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Improvement of Academic Analytics Processes Through the Identification of the Main Variables Affecting Early Dropout of First-Year Students in Technical Degrees. A Case Study

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Abstract

The field of research on the phenomenon of university dropout and the factors that promote it is of the utmost relevance, especially in the current context of the Covid-19 pandemic. Students who have started degrees in the last two years have completed their university studies in periods of lockdown and unlike traditional education, this has often involved taking online classes. In this scenario, the students' motivation and the way they are able to cope with the difficulties of the first year of a university course are very relevant, especially in technical degrees. Previous studies show that a large number of undergraduate students drop out prematurely. In order to act to reduce dropout rates, schools, especially technical schools, should be able to map the entry profile of students and identify the factors that promote early dropout. This paper focuses on identifying, categorizing and evaluating a number of indicators according to the perception of tutors and the field of study, based on the application of quantitative and qualitative techniques. The results support the approach taken, as they show how tutors can identify students at risk of dropping out at the beginning of the course and act proactively to monitor and motivate them.

Keywords

Academic Analytics, Early Dropout, First-Year Students, Learning Analytics, Predictions, Tutoring.

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I. Introduction

Students at almost all levels of education have experienced an abrupt change in their education as a result of the COVID-19 pandemic that began in the spring of 2020 [1]. They have gone from mainly face-to-face education to new online models that are not always well-designed, especially in some technical subjects and in student assessments [2]–[4]. Over the last few academic years, training courses have been constantly modified to be adapted to an online format at specific times. All these changes have had a global impact on the level of education. There are consequences which have already begun to be studied, but that will undoubtedly become evident over the next few years [5]–[7].

School failure is a key factor inherent in educational change. In fact, it is a variable under constant study, and there is a global effort to reduce it [8]. In this respect, authorities have systematically focused their attention on education at pre-university levels. However, recent studies have shown that university dropout has gained importance over the years due to its large increase [9], [10]. The causes of dropout are very diverse, such as economic reasons, family reasons, lack of motivation, etc. [11], [12], but most studies only reflect the data from a descriptive rather than a proactive point of view.

As can be inferred, this fact is more relevant in non-compulsory studies, where students enter voluntarily [13]. The increase in the number of dropouts in the first year of the degree is close to 20% on average (studies put it at 18.72% in 2018 [14]). This increase differs depending on the subject area of the degree, location, etc. [15]–[20]. With the aim of improving this situation, some studies have focused their objectives on the personalisation of student monitoring as a differential factor to reduce the probability of dropout and academic success [21]–[25]. Personalisation is based on the parameterisation of the students' profile and a process of understanding which variables can improve the accompaniment processes [26].

This article focuses on a multidisciplinary research project with the aim of parameterising the factors that define the entry profile of undergraduate students at a Spanish national level. The aim is to achieve a better way for tutors to monitor students. This strategy is proposed as an objective to reduce the dropout rate in the first year of study towards a degree. The following research questions have been defined:

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RQ1: Is it possible to define an indicator that averages several variables and predicts, in agreement with the tutors, the risk of a first-year undergraduate student dropping out?

RQ2: What level of dropout risk is considered an acceptable range of success for the predictive model?

This document is organized as follows: Section II describes the context in which the study is carried out. Section III explains the methodology followed, as well as the data and variables needed. Section IV shows the data obtained and the associated discussion. Finally, Section V presents the conclusions and possible lines for future research.

II. Context

A. Educational Assessment: Academic Analytics

As we have explained above, the research focuses on identifying and weighing the personal variables that may affect the student's adaptation to the first year of study towards a degree and that may lead to early dropout. Once the identification and weighting process has been completed, relationships will be established between the tutors' perceptions and the results obtained from weighting the variables based on the students' answers, which will allow us to identify possible students at risk and have tutors provide an intervention for the students. In short, we are in front of research that we can circumscribe in the field of evaluation and analysis of educational processes.

While there are no precise definitions in the academic context, training assessment may be defined as "the process of assessing and interpreting organization data collected from university systems for reporting and decision-making purposes" [27], [28]. Learning analytics has arisen as a technique of analysing knowledge acquisition in connection to specific learning objectives, according to this description [29]–[31]. In most situations, it is based on a review of learning outcomes at the conclusion of the training (based on the effectiveness of training, where objectives, content and design of training become the object of evaluation) [32], [33]. "The measurement, gathering, analysis, and reporting of data on learners and their surroundings for the sake of understanding and optimizing learning and the environments in which it happens," according to Ferguson [34].

Academic analytics, in addition to learning analytics, are used to examine the training process at all levels of education, including those that precede training programs and the consequences of these programs [35]. We might suppose that educational data mining [36], [37] is a broad concept that encompasses both learning and academic analytics. Academic analytics is a hybrid method that provides data to higher education institutions to enhance operational and financial decision-making [38]–[40]. While learning analytics is more concerned with course-level and departmental data (to enhance students and professors), academic analytics is more concerned with other factors [41], clearly related to the main topics of our research [42]–[44]:

- learner profiles,
- performance of academics,
- and knowledge flow.

Academic analytics is a field that focuses on the analysis of data from student interactions to improve educational, academic and teaching-related processes [27]. The management of such data provides critical information to educational institutions to make decisions to improve programmes and student tracking and thus maximize student performance [45].

In both research and practice, learning/academic analytics has proven its usefulness in identifying variables that influence learning outcomes and establishing relationships between competencies, educational methodologies and curricular structures [32]. These analyses provide information to personalise courses and to detect at-risk students to provide early intervention. In this way, it is also possible to improve teaching to retain more students throughout the course [46].

B. Tutoring

Tutoring is an activity that has been gaining importance in recent years and has been especially relevant in the period resulting from the COVID-19 pandemic [47], [48], [49]–[51]. The motivation of the student, his or her state of mind derived from the period of lockdown, the need to follow up with students, the difficulty of meeting in-person to complete group work, the review of material needed due to the fact that some subjects are not suited for online learning, and other aspects, are reasons why it's now more important than ever to assist students by providing tutorial services. The pace of work of current students who start a university degree has been weighed down by these last two very educationally complex years, and in a very subjective way, we are noticing a sense of idleness in the daily routine among many of these students. This apathy is caused by a lack of rhythm in their previous studies, constant interruptions and unforeseen changes in the learning model.

Tutorial services are considered a very important intervention in the student's activity throughout their studies. In preuniversity courses, the tutor's main objective is to prevent students from dropping out of school and to identify, in coordination with the teaching staff, learning problems that affect the student [52], [53]. This information is shared with parents and used to initiate the appropriate follow-up.

At the university level, the situation is similar in terms of problem detection and the management of following up with students, but the processes are different [54]. Given that students are adults, the identification of learning problems, their management and the corresponding follow-up are private matters between students and tutors. This means that problems can be more difficult to identify and manage at certain times. Solving the problems of predicting the final marks and combining face-to-face and virtual classes with different student profiles and previous training is a goal for all higher education programs to improve their quality standards [55], [56].

Students recognize the need for generic content in preuniversity studies; however, they do not find a sense of meaning in their choice of university degree , especially when they have chosen a degree with technical-technological-scientific content [57]. This fact, together with the difficulty associated with the educational level, leads to processes of frustration. When other factors are added to this, such as incorrect or insufficiently adapted study habits, the lack of knowledge of how to deal with occasional associated failures, distance from the family environment, greater freedom of movement, etc. [58], the result is that students lack adaptation to university studies.

Therefore, tutoring in the first year of university is of particular importance. The tutor can advise the student on the most critical points of the course, as well as personalise the activity to generate a greater impact and ensure that the student gets through the first year with fewer difficulties [59]–[61]. If the tutor has the ability to collect, analyse and manage data related to the entry profile of his or her students, he or she will be able to anticipate the actions to be taken during the course for those students who may be at risk of dropping out or affected by a situation that may lead to an increase in this risk. In all these cases, using individual approaches such as coaching, it has been shown that it is possible to address complex situations of the student, starting from the support such as that of a tutor who can help the student discover how to organize him- or herself better, how to take on difficult subjects and how the student perceives the different modes of educational delivery [62]–[64].

C. Methodological Designs

User experience is a discipline that considers the perceptions and responses of people to the behaviour of interaction with a service [65]. It considers both factors linked to the process, and factors related to the emotions of users during the process. The aim is always to achieve good user satisfaction. Therefore, it is based not only on a good process but also on a good experience that encompasses all the points that influence it. Among the possible methodological designs for student monitoring, iterative design stands out as one of the most practical, as it can allow for greater data collection and time management [66].

On the other hand, participatory design actively takes into account all parties involved [67]. Combining iterative and participatory approaches improves the data collection of any study centred on the user who, in the context of our research, is the student. Students are at the centre of the research. The values that are proposed are defined by the students themselves. In this way, it is possible to obtain their profiles and take actions to improve their performance, as well as to help them in the initial adaptation process.

The method applied in the study is based on iterative and participatory design, where the variables selected provide detailed information about the student's profile. From this premise, the User-Centred Design (UCD) [68] methodology is a philosophy that takes into account the user as part of the process of creating the service, providing their motivations, needs or desires during each of the phases [69]. The phases of the iterative process are shown in Fig. 1.

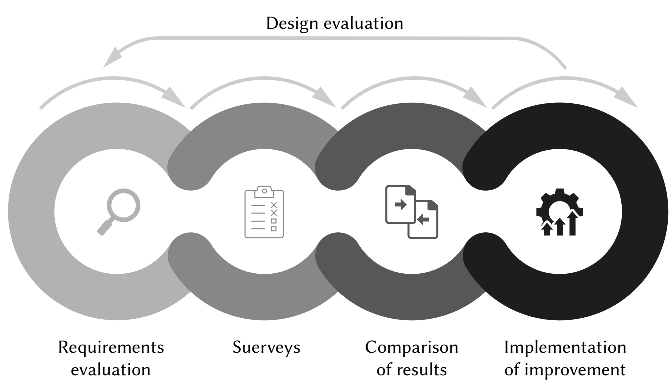

Fig. 1. UCD scheme.

III. Methodology

A. Requirements Assessment

Studies on early dropout may be based on secondary data taken from university computer systems or primary data from a representative sample of students [70]. Those based on secondary data are inexpensive, consider all students and allow multiple analyses by variables. Of this type is the analysis carried out from 1992 to 2006 on 75,830 students pursuing 27 degrees at the University of Granada, which identifies the age of beginning study, the parents' academic degrees and the previous academic results as variables generally associated with early dropout. They also conclude that the profile of the student who drops out is different according to the area of knowledge[71].

More recently, we found data from 2018 in a study where 1071 students from the National Polytechnic School (Quito, Ecuador) were evaluated, which also takes into account the results of university entrance exams. This study concludes that previous academic performance, emotional factors such as attention to emotions and self-esteem are factors that are associated with early dropout [72]. However, this type of analysis has the limitation of ignoring other contextual variables, such as sociopsychological and educational variables, which can be determinants of academic failure.

The study presented in this paper uses primary sources from different faculties and areas of knowledge. It is the students themselves who have directly offered their data to their tutors, which allows the consideration of variables of psychosocial and educational context that may be determinants in the probability of dropout and, on the other hand, will facilitate the approach of interventions that are more tailored to the needs of the students analysed. The disadvantages of this type of study are that it is more expensive and, as we will see later, it requires the design of an instrument for collecting information and the selection of variables a priori.

An example of this type of approach is the 2010 study carried out at Universidad Siglo XXI in Córdoba, Argentina, which concluded that the most influential variable was academic performance, followed by the student's verbal skills [73]; another example is the one carried out in Colombia in 2016, in the department of nursing studies at the Industrial University of Santander, where the variables most related to dropout were academic (low interest in the subject, regular communication with the faculty) and individual types of variables (anxiety, depression and low socioeconomic status) [19].

Finally, it should be noted that there is also room for mixed studies, combining secondary and primary sources. One example is that carried out in Catalan public universities over the course of two academic years (2000 to 2002), which concludes that the first year is the key year that determines the dropout rate and that the most related variables have to do with lack of motivation due to the low quality of the university experience, work or family responsibilities and economic difficulties. A second example of this type is that of the Alfa Guía Project that took place in different European universities over the course of three academic years (2008 to 2011) [72], which, taking into account sociodemographic variables and previous academic performance and vocation, concludes that, among all of the factors, vocation is the most determining. However, this analysis did not incorporate a third block of variables of the area of knowledge or the student's personal adaptation to the university as the most critical aspect.

B. Preliminary Work

As the first phase of UCD, a search, analysis and selection of the different variables to be taken into account to create the student profile was carried out. The variables were selected through a modified Delphi process to determine the content validity of the questionnaire using expert users [74]. The selection of the group of experts to create the first approach was made based on their years of experience in tutoring university students, which in all cases was at least 10 years. There were 12 experts in university tutoring from La Salle URL, 5 tutors from the School of Engineering, 4 tutors from the School of Business, 2 from the School of Architecture and 1 from the School of Digital Arts. In any case, the number of tutors was considered to be sufficient according to the approach used by authors such as Landeta [75] and Cabero and Barroso [76]. Additionally, the time to complete the process, wich was less than two months, is within the limits recommended in the literature [77]–[79]. This method was chosen because its validity in educational research has been widely demonstrated [80], increasing reliability of the study because of the knowledge and consensus of the group consulted [81].

As the first step, a first questionnaire was prepared with 13 items obtained from the review of the existing literature on the research variables and grouped into 3 dimensions: personal data, study habits and motivation. In the first round, the group was asked to rate the items qualitatively. The evaluations were collected personally by e-mail.

Based on the experts' responses, the questionnaire was redesigned to make the study variables measurable, and a second round of validation was subsequently carried out. After the two rounds, the data were statistically processed and returned to the experts to achieve optimal weightings. Based on the answers obtained after the second round and their subsequent analysis, a questionnaire was developed for use in the second phase of UCD.

The 13 data or factors were classified into three main blocks: personal data, study habits and personal motivation.

1. Personal Data

The aim of this block was to collect a set of demographic and social factors that were present before the student began studies toward the degree and that provide information about the student.

- Factor 1, age: this is associated with the variable of the origin of previous studies. There may be students who have begun studies after university entrance exams, who have completed vocational training, who have been in a university program for those over 25 years of age, who have transferred from a different university, who are pursuing a second degree, etc. The combination of this datum together with number 3 (the origin of previous studies) provides information that is related to the motivation variables, as one of the main axes of the instrument [82]–[84].
- Factor 2, gender: Previous research has reported differences in both dropout and academic performance due to this factor [21]. Relationships have been identified between study habits and the gender of the students, as well as a somewhat higher academic performance being associated with study habits in women [85]–[87]. In these studies, it is significant that 25.6% of male students end up dropping out of the selected grade compared to 18.1% of female students [21], [87], which means that gender is an important aspect of the design of the instrument.
- Factor 3, origin of previous studies: as mentioned in the first factor, students with a wide variety of patterns in previous studies can be identified: students from the baccalaureate program, students from the vocational training program, those who have transferred from another university or students over 25 years of age. Previous studies show a higher drop-out rate in those students who have come from a vocational training program or who have completed the entrance exam for students over 25 years of age, while students coming from a baccalaureate program are more likely to change their degrees [13].
- Factor 4, entrance examination marks: depending on the difficulty of the studies, the classic assumption is to associate a lower entrance examination mark with a higher probability of student dropout. The aim of incorporating this factor is to see if there are differences depending on the field of knowledge and to corroborate whether previous data in other fields are confirmed. For example, in the area of health sciences, 89.1% of students obtain an entrance examination mark of 7.5 or higher and have a dropout rate of 11.11%, while in architecture and engineering, the rate of students with an entrance examination mark of 7.5 is only 65.4% and they have a dropout rate of 25.65% [14]. The grade is positioned as a determining factor and, in conjunction with degree changes, it can be highly significant in the parameterisation of the student profile [70], [88].
- Factor 5, country of precedence of compulsory studies: the ORCE (Organisation for Economic Co-operation and Development, which is responsible for analysing the academic performance of each of the member countries) has found that Spain is within the average of the member countries in terms of the diversity of origin of students [89]. In these studies, origin is considered a highly significant factor in the possibility of dropout, in many cases resulting from a lack of integration of the student (both academic and social) and/or due to bureaucratic or economic obstacles that complicate the student's day-to-day life.

2. Study Habits

The section on study habits includes factors related to the student's way of studying: how he or she had worked before entering university and how he or she structured and managed time and resources when studying. In this sense, three types of data have been defined that make up the instrument on work:

- Factor 6: I do homework at the last minute.
- Factor 7: I schedule myself daily study time.
- Factor 8: how many days I study before exams or final papers.

The need for these data is referenced in previous studies where a correlation has been observed between academic performance and study habits [90]. It was identified that up to 50% of students do not have good study habits and do not follow the course of study in a subject. For this reason, they need to undertake a process of adaptation during the first year of the degree to enable them to pass the course [91], taking into account the higher level of difficulty of the subjects compared to those in their previous years of study.

3. Motivation

The third and last block of data was concerned with the concept of student motivation. The aim is to evaluate the attitude of students towards continuing their studies despite the difficulties they may encounter during a course:

- Factor 9, students' conviction of their choice of degree: This question is a very relevant aspect of this study that is complemented by the lack of information on the degree in which the students have enrolled. Previous studies have identified that approximately 45% of the students who start a degree do not have the necessary information about it, and 24.3% have not selected it as their first choice [92]. Vocation is one of the most important aspects, together with conviction (related to information about the studies) of the student in regard to making the right choice of degree programme. Students who do not have a strong vocation for their chosen field of study are twice as likely to drop out [93].
- Factor 10, first choice: the degree selected as first choice demonstrates that students have a feeling of conviction in regard to studying. Previous work has identified that a large proportion of students who dropped out were in a field of study that was not their first choice. Up to 82% of students who dropped out of their chosen degree program did not select it as the first choice, with 49% of these students dropping out during the first year [94].
- Factor 11, branch of education: The Conference of Rectors of Spanish Universities (CRUE) has studied dropout rates according to the corresponding subject area. Some examples are that 25.63% of architecture and engineering students drop out in the first year, 22.57% of students in the humanities and arts, 16.81% of students in the social or legal area and 11.11% of students in health sciences [14]. Studying these data in a limited context (studies at La Salle, Ramon Llull University) in four different degree courses in different subject areas would make it possible to corroborate, qualify and extend previous studies, generating an innovative contribution to the field of research on evaluation methods in didactics.
- Factor 12, distance to the university: many of the students who come to the university come from faraway places. Due to this distance, these students may stay in a university residence, in a shared flat, in a flat on their own, with relatives, or make very diverse journeys every day. Journeys of one up to two or more hours to get to the centre are factors that can directly influence students' academic performance and motivation [95].

- Factor 13, scholarship: In the case of public schools and to even a greater extent in private schools (such as the one in this study), obtaining and maintaining a scholarship is essential to support the cost of university studies. The stress that can be caused by maintaining an average grade necessary to fulfil the requirements of a scholarship for excellence, or the need to work to earn money, can influence the student's performance, cause greater fatigue and afffect motivation. This factor is therefore incorporated into the instrument. As seen from previous studies, 18.6% of nonscholarship students eventually drop out of their chosen degree, while 14.2% of scholarship students drop out. In private universities, differences are also observed in the dropout rates of students with and without scholarships, with a dropout rate of 13.2% of students without scholarships and 10.1% of students with scholarships [96].

C. Questionnaire

An instrument was created in the form of a questionnaire to characterise the student profile based on the significant data identified in the previous process. On the one hand, students were asked to give a first approximation of their personal characteristics (quantitative approximation considering the number of samples). On the other hand, first-year tutors were asked to give a qualitative weight for each data or factor according to its level of importance. Weights were given by the tutors to each of the 13 factors studied, and the aim was for the weight to be applied to the students' assessment of each factor in their personal situation. This way, students classify themselves, and their risk of dropping out can be identified.

1. Students

The aim is to obtain the data from new students at the first stage in the university: the "Welcome Week" (see Table I). In this initial week of the course, students are welcomed by their assigned tutors, who introduce them to the physical spaces, digital systems and management and monitoring aspects of the course. This creates a link that allows for greater empathy between students and tutors in terms of monitoring and action.

TABLE I. Student Survey

#	Question
Data 1	Date of birth
Data 2	Gender
Data 3	What did you study?
Data 4	Average mark for selectivity or other studies (Example: 8.85)
Data 5	Where did you study in high school or the last compulsory course? (Country)
Data 6	Do you do the homework at the last minute or when they are sent to you?
Data 7	Do you study and review the subject every day?
Data 8	How many days before an exam do you start studying?
Data 9	How sure are you of the degree you have chosen?
Data 10	Was studying for this career your first option?
Data 11	What field does your career belong to?
Data 12	How long does it take you to get to the university?
Data 13	Do you have a scholarship?

2. Tutors

As mentioned above, a questionnaire was carried out among the tutors with the aim of finding the weighting method for each factor/data component of the predictive instrument created. A total of 11 first-year tutors from the four fields of study, which were engineering, architecture, business and digital arts, participated. In this survey, the tutors ranked the 13 pieces of information required from the students from most to least important. Fig. 2 shows the differences obtained in the weighting of the importance of each factor by subject area.

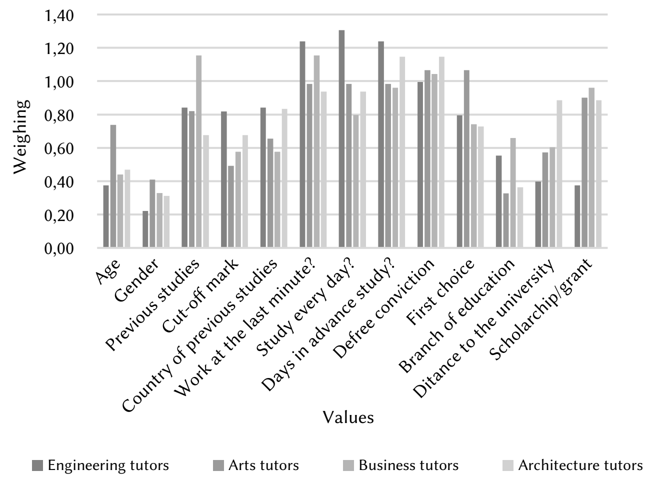

Fig. 2. Weighting by areas of knowledge.

The average for each factor, obtained from the responses of the 11 tutors without distinction of the area of knowledge, was used for this first iteration of the research. The final weighting for each factor is shown in Table II.

TABLE II. Final Weights and Standard Deviation

Value	Analytical technique	
	μ	σ
Age	0.45	0.26
Gender	0.29	0.17
Previous studies	0.91	0.32
Cut-off mark	0.68	0.33
Country of previous studies	0.73	0.26
Work at the last minute?	1.13	0.25
Study every day?	1.04	0.30
Days in advance study?	1.11	0.24
Degree conviction	1.04	0.24
First choice	0.80	0.36
Branch of education	0.53	0.37
Distance to the university	0.57	0.31
Scholarship/grant	0.71	0.38
	Base MVA=10	

D. Results Comparison

Once the tutors had assessed the weight of each piece of information and each of them had been weighted to obtain the prediction instrument, the students' responses were integrated. To do this, the next step was the classification of the students by all their first-year tutors.

The aim was to establish categories according to the drop-out risk perceived by the tutors after the first six weeks of class and before the mid-semester checkpoint.

Furthermore, the aim is that this prediction made independently by the tutor is repeated at the end of the first semester and at the second semester checkpoint so that a relationship can be established between the evolution perceived by the tutor without marks, at mid-term, and facing the final stretch, with the perception of the student in his or her initial state.

The classification made by the tutors at the three points in time described is based on a traffic light with three levels according to the low, medium or high risk of the student dropping out. These perceptions are then compared with the result of the initial perception after the survey of each student.

E. Implementation of Improvements

The last phase of the iterative process is based on adjusting the weights of each data item according to the results obtained from the comparison between the data collected from the student and the perception of the tutors. In this way, a more approximate estimation can be achieved, and the performance of the instrument can be improved.

The aim is not only to improve the weighting of each piece of data but also to provide the tutor with an active monitoring and intervention tool for students at risk of dropping out. Moreover, as an iterative methodology, over the following academic years, the aim is to integrate new students, tutors and grades so that an increasingly fine-tuned instrument can be developed that can be used with modifications of weights depending on the field of study.

Fig. II shows that there are differences between the perceptions of each factor in terms of its relevance to the risk of dropout according to subject area.

IV. Case Study

A. The Sample

The results obtained come from a sample of 309 new undergraduate students from the four previously identified areas of knowledge of La Salle - Ramon Llull University. The average age of the sample was 18.96 years old. 36% of the students surveyed were female, 63% were male, and 1% preferred not to specify their gender.

80% of the students came from a baccalaureate program, compared to 11% who come from vocational training and 8% who were transfer students from another university. 55% percent of the respondents were from the ICT Engineering and Technology area, 16% were from Business and Management, 16% were from Digital Arts, Animation and VFX and 13% were from Architecture.

TABLE III. Personal Data Collected

Value	Answer	Analytic	
		n	%
Age	<20	246	80%
	>=20	58	19%
	>=25	5	2%
Gender	Female	110	36%
	Male	196	63%
	Unspecified	3	1%
Previous studies	Secondary school	246	80%
	Higher Vocational Training	34	11%
	University transfer	25	8%
	Other	4	1%
Cut-off mark	>= 7.5	204	66%
	>= 6	81	26%
	>= 5	19	6%
	<5	5	2%
Country of previous studies	>Spain	254	82%
	<Spain	7	2%
	<<Spain	48	16%

74% of the total sample of students considered the selected degree to be their first choice, and the average score for the level of security of the selected degree was 4.28 out of 5.

Finally, it should be noted that 53% of the students had a financial grant, which represented an increase in funding for grants due to the pandemic.

Table III shows the results obtained in the personal data area, showing the total number of students who chose each answer and the corresponding percentage.

Table IV Shows the Results Obtained in the Area of Study Habits. It can be Observed how the Different Students Work.

TABLE IV. Study Habits Data Collected

Value	Answer	Analytic	
		n	%
Work at the last minute?	No	208	67%
	Yes	101	33%
Study every day?	No	198	64%
	Yes	111	36%
Number of days in advance to study?	More than a week	29	9%
	One week	80	26%
	3 to 5 days	126	41%
	1 to 2 days	69	22%
	The day before	5	2%

Table V shows the results obtained in the area of student motivation, the confidence with which the student chose the degree and the other factors identified.

TABLE V. Motivational Data Collected

Value	Answer	Analytic	
		n	%
Degree conviction	5	127	41%
	4	150	49%
	3	24	8%
	2	6	2%
	1	2	1%
First choice	No	81	26%
	Yes	228	74%
Branch of education	Business	48	16%
	Art	49	16%
	Architecture	41	13%
	Engineering	171	55%
Distance to the university	Less than 15 min	62	20%
	15 to 30 min	57	18%
	30 to 45 min	57	18%
	45 to 60 min	66	21%
	More than 1 h	67	22%
Scholarship/grant	No	144	47%
	Yes	165	53%

B. Weighting of Results

The data obtained, subsequently weighted, are ranked according to the final mark obtained. Each data point receives either the full weighting or a part of it, depending on the weight of the data analysed

TABLE VI. Example of Users With Different Weightings

Name	User 1	User 51	User 67	User 184	User 203
Age	19	18	18	30	18
Gender	Male	Male	Female	Male	Female
Previous studies	Baccalaureate	Baccalaureate	Baccalaureate	Other	Baccalaureate
Cut-off Mark	7.33	9.2	6.8	7	7.5
Country	Spain	Spain	Spain	Argentine	Spain
Last minute?	No	No	No	No	Yes
Every day?	Yes	Yes	No	Yes	No
Days in advance to study	One week	One week	One week	More than one week	3 to 5 days
Conviction	5	5	4	4	3
First option	No	Yes	Yes	No	No
Degree	Business	Architecture	Engineering	Engineering	Arts
Time-distance	30-45 min	Less than 15 min	More than 1 h	30-45 min	45-60 min
Grant	Yes	Yes	No	Yes	No
Score	**8.722**	**7.856**	6.386	6.109	4.597

in previous research. For example, in the case of the conviction of the selected degree, 5 receives the full weighting and 1 receives nothing; for other values, the proportional part is assigned. Responses with two options are either fully weighted or not weighted at all. Finally, all the weights obtained for each of the values are added together to obtain a single value for ranking. Those students with a score below 5 are considered to be at very high risk of dropping out, between 5 and 6, high risk, between 6 and 7 medium risk, and finally those with a score above 7 are considered to be at low or very low risk of dropping out. Table VI shows the classification of the different profiles. Each of the users is part of a sample response according to their risk. User 1 would have a very low probability of dropout and user 203 would have a very high probability of dropout. The value of the score is the result of weighting the different responses.

C. Results Analysis

Based on the tutors' initial classification of the risk of their students dropping out (low, medium, high), it was observed that after a few weeks, 1% of the students dropped out of the degree course. The explanation for this fact is based on possible double enrolments and the inclusion of students who had been accepted at a university but finally decided not to attend. Then, 12% of the students were identified as being at high risk of dropping out, 33% had a medium risk, and 54% had no apparent risk. In monitoring processes with tutors, it was found that they carried out monitoring actions in the first instance, with 12% of students identified as being at high risk of dropping out through immediate and regular meetings. The percentage distribution of students by area and perceived drop-out risk is shown in Table VII. Overall, 16.83% of students are at a very high risk of dropping out of the degree, 20.79% are at high risk, and 26.07% are at medium risk. On the other hand, 26.4% have a low risk, and 9.9% have a very low risk of dropping out.

TABLE VII. Weighting of the Initial Surveys of Students in the Different Areas

	ARTS	BUSIN	ENG	ARQ	TOTAL
Very low	16.33%	25.00%	4.14%	8.11%	9.90%
Low	32.65%	33.33%	23.08%	24.32%	26.40%
Medium	24.49%	18.75%	26.04%	37.84%	26.07%
High	12.24%	18.75%	25.44%	13.51%	20.79%
Very high	14.29%	4.17%	21.30%	16.22%	16.83%

D. Results Obtained

The results obtained are compared with the perception of the tutors at the beginning and at the end of the course (see Table VIII). At the end of the course, a new study is carried out to show student enrolment in the new year of the course. A comparison is made between the end of the course and the initial questionnaire in order to know the exact results obtained by those students who started their studies. The similarity of the results drops to 53% due to the different actions carried out by the tutors during the course to mitigate the drop-out rate.

TABLE VIII. Comparison Between Survey and Perception of Tutors

	Beginning of the course	End of the course
Same	72%	53%
Medium	19%	24%
Opposite	9%	23%

Finally, Table IX shows that a total of 32.79% of the students initially classified with a very high risk of dropping out finally left the grade selected. Similarly, 18.03% of the students who were classified as high risk dropped out. On the other hand, only 3.28% of students classified as very low risk dropped out.

TABLE IX. Initial Prediction of Students Who Finally Dropped Out

	ARTS	BUSIN	ENG	ARQ	Total
Very low	20.00%	0.00%	0.00%	20.00%	3.28%
Low	60.00%	0.00%	16.33%	20.00%	19.67%
Medium	0.00%	100.00%	26.53%	20.00%	26.23%
High	0.00%	0.00%	20.41%	20.00%	18.03%
Very high	20.00%	0.00%	36.73%	20.00%	32.79%

Once the final results of the students had been obtained, those who finally dropped out were selected to analyse the profile and observe which of the variables are the most important in predicting early dropout. Table X shows the personal data of those students who finally dropped out, as well as the percentage they represent with respect to the total number of students who chose the same answer.

TABLE X. Personal Data of Students Who Dropped Out

Value	Answer	Analytic		
		n.total	n.dropout	%
Age	<20	246	46	18.70%
	>=20	58	10	17.24%
	>=25	5	4	80.00%
Gender	Female	110	14	12.73%
	Male	196	46	23.47%
	Unspecified	3	0	0.00%
Previous studies	Secondary school	246	47	19.11%
	Higher Vocational Training	34	6	17.65%
	University transfer	25	4	16.00%
	Other	4	3	75.00%
Cut-off mark	>= 7.5	204	36	17.65%
	>= 6	81	17	20.99%
	>= 5	19	4	21.05%
	<5	5	3	60.00%
Country of previous studies	>=Spain	254	47	18.50%
	<Spain	7	4	57.14%
	<<Spain	48	9	18.75%

From the results obtained and summarized in Table X, it can be observed that 80% of the students over 25 years of age dropped out of the course, and the dropout rate among men was practically double that of women, with 75% of dropouts being identified in those students who came from other access modalities than those indicated, although given the number of these exceptional cases, we cannot consider it to be significant. On the other hand, students with a grade lower than 5 accounted for 60% of dropouts, followed by those with a grade between 5 and 6 (21.05%) and those with a grade between 6 and 7 (20.99%). Finally, another relevant fact is that students from abroad (not Spain) account for 57.14% of dropouts, which may suggest problems of rootedness, homesickness or lack of adaptation to a higher academic level. Table XI analyses the habits of the students:

TABLE XI. Data on the Study Habits of Dropouts

Value	Answer	Analytic		
		n.total	n.dropout	%
Work at the last minute?	No	208	34	16.35%
	Yes	101	26	25.74%
Study every day?	No	198	34	17.17%
	Yes	111	26	23.42%
Days in advance study?	More than a week	29	4	13.79%
	One week	80	14	17.50%
	3 to 5 days	126	23	18.25%
	1 to 2 days	69	17	24.64%
	The day before	5	2	40%

Analysing the results of the study habits reported by the students, it is observed that among the confirmed dropouts, there was a tendency to work at the last minute, which was almost double that of those who plan ahead of time, with approximately 25% of the dropouts being students who report such habits. Finally, Table XII shows the results about the third section of the questionnaire, related to the motivation of the student:

TABLE XII. Motivational Data of Dropouts

Value	Answer	Analytic		
		n.total	n.dropout	%
Degree conviction	5	127	21	16.54%
	4	150	29	19.33%
	3	24	4	16.67%
	2	6	4	66.67%
	1	2	2	100.00%
First choice	No	81	25	30.86%
	Yes	228	35	15.35%
Branch of education	Business	48	2	4.17%
	Art	49	5	10.20%
	Architecture	41	5	12.20%
	Engineering	171	48	28.07%
Distance to the university	Less than 15 min	62	11	17.74%
	15 to 30 min	57	9	15.79%
	30 to 45 min	57	12	21.05%
	45 to 60 min	66	16	24.24%
	More than 1 h	67	12	17.91%
Scholarship/grant	No	144	36	25.00%
	Yes	165	24	14.55%

When analysing the motivation of the students who dropped out (Table XII), it can be seen that 100% of the students who had marked 1 (low) were convinced of their choice of degree dropped out, followed by 66.67% of the students who had marked 2. A total of 30.86% of the students who had said that the degree was not their first choice finally dropped out. It can also be observed that 28.07% of engineering students dropped out, followed by architecture students with 12.20%. With regard to the distance to the university, there were few differences, but 24.24% of the students who dropped out were between 45 and 60 minutes away from the university, followed by those who were between 30 and 45 minutes away, with 21.05%. Finally, 25% of students who did not have a grant left the degree program in the first year. More specific profiles can be created depending on the area, but it should be noted that, of the total number of dropouts, most were in engineering, and 100% of the dropouts in architecture were women.

As shown in the first phase of the method, it is possible to detect and define different indicators that, when averaged, give a dropout risk value to each of the new students, thus resolving the RQ1 formulated in the research in the affirmative. Table IX shows the evolution of the comparison during the course, where in the middle of the course, the perception of the tutors coincides by 72% in relation to the average of the different indicators.

Finally, if we analyse only the dropouts at the end of the course and according to the result obtained in the initial weighting, we can conclude that those students identified with an average below 5 are potential dropouts. In detail, Table IX provides us with the complementary information that those students with an average between 5 and 7 have a very high risk of dropping out; therefore, urgent actions are necessary at the tutorial level. Above 7, the risk of the student dropping out during the first-year decreases, and this value is the limit to be monitored. This analysis confirms the feasibility of the second proposed RQ2 and establishes a given mean that identifies the student's dropout risk.

V. Conclusion and Future Research Lines

This project shows that the initial survey can be used to create the student's profile, as well as to detect the variables necessary to predict possible dropout. Thanks to this survey, the tutor reduces the initial effort and helps the student to anticipate his or her work. Initially, the tutor does not receive information about the student until they meet. By means of the survey, the tutor can receive the data at the beginning of the course so that he or she can speed up his or her work and detect those students at risk as early as possible.

The study has proven the high similarity between the initial prediction extracted from the student questionnaire and the perception at the beginning of the course of each of the tutors about their students. This similarity will be corroborated with the iteration of the study to verify the degree of correlation in future iterations, but it has already allowed us to affirm that it is possible to define an indicator that by averaging various factors, we can use to predict the risk of dropout in relation to the weighting of these factors by the tutors. It has also been proven that this value decreases throughout the year, which is presumably due to the work carried out by the tutors from the initial state to reduce the risk of abandonment.

It can be observed that those students classified as having a very low probability of dropping out do not have a high degree of dropout, unlike those who were initially classified as having a high or very high degree of dropout. It could be said that the weighting limit would be at a value of 7, and above this value, they would be at a medium risk of dropping out. Those cases that are in the middle should be taken into account; they may drop out for reasons that were not detected at the beginning and can only be mitigated with tutorial actions.

These aspects are fundamental in the university environment, as it has been demonstrated that there is a large increase in dropouts at the beginning of the degree program, even in the first months. As this process iterates and is evaluated over the years, possible dropouts due to frustration, lack of motivation or lack of knowledge about the selected degree can be controlled.

Evaluating the results of the demographic aspects, the study demonstrated that age and university entrance exam score, as well as motivation in the selection of the degree, are aspects that are highly influential on student dropout. Regarding study habits, it is confirmed that students with less regular study habits and/or those who study at the last minute are also identified by the instrument as being at high risk.

With the information provided by the instrument, the tutor has tools for follow-up and action to help the at-risk student. In this sense, once those students who stand out negatively either totally or partially by looking at indicated factors are identified, the following actions are proposed by the tutor: a) imminent follow-up meeting, even before the first checkpoint, b) creation of study guidelines, c) approaching the student to invite him or her study and/or reinforcement groups, d) establish contact with the teachers for a closer follow-up of the student, and e) proposal of a personalized follow-up based on the application of coaching techniques. All these actions have been demonstrated to be effective in past courses and in pilot activities that reduce the dropout rate of students at risk [63], since there is a rapprochement between the student, teachers and tutors that minimizes negative emotional aspects such as embarrassment, shyness, feelings of frustration, and fear and improves the motivation, tranquillity and satisfaction of the student. Getting the student to overcome the invisible barrier that separates him or her from teachers and subjects that he or she does not handle or manage well is the first step for the effective reduction of early dropout.

Another aspect to take into account to reduce dropout rates is educational reform, considering the development of emotional competencies for the better development of students. These competencies help university students face challenges more easily, thus promoting entrepreneurship and reducing dropout rates. [85], [97]–[99].

For the next iterations, a survey will be generated where more specific data provided by the student will be needed. These data will be selected by the tutors of the different areas and weighted by tutors themselves according the field of knowledge. In this way, tutors will use their collective experience to create exhaustive profiles of each of the new students according their personal data and their relation with the educational field.

The student's personal and educational aspects as well as his or her motivation and study habits will be taken into account. The aim is to create a report that is detailed and has as much information as possible to be able to weigh the data and obtain the most relevant information from each of them.

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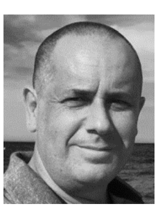

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