.348	0.102	0.448	0.200	0.600	0.200	0.260	0.106	0.633
Exp. 6	0.069	0.323	0.197	0.161	0.216	0.034	0.348	0.087	0.415	0.149	0.500	0.250	0.250	0.118	0.201	0.681
Agreg.	0.056	0.219	0.323	0.130	0.193	0.079	0.130	0.221	0.317	0.332	0.453	0.310	0.237	0.214	0.216	0.570

Table 5 below shows the results of the aggregated consistency coefficients for this evaluation model.

Table 5. Aggregate consistency coefficients

Sub criteria / Criteria	Index			
	CI	RI	CR	¿Consistence?
Self-regulation	-0.011	1.252	-0.009	Yes
Satisfaction	0.016	0.882	0.018	Yes
Adaptation	0.001	0.525	0.001	Yes
Dropout Intention	0.001	0.525	0.001	Yes

Once the adequate consistency of individual and aggregate analyses was confirmed, the weights obtained were used to define the corresponding fuzzy inference systems.

4.2. Fuzzy Inference Systems (FIS)

In order to design the inference model, the same 6 experts in dropout participate in a dynamic group. Its purpose was to establish the number of labels to be considered in the input and output variables of the model and to define the concrete partitions of those variables.

This process determined that the model would consist of three labels for the input variables and five for the output. A 2-tuple linguistic representation model was then used to establish the partitioning of the variables to agree on the aggregate preferences of the experts with respect to the three labels of the input variables and the five labels of the output variables. Figure 6 shows the consensus partitions for the input and output variables of the evaluation system.

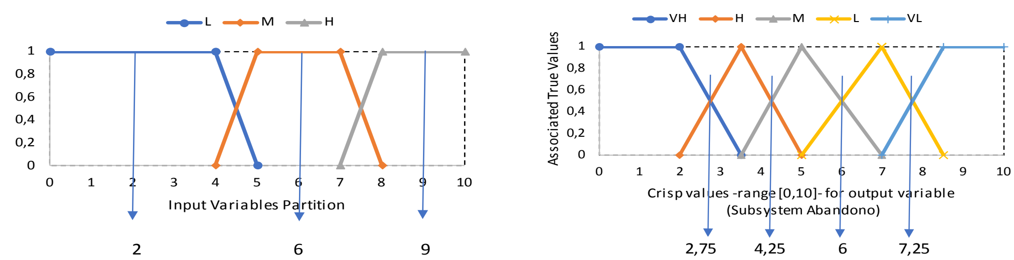

Figure 6. Partitions of the input (left) and output (right) variables.

As shown in Figure 6, triangular labels were chosen for the intermediate and trapezoidal assessments at the ends, as they allow better interpretation of the evaluation results, thus eliminating the fuzzy inference maps.

Once the partitions were defined, the methodology described in Section 3 was used to obtain the label to be assigned in the output variable of each rule. As an example, Table 6 shows the distances obtained for each of the rules and their corresponding output subsystems that evaluate university permanence based on the results obtained in the previous self-regulation, adaptation and satisfaction subsystems.

Table 6. Minimum distance results to determine the output labels on each rule.

Self-regulation	Adaptation	Satisfaction	Weighted output trapezes				Distances					Labels Output Variable
							D(VL)	D(L)	D(M)	D(H)	D(VH)	
L	L	L	0.00	0.00	4.00	5.00	6.67	4.85	3.26	2.23	1.27	**VH**
L	L	M	0.88	1.1	4.66	5.66	5.84	4.03	2.49	1.67	1.83	**H**
L	L	H	1.54	1.76	5.32	6.10	5.24	3.47	2.04	1.55	2.38	**H**
L	M	L	2.28	2.85	5.71	6.71	4.52	2.73	1.41	1.46	2.99	**M**
L	M	M	3.16	3.95	6.37	7.37	3.70	1.93	1.06	1.87	3.77	**M**
L	M	H	3.82	4.61	7.03	7.81	3.09	1.45	1.28	2.39	4.37	**M**
L	H	L	3.99	4.56	7.42	7.85	2.97	1.48	1.51	2.61	4.54	**L**
L	H	M	4.87	5.66	8.08	8.51	2.14	1.02	2.00	3.28	5.33	**L**
L	H	H	5.53	6.32	8.74	8.95	1.54	1.15	2.53	3.85	5.94	**L**
M	L	L	0.84	1.05	4.63	5.63	5.88	4.06	2.52	1.69	1.80	**H**
M	L	M	1.72	2.15	5.29	6.29	5.05	3.25	1.80	1.40	2.50	**H**
M	L	H	2.38	2.81	5.95	6.73	4.45	2.70	1.46	1.60	3.09	**M**
M	M	L	3.12	3.9	6.34	7.34	3.74	1.97	1.06	1.85	3.74	**M**
M	M	M	4.00	5.00	7.00	8.00	2.91	1.21	1.26	2.47	4.54	**L**
M	M	H	4.66	5.66	7.66	8.44	2.31	0.89	1.75	3.04	5.14	**L**
M	H	L	4.83	5.61	8.05	8.48	2.18	1.03	1.97	3.24	5.30	**L**

M	H	M	5.71	6.71	8.71	9.14	1.35	1.11	2.63	3.97	6.10	**L**
M	H	H	6.37	7.37	9.37	9.58	0.76	1.57	3.21	4.57	6.71	**VL**
H	L	L	1.47	1.68	5.26	6.05	5.30	3.53	2.09	1.56	2.33	**H**
H	L	M	2.35	2.78	5.92	6.71	4.48	2.73	1.48	1.58	3.06	**M**
H	L	H	3.01	3.44	6.58	7.15	3.87	2.21	1.34	1.95	3.66	**M**
H	M	L	3.75	4.53	6.97	7.76	3.16	1.50	1.25	2.34	4.31	**M**
H	M	M	4.63	5.63	7.63	8.42	2.34	0.90	1.72	3.02	5.11	**L**
H	M	H	5.29	6.29	8.29	8.86	1.73	0.91	2.27	3.60	5.72	**L**
H	H	L	5.46	6.24	8.68	8.9	1.61	1.13	2.48	3.79	5.88	**L**
H	H	M	6.34	7.34	9.34	9.56	0.79	1.54	3.18	4.54	6.68	**VL**

Reproducing the previous steps would produce each of the rule phases defining the proposed evaluation model to determine permanence / dropout intention at university, as shown in Figure 7.

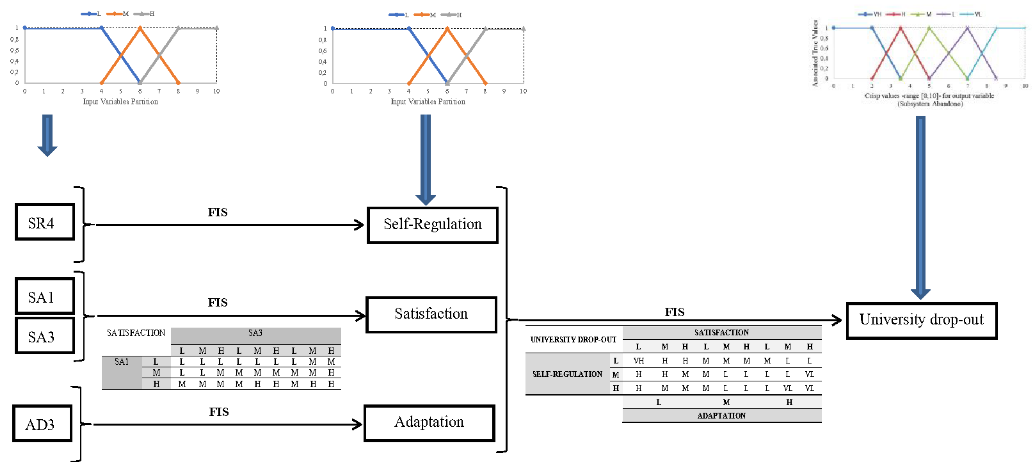

Figure 7. Sample of Fuzzy evaluation.

Once the labels and the rule base are defined, inference of the variables is done using *Matlab's Fuzzy Logic Toolbox* to easily and intuitively infer the assessment of dropout intention / permanence according to the variables assigned to the input variables through fuzzy inference maps. In this way, it is possible to evaluate which factors affect the decision to drop out or to remain on a university degree and to predict the student's behaviour before such a decision is taken in order to improve results and reduce the university dropout rate. As an example, Figure 8 shows the fuzzy inference maps for the evaluation of the intention to remain at university according to different satisfaction ratings.

The fuzzy inference maps in Figure 8 also show the evaluation of the intention to remain at university based on different adaptation ratings.

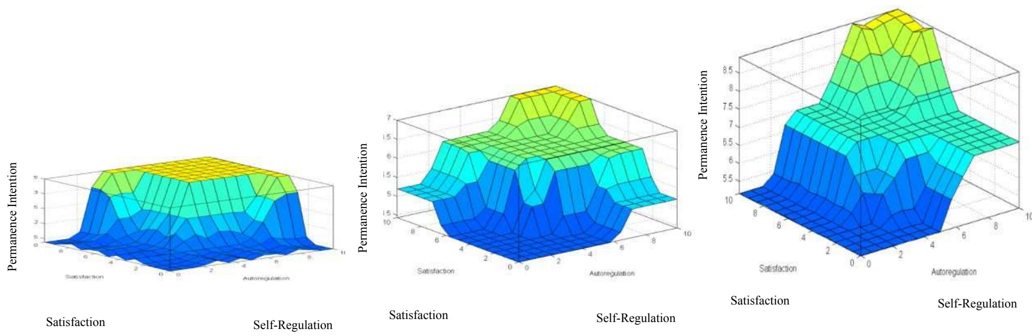

Figure 8. Fuzzy inference maps for Low (left graph), medium (central graph) and Very High adaptation (right graph).

We can see that when the level of social adaptation is low, and the satisfaction and self-regulation values are low, the output is null. However, as the scores of these variables increase, so does permanence intention. This means that low levels of social adaptation can be compensated for to some extent by higher levels of satisfaction with the degree and self-regulation of learning.

The same occurs for average values of social adaptation: if satisfaction values and self-regulation are low, the output is null. However, starting from a medium-low score, permanence intention increases.

In contrast, for very high levels of social adaptation there is a difference in self-regulation and satisfaction scores. For low scores, the output is null as in previous cases. However, the probability of permanence increases more gradually as the satisfaction score increases and more sharply when self-regulation increases.

5. Conclusion

Dropout and performance theories in Higher Education have highlighted the importance of considering the interaction between multiple variables. Within this holistic approach, academic and social variables have been of great importance in the recent years.

The model resulting from the classification tree confirm the importance of the variables self-regulation, adaptation and satisfaction in the student's dropout intention for university studies. In addition, we select a fuzzy inference system methodology that allows to improve the multicriteria decision making process thanks to a more intuitive interpretation than previous models on the variables that predict permanence in university studies.

However, the human preferences and judgments are often imprecise and vague, and this is why this research has been conducted. The Fuzzy Sets methods allowed to analyse the subjective assessments, the uncertainty, and the variables which are difficult to precisely or rigorously describe in the multi-criteria decision making problem. That is why this research shows that the dual application of AHP and FDSS methods could help to incorporate the uncertainty associated with the evaluation problem, and therefore a more appropriate solution for real-life. Therefore, it contributes to a better understanding of current models and improving existing theories.

The proposed method will also enable institutions to know where to direct resources optimally in order to reduce the number of university dropouts as much as possible.

Nevertheless, we can appreciate, from the educational point of view, the importance of the adjustment that must take place between the student and the university, a two-way adjustment that affects to both the fulfilment of the student's expectations, that will determine the level of satisfaction with the degree, and the correct process of academic and social adaptation, the former being highly influenced by the correct use of self-regulation strategies.

The paired comparison results are based on the researchers' own perceptions and do not consider interdependence among the criteria, which is a limitation of AHP. Additionally, the fuzzy inference system method allows to create 3D maps more interpretable that the traditional methods. However, it is recommended that the fuzzy inference systems designed have no more than three input variables to avoid increasing the number of rules in their knowledge base and making the results of the maps more interpretable. On the other hand, the study sample could be limited, so it would be interesting to extrapolate the research results to other universities and European institutions. Likewise, in the future, it would be convenient to incorporate new variables into the evaluation model such as economic capacity, university services or social environments which could complement the evaluation of the dropout intention.

Dropout and performance theories in Higher Education have highlighted the importance of considering the interaction between multiple variables. Within this holistic approach, academic and social variables have been of great importance in the recent years.

Disclosure Statement

No conflict of interest.

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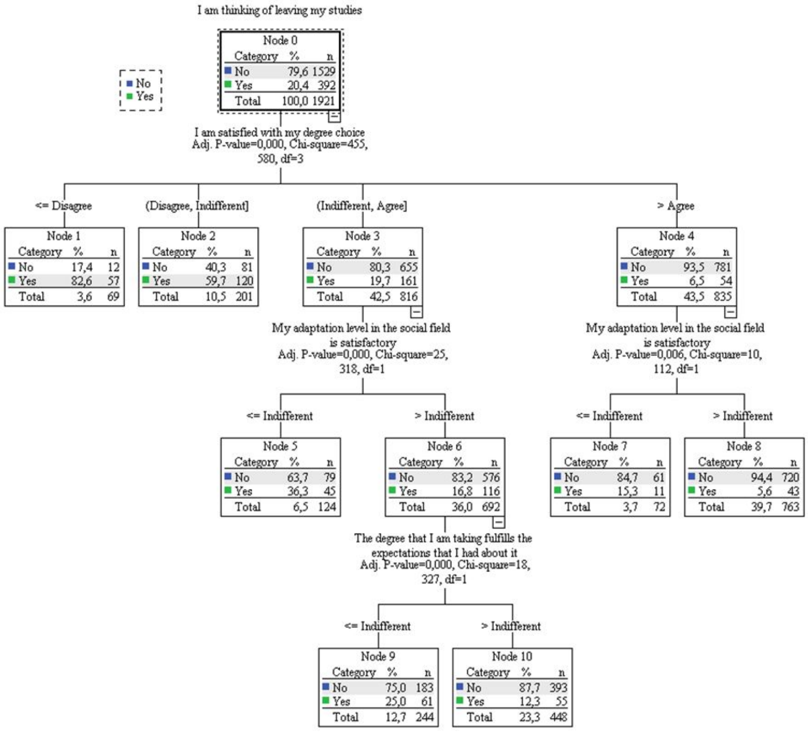

Figure 3. Classification tree relating to the intention of dropping out from university.

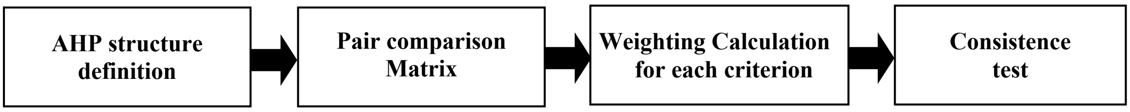

Figure 1. Phases method AHP (Source: Adapted from Yu et al. 2011).

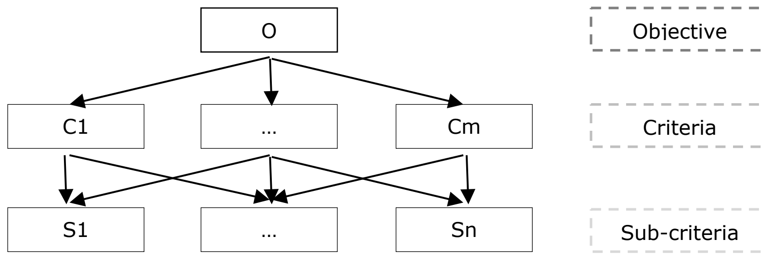

Figure 2. Structure AHP (Al-Husain and Khorramshahgol 2020).

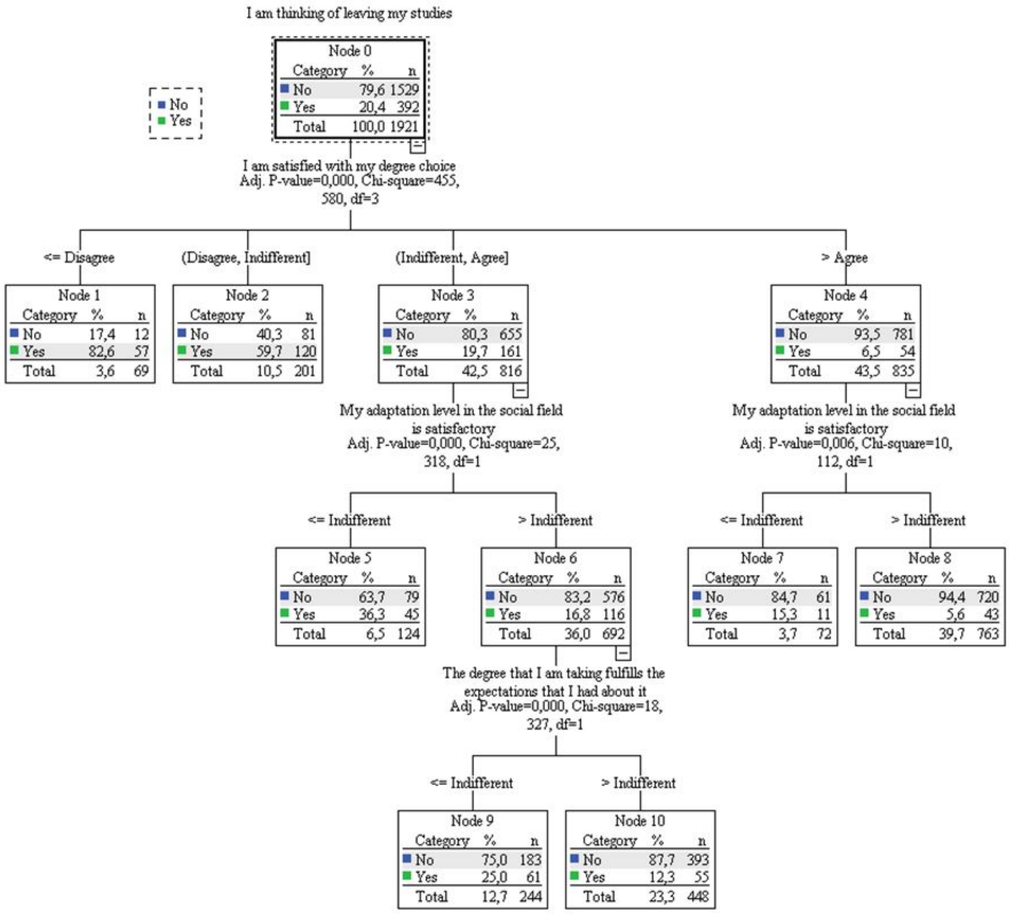

Figure 3. Classification tree relating to the intention of dropping out from university.

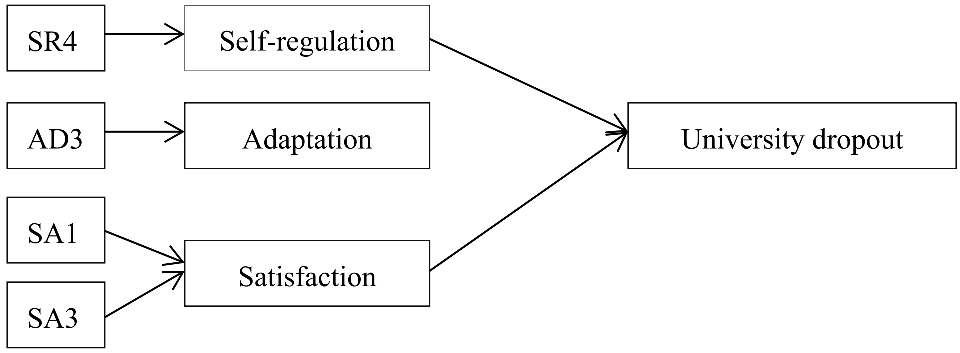

Figure 4. Evaluation model.

SELF-REGULATION						
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
C1	1	0.248	0.169	0.452	0.383	0.757
C2	4.036	1	0.661	1.665	0.605	1.864
C3	5.904	1.513	1	2.376	0.953	4.079
C4	2.211	0.600	0.421	1	0.794	2.376
C5	2.608	1.653	0.421	1.260	1	3.141
C6	1.322	0.536	0.245	0.421	0.318	1

SATISFACTION				
	C1	**C2**	**C3**	**C4**
C1	1	0.566	0.318	0.504
C2	1.766	1	0.707	0.661
C3	3.141	1.414	1	0.750
C4	1.985	1.513	1.334	1

ADAPTATION			
	C1	**C2**	**C3**
C1	1	1.513	1.849
C2	0.661	1	1.348
C3	0.541	0.742	1

DROPOUT INTENTION			
	C1	**C2**	**C3**
C1	1	1.513	1.849
C2	0.661	1	1.348
C3	0.541	0.742	1

Figure 5. Example of global comparison matrices.

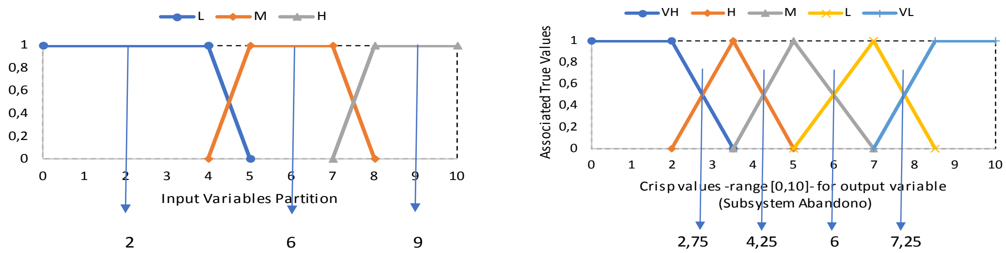

Figure 6. Partitions of the input (left) and output (right) variables.

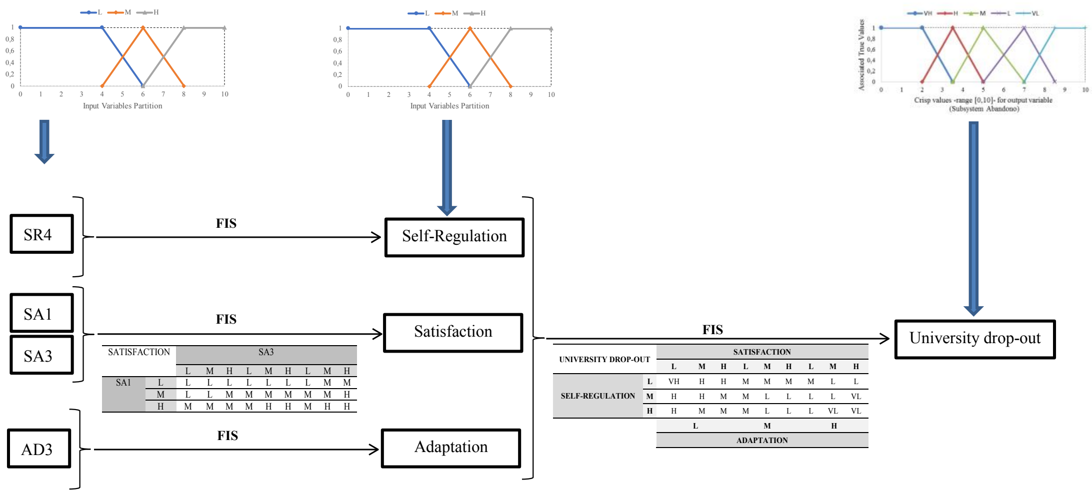

Figure 7. Sample of Fuzzy evaluation.

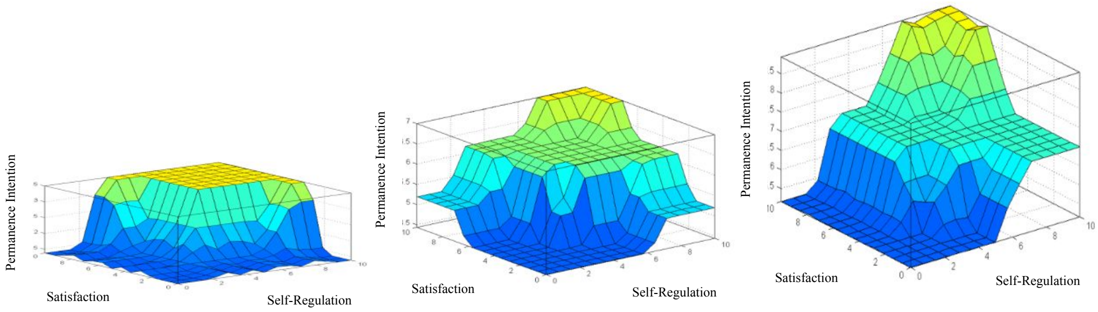

Figure 8. Fuzzy inference maps for Low (left graph), medium (central graph) and Very High adaptation (right graph).

Table 1. Standard comparison scale in nine levels

Definition	Value
Equally important	1
Weak importance	3
Essential importance	5
Demonstrated importance	7
Extreme importance	9
Intermediate values	2, 4, 6, 8

Source: Adapted from Saaty (1980).

Table 2. Consistency ratio

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Source: Saaty (1980).

Table 3. Model classification table

	Risk
Estimate	.166
Standard error	.008

Table 4. Results weights of each criterion

	Self-Regulation						Satisfaction				Adaptation			DropOut Intention		
	C1	C2	C3	C4	C5	C6	C1	C2	C3	C4	C1	C2	C3	SR	SA	AD
Exp.1	0.144	0.317	0.336	0.077	0.068	0.058	0.282	0.179	0.439	0099	0.539	0.164	0.297	0.110	0.581	0.309
Exp. 2	0.126	0.316	0.316	0.104	0.087	0.050	0.381	0.108	0.342	0.169	0.548	0.211	0.241	0.101	0.433	0.466
Exp. 3	0.042	0.060	0.384	0.103	0.217	0.193	0.060	0.111	0.278	0.551	0.568	0.334	0.098	0.557	0.123	0.320
Exp. 4	0.035	0.193	0.276	0.109	0.288	0.099	0.040	0.368	0.202	0.389	0.333	0.333	0.333	0.297	0.164	0.539
Exp. 5	0.040	0.143	0.123	0.351	0.199	0.144	0.102	0.348	0.102	0.448	0.200	0.600	0.200	0.260	0.106	0.633
Exp. 6	0.069	0.323	0.197	0.161	0.216	0.034	0.348	0.087	0.415	0.149	0.500	0.250	0.250	0.118	0.201	0.681
Agreg.	0.056	0.219	0.323	0.130	0.193	0.079	0.130	0.221	0.317	0.332	0.453	0.310	0.237	0.214	0.216	0.570

Table 5. Aggregate consistency coefficients

Sub criteria / Criteria	Index			
	CI	RI	CR	¿Consistence?
Self-regulation	-0.011	1.252	-0.009	Yes
Satisfaction	0.016	0.882	0.018	Yes
Adaptation	0.001	0.525	0.001	Yes
Dropout Intention	0.001	0.525	0.001	Yes

Table 6. Minimum distance results to determine the output labels on each rule.

Self-regulation	Adaptation	Satisfaction	Weighted output trapezes				Distances					Labels Output Variable
							D(VL)	D(L)	D(M)	D(H)	D(VH)	
L	L	L	0.00	0.00	4.00	5.00	6.67	4.85	3.26	2.23	1.27	**VH**
L	L	M	0.88	1.1	4.66	5.66	5.84	4.03	2.49	1.67	1.83	**H**
L	L	H	1.54	1.76	5.32	6.10	5.24	3.47	2.04	1.55	2.38	**H**
L	M	L	2.28	2.85	5.71	6.71	4.52	2.73	1.41	1.46	2.99	**M**
L	M	M	3.16	3.95	6.37	7.37	3.70	1.93	1.06	1.87	3.77	**M**
L	M	H	3.82	4.61	7.03	7.81	3.09	1.45	1.28	2.39	4.37	**M**
L	H	L	3.99	4.56	7.42	7.85	2.97	1.48	1.51	2.61	4.54	**L**
L	H	M	4.87	5.66	8.08	8.51	2.14	1.02	2.00	3.28	5.33	**L**
L	H	H	5.53	6.32	8.74	8.95	1.54	1.15	2.53	3.85	5.94	**L**
M	L	L	0.84	1.05	4.63	5.63	5.88	4.06	2.52	1.69	1.80	**H**
M	L	M	1.72	2.15	5.29	6.29	5.05	3.25	1.80	1.40	2.50	**H**
M	L	H	2.38	2.81	5.95	6.73	4.45	2.70	1.46	1.60	3.09	**M**
M	M	L	3.12	3.9	6.34	7.34	3.74	1.97	1.06	1.85	3.74	**M**
M	M	M	4.00	5.00	7.00	8.00	2.91	1.21	1.26	2.47	4.54	**L**
M	M	H	4.66	5.66	7.66	8.44	2.31	0.89	1.75	3.04	5.14	**L**
M	H	L	4.83	5.61	8.05	8.48	2.18	1.03	1.97	3.24	5.30	**L**
M	H	M	5.71	6.71	8.71	9.14	1.35	1.11	2.63	3.97	6.10	**L**
M	H	H	6.37	7.37	9.37	9.58	0.76	1.57	3.21	4.57	6.71	**VL**
H	L	L	1.47	1.68	5.26	6.05	5.30	3.53	2.09	1.56	2.33	**H**
H	L	M	2.35	2.78	5.92	6.71	4.48	2.73	1.48	1.58	3.06	**M**
H	L	H	3.01	3.44	6.58	7.15	3.87	2.21	1.34	1.95	3.66	**M**
H	M	L	3.75	4.53	6.97	7.76	3.16	1.50	1.25	2.34	4.31	**M**
H	M	M	4.63	5.63	7.63	8.42	2.34	0.90	1.72	3.02	5.11	**L**
H	M	H	5.29	6.29	8.29	8.86	1.73	0.91	2.27	3.60	5.72	**L**
H	H	L	5.46	6.24	8.68	8.9	1.61	1.13	2.48	3.79	5.88	**L**
H	H	M	6.34	7.34	9.34	9.56	0.79	1.54	3.18	4.54	6.68	**VL**