

## ON THE IMPACT OF SUBJECT OF STUDY, SELF-REGULATION LEARNING AND MATHEMATICS ANXIETY ON ACADEMIC DROPOUT

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### Abstract

Early dropout is a common problem in many universities due to its financial and social impact on the students themselves. In recent years, studies on variables that affect dropout and predictive models of dropout have become increasingly popular. By understanding the relationship between these variables, it is possible to design intervention strategies that help reduce dropout. In this study, we analyse the relationship between the relationship between two subdimensions of a construct of risk of university drop-out, subdimensions of the related to self-regulation construct, mathematics anxiety and subject of study. In particular, we wonder whether students from degrees of the same knowledge area attain similar scores on the variables considered. Data are collected from a sample of more than 700 students from three different universities. The results indicate several intercorrelations between the variables considered. Last, the degrees of Medicine and Architecture seem to be the most successful on retaining students, despite being from different knowledge areas. Testimonials from programme coordinators were gathered from each of these two degrees separately to provide insights on the reasons for this. The testimonials coincided in the need of professional academic advising programmes to support the transition to university as well as for preventing student burnt-out.

**Keywords:** *Self-regulation, motivation, drop-out, student retention, mathematics anxiety.*

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### 1. Introduction

University dropout in Spain is one of the main weaknesses of the Spanish University System, affecting between 20% and 33% of undergraduate students, particularly during the first two years. Rates are lower in face-to-face public universities (around 20%) and higher in distance-learning institutions (above 40%), with the Canary Islands and the Balearic Islands showing the highest percentages (CRUE, 2024). This phenomenon, which is multicausal in nature, responds to academic, socioeconomic, personal, psychological, and institutional factors, including low academic performance, insufficient preparation, financial difficulties, lack of motivation, stress, and the absence of proper guidance (Nicoletti, 2019). Degree choice, limited access to the student's preferred programme, and difficulties balancing studies with other responsibilities also play a role. Its consequences are significant: at an individual level, it generates feelings of failure and loss of resources; at an institutional level, it entails inefficiency and worsens key indicators; and at a societal level, it reduces the proportion of graduates, thereby affecting the country's competitiveness.

Currently, there are three main approaches to studying dropout risk: the psychosocial approach, the predictive approach, and the hybrid approach. Psychosocial approaches aim to study how a set of psychosocial variables interact in academic dropout. One example of this type of model is Kerby (2015), which attempts to improve upon earlier models by Tinto (1975) and Bean (1985).

These models are useful for understanding the causal relationships among the different factors that contribute to the decision to withdraw from university studies. However, using this model as a computational system to predict student dropout risk would require a major effort to collect error-free data from many different sources. Therefore, there is a need to develop a more easily implementable instrument that can help lecturers or programme directors prioritise resources without requiring massive amounts of

data or high financial investment. A promising solution is offered in the study by Llauro (2024), which conducted a systematic three-year longitudinal study through structured interviews with tutors involved in the tutorial action plan, aiming to identify indicators of university dropout. These indicators were later correlated with actual dropout data. Although the original Llauro's instrument categorises the items into five dimensions, only two are considered in this paper: (1) academic satisfaction and (2) motivation and student habits. The rationale of choosing these two dimensions stems from a factor analysis exploration and a confirmatory factor analysis of this tool which concluded that these two dimensions have high reliability (reliability measures shall be reported in the upcoming sections). From Llauro's work (2023, 2024), these two dimensions are predictors of student drop-out. Therefore, these variables can be used as measures of the risk of dropping out. Measuring this risk is required to develop and implement support interventions to reduce this risk.

The main objective of this work is analysing the relationship between the self-regulation strategies (Vermunt, 2005), a three-dimensional construct consisting of: (I) self-regulation of learning process and content, (II) external regulation and (III) lack of regulation and the aforementioned dimensions of drop-out risk.

On the other hand, in (Barrera-Romero et al, 2025), it was shown that the construct of Mathematics Anxiety was positively correlated with "Lack of Regulation". Quantifying the relationship of Mathematics Anxiety and the corresponding measures of risk of drop-out is essential for understanding the scale of the effect of mathematics anxiety, especially, in STEM subjects. Quantifying this effect may help faculty staff to advocate for the appropriate mathematics support to enable students to overcome mathematics anxiety.

Last, we aim to understand whether interventions should be addressed at a degree level or rather to a set of degrees of a specific subject, i.e. Health Sciences, Engineering, Sciences, Social Sciences. This would imply that subject-related degrees attain similar profiles on the risk of drop out.

## 2. Method

To address the objectives of this project, a sample of 729 first-year undergraduate students from three different universities was collected. This sample completed an online questionnaire that included: (1) a modified version of the Vermont's ILS (1995) from Raisanen (2020), we shall refer to this as ILSm, (2) the Anxiety Towards Mathematics Scale (ATMS-11) instrument (Sarfo et al., 2022), and (3) the following items from the risk of dropout model of Llauro et al. (2023), listed below.

*Table 1. Risk of drop out instrument considered.*

| Item No. | Item                                                                                              | Dimension                     |
|----------|---------------------------------------------------------------------------------------------------|-------------------------------|
| 1*       | You identify yourself as a student that usually attains ____ marks.                               | Satisfaction                  |
| 2        | How convinced are you that you made the right choice regarding the degree you are going to study? | Satisfaction                  |
| 3        | Do you believe that the study plan matches your expectations?                                     | Satisfaction                  |
| 4*       | So far, how many hours of study do you dedicate each day to keeping up with the subjects?         | Motivation and student habits |
| 5        | I identify myself as a student who plans their work from the very first day.                      | Motivation and student habits |
| 6        | What level of daily motivation do you have for studying?                                          | Motivation and student habits |

\*Items 1 and 4 were answered in a 1-5 likert scale with answers "very low, low, average, high, very high" for item 1, and "very few, a few, average, more than average, many". Remaining items were answered with a 1-5 Likert scale with 1 being none or nothing, to 5 meaning much or a lot.

To analyse the relationships between the variables, we will carry out a correlation analysis, using the Spearman correlation coefficient, more appropriate for data from Likert scales with lack of normality. To obtain data about the dimensions of the instrument from Table 1, a mean average was calculated from the set of items of each dimension.

Regarding the internal consistency the  $\omega$  of McDonald (Dunn et al., 2014) was calculated for each subscale:  $\omega = 0.61$  for Academic Satisfaction and  $\omega = 0.768$  which are acceptable for scales of 3 items. Similarly, the Cronbach alpha coefficients were  $\alpha = 0.579$  and  $\alpha = 0.764$  for each dimension respectively.

### 3. Results

Table 2. Spearman correlation matrix.

|                                    | Self-regulation | External Regulation | Lack of Regulation | Mathematics Anxiety | Motivation and study habits |
|------------------------------------|-----------------|---------------------|--------------------|---------------------|-----------------------------|
| <b>External Regulation</b>         | 0.259***        |                     |                    |                     |                             |
| <b>Lack of Regulation</b>          | 0.104**         | -0.021              |                    |                     |                             |
| <b>Mathematics Anxiety</b>         | -0.030          | 0.037               | 0.426***           |                     |                             |
| <b>Motivation and study habits</b> | 0.364***        | 0.249***            | -0.079*            | 0.003               |                             |
| <b>Academic Satisfaction</b>       | 0.249***        | 0.271***            | -0.376***          | -0.241***           | 0.368***                    |

\*, \*\*, \*\*\* indicate p-value less than 0.05, 0.01, and 0.001 respectively.

Table 3. Descriptive statistics of the dimensions of risk of drop out: S "Academic Satisfaction and M "Motivation and study habits".

| Degree                        | mean (S) | median (S) | sd (S) | mean (M) | median (M) | sd (M) |
|-------------------------------|----------|------------|--------|----------|------------|--------|
| <b>Medicine</b>               | 4,38     | 4,33       | 0,39   | 3,58     | 3,67       | 0,74   |
| <b>Architecture</b>           | 4,01     | 4          | 0,49   | 3,6      | 3,67       | 0,69   |
| <b>Computing</b>              | 3,89     | 4          | 0,7    | 3,12     | 3          | 1,04   |
| <b>Biomedical Engineering</b> | 3,86     | 4          | 0,47   | 2,98     | 3          | 0,68   |
| <b>Law</b>                    | 3,81     | 4          | 0,49   | 2,94     | 3          | 1,08   |
| <b>Engineering</b>            | 3,81     | 3,67       | 0,6    | 3,13     | 3          | 0,8    |
| <b>Mathematics</b>            | 3,79     | 4          | 0,69   | 2,69     | 2,67       | 0,99   |
| <b>Biotechnology</b>          | 3,76     | 4          | 0,73   | 3,04     | 2,83       | 0,97   |
| <b>Primary Education</b>      | 3,62     | 3,67       | 0,59   | 3,1      | 3          | 0,81   |
| <b>Videogames</b>             | 3,6      | 3,67       | 0,71   | 2,25     | 1,67       | 0,86   |
| <b>Busines and Management</b> | 3,58     | 3,67       | 0,57   | 2,62     | 2,67       | 1,11   |

### 4. Discussion

The first result is that there is a statistically significant relationship between the three dimensions of ILSm: self-regulation, external regulation, and lack of regulation, and the two dimensions of the risk of drop out. While self-regulation and external regulation are positively correlated with the dimensions of the risk of drop out, lack of regulation correlates negatively, being the correlation with motivation and study habits particularly weak ( $\rho = -0.079$ ). Last, Mathematics Anxiety has a significant negative correlation with academic satisfaction.

Secondly, from Table 3, it can be observed that students from the degree in Medicine obtain the highest scores on "Academic Satisfaction" and "Motivation and Student Habits", followed by Architecture.

One could think that students from Architecture would behave in a very different manner as those from Medicine. To find out some insights on what the explanation for this could be, we asked the corresponding programme managers for their views on this matter.

Both managers reported that the degrees of Medicine and Architecture are more extensive programmes consisting of six and five years of duration and demand a high level of autonomy. In both degrees, bilingual and even trilingual teaching is promoted. Furthermore, all the students of these two programmes go through a thorough academic advising track with trained professionals that provide not

only academic support but also personal support and guidance. It was clear from their testimonials, that the academic advising is strongly supported institutionally as a strategy to enhance student retention.

Regarding the challenges faced in these degrees, emphasis was made on the risk of burnout of Medicine students and the transition from high school to university. As a result, the academic advising serves not only to support students, but also as a path to investigate the factors leading to burnout or to better adaptation skills.

These findings are in line with Tinto's drop out model (1975) or Bean's model (1985) which state that lack of adaptation skills and thus of academic integration is one of the causes of drop-out. At the same time, the perception of the institutional commitment contributes to student retention what could explain, at least partly the positive effects of the academic advising services, according to Kerby's model (2015) of student retention.

Last but not least, coming back to the main research question of whether the subject of study has a relationship with academic drop out, we can state that the subject indeed affects to both dimensions of risk of drop out at a degree level, rather than at a subject or knowledge area level, since degrees of different areas such as Architecture and Medicine behave in a similar fashion. Further research could be conducted via cluster analysis and classification techniques to categorise degrees into groups having similar scores on self-regulation and drop out risk for facilitating tailored support programmes considering the corresponding needs. Last, a similar analysis could be carried out a student level for the same purpose of providing tailored support to a range of students with similar scores on academic satisfaction, motivation and study habits as well as other scores on relevant variables.

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