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Relationship between time management and class attendance in university students: clustering techniques for detection of profiles

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Abstract

Low class attendance by university students is one of the factors that may be related to abandonment ratios, which constitute a serious socio-economic issue. The aim of this work is to confront the influence of the time management capacity of first-year students with their class attendance. With a factorial analysis of a survey carried out, four factors emerged: the students' perception of how they manage their time, the time they spend on less productive tasks, the ability to finish tasks on time and the use of time management tools. Moreover, with classification trees it was seen that students who are able to finish the tasks on time, have a greater capacity for concentration and spend less time on trivial tasks, have higher class attendance. With these profiles identified, it is expected to guide them to improve their time management, increase their class attendance and, as a consequence, decrease dropout rates.

Keywords: *Time management; class attendance; factorial analysis; classification trees.*

1. Introduction

High university dropout rates are a prominent social as well as economic problem. On the one hand, students change their life goals and on the other hand, the investment made, and the opportunity cost have a strong impact on the organizations and governments in charge of university educational management. In Spain, 33% of students do not finish the degree in which they began their higher education stage, of which 21% drop out and the remaining 12% change their degree, which implies an annual loss of €974 million (Pérez & Aldás, 2019). Undoubtedly, figures are high enough to try to reduce the dropout rate of students.

The reasons for school dropout can be approached from three perspectives (González Tirados, 1985): (1) from the perspective of the student's characteristics (aptitudes, abilities, motivation, etc.) (Esteban et al., 2016), (2) from the perspective of the institution (complexity of the studies, student-teacher relationship, educational methodologies, etc.) (Bartual Figueras & Poblet Farrés, 2009), and (3) from the perspective of society (family, cultural, socioeconomic, etc.) (Cervero-Fernández et al., 2017).

Among all these reasons, we pay special attention to those related to the student himself. Concretely, to the way in which these students manage their time. Other authors have studied time management by students. For example, Adams & Blair (2019) found a significant correlation between time management and grades obtained, although there was no difference according to gender, age or entry qualification. In contrast, Oreopoulos et al., (2022) suggest that low-touch programs that offer scheduling assistance, encouragement, and reminders for studying lack the required scope to significantly affect academic outcomes. On the other hand, Murray et al., (2022) provide methods, resources, and strategies to help students better manage their time, offering their combined experience in mentoring and training STEMM students and their time management skills, and Khiat (2022) uses an automated adaptative time management enabling system to guide students in managing their time more efficiently, thus impacting in their performance.

There are also studies that analyze the determining factors regarding the degree of attendance to classes by university students, such as the one carried out by Moores et al. (2019), and even Sloan et al. (2020) indicate that there are studies in which poor time management is pointed out, among other factors, as a cause of school absenteeism. Nevertheless, we believe that the relationship between time management and student attendance in face-to-face classes has not been sufficiently analyzed due to its economic and social importance as mentioned above.

So, to deepen this gap, the objective of the work proposes to analyze the relationship between the management that students make of their time and class attendance in university studies. The identification of student profiles will make it possible to offer proposals for improvement in time management and, consequently, we hope that there will be an increase in class attendance by students. We also hope that this increase in class attendance will have a direct impact on the reduction of university dropout rates.

To achieve this objective, the rest of the work is divided into 3 further sections. In section 2, we show the methodology used to develop the study. Section 3 shows the results obtained and finally, section 4 presents a series of conclusions and possible future lines of research.

2. Methodology

In this section is explained the dataset used, the factorial analysis and classification trees employed in the study.

2.1 Data Collection

To collect the answers from the students, a survey about time management, based on the publication by Neill (1996) has been carried out. The questionnaire consists of 28 questions which answers are represented by a scale that goes from 1 to 8; 1 being the statement “doesn't describe me at all; it isn't like me” and 8: “this statement describes me very well; it is very much like me”.

The sample is made up of 135 first-year students of Business Administration and Management, and Finance and Accounting degrees. This data has been cross-referenced with face-to-face attendance at the classes of the subject Applied Computer for Business, common to both degrees in three levels, low for students who attended less than one third of the classes, medium for the students who attended from one to two thirds, and high for those who attended more than two thirds. Personal data such as gender or age has not been included in the study because of privacy limitations.

2.2 Factorial analysis

A factorial analysis of the survey data has been carried out, with a double objective. Firstly, to identify representative factors of student time management and secondly, to reduce the dimensions of the data set.

2.3. Cluster analysis

With the factors obtained and normalized, the objectives are, on the one hand, to classify the students in different groups according to their attendance and, on the other hand, to see how time management factors influence this classification.

To do so, among the range of existing classification techniques, it has been decided to use recursive partitioning for classification trees Breiman (2017). The reason is to obtain an easily interpretable taxonomy by levels that allows dividing the students according to the rules of the tree based on the values of the factors which allows to see their importance and influence in the classification. This gives the possibility of identifying in which aspects of time management each student should be guided individually.

3. Results

The results have been obtained using the programming language for statistical computing R, highlighting the nFactors library to calculate the number of factors for the factor analysis, stats library for factor analysis and rpart2 library for classification trees.

3.1 Factorial analysis.

Initially, a correlation matrix of the responses to the survey is calculated. In Figure 1 it can be observed a slight correlation between the survey answers.

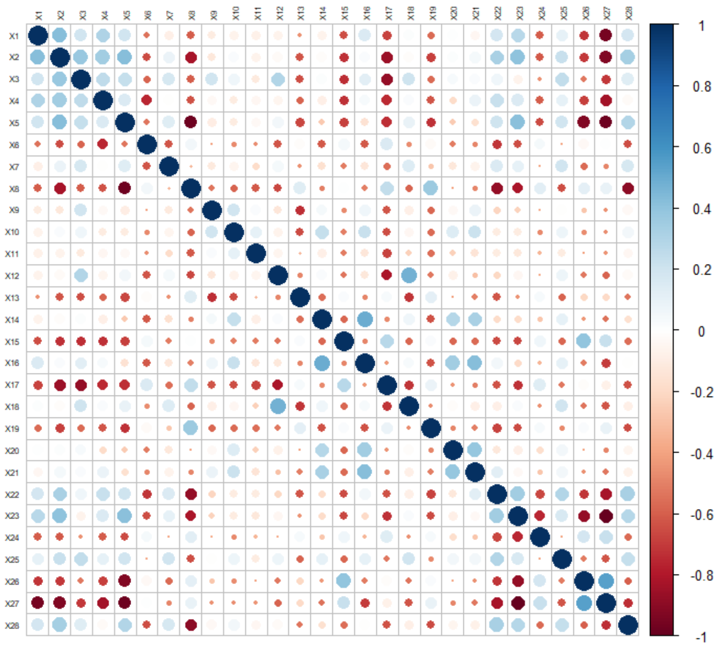

Figure 1 Correlation Matrix.

In order to ensure that the factor analysis can be carried out with guarantees, the KMO values have been calculated with a value of 0.84 greater than 0.5 and Barlett's sphericity test, which offers a K-squared value of 204.72 and a p-value of < 2.2e-16. This indicates that the factory analysis can be carried out with guarantees.

Four metrics have been tested to select the number of factors according to Raîche (2013): Eigenvalues: Eigenvalues with a value higher than one. The acceleration factor indicates where the elbow appears. The optimal coordinates (OC) correspond to an extrapolation of the preceding eigenvalue by a regression line between the eigenvalue coordinates and the last eigenvalue coordinates. The parallel analysis criterion compares the eigenvalues of the sample correlation matrix with the eigenvalues obtained from a random correlation matrix for which no factors are assumed. According to the results obtained, the number of factors to be retained is 4.

Analyzing the results of performing a factorial analysis with varimax rotation shown in Table 1, Factor 1 represents the student's perception of his good time management. Factor 2 explains the waste of time. Factor 3 indicates the student's ability to complete tasks on time, and Factor 4 explains whether the student relies on any tool to keep track of his time. Regarding to Factor 4 it is true to that only question 12 has the highest value, but we decide to keep it because other questions has similar values and influence in Factor 4.

3.2 Cluster analysis.

The survey data has been divided randomly in train (110 students) and validation (25 students). The process to train the classification tree is a cross-fold validation, with a fold of 5 and 10 repetitions. The maximum depths tested are 1, 3, 5, 7 and 9. The metric to choose the best configuration is the accuracy of classification. The results obtained indicate that the maximum depth obtained is 5 and an accuracy of 36.8% which is low. However, with the validation set results shown in Table 2, the accuracy is 40%. Observing that it's difficult distinguishing between students with a high or medium assistance.

The final classification tree can be observed in Figure 2, this taxonomy allows to classify the students according to their answers to the survey.

The values shown in the leaves of the tree correspond to the probability of each class, high (left), low (center) and medium (right) value. Analyzing the taxonomy, it can be concluded that Factor 3 is the most important. That is, whether or not they complete their tasks on time. Those who do not complete their tasks tend to have a low-medium attendance and those who do comply to a medium-high attendance.

Table 1 Components matrix result of the factorial analysis.

Question	Factor 1	Factor 2	Factor 3	Factor 4
01 My life is very well organised.	**0.592**	-0.171	0.265	
02 I manage the way I use my time really well.	**0.710**	-0.232	0.201	0.103
03 I make effective plans for getting things done.	**0.505**	-0.150	0.310	0.365
04 I am good at breaking complex tasks down into achievable chunks.	**0.513**	-0.221	0.231	
05 I use my time effectively.	**0.712**	-0.287		
06 I procrastinate over doing difficult tasks.		**0.476**	-0.109	
07 I accurately predict how long tasks will take.	**0.531**		0.128	0.185
08 I waste a lot of time.	-0.244	**0.589**		-0.190
09 I am on top of my important tasks at the moment.	0.185		**0.376**	0.353
10 I accomplish what needs to be done each day.	0.217		**0.509**	0.268
11 I do the most important tasks during my most energetic periods of the day.	**0.254**		0.183	0.237
12 I prepare a daily or weekly "to do" list.	0.346	-0.125	0.174	**0.370**
13 I spend a lot of time mucking around.		**0.433**		-0.333
14 I meet deadlines on time			**0.753**	0.112
15 I easily get distracted from important tasks	-0.117	**0.632**		
16 I get important tasks done on time.	0.202		**0.810**	
17 I find myself procrastinating over tasks that need to be done.	-0.163	**0.584**		-0.423
18 I have a weekly schedule on which I record fixed commitments.	**0.378**	-0.107	0.269	0.286
19 I spend too much time on trivial matters		**0.568**	-0.124	
20 I always complete tasks before they are due	0.194		**0.642**	
21 Despite interruptions, I get important tasks done.	0.234		**0.676**	
22 I am in control of how my time is spent.	**0.617**	-0.189	0.178	
23 I am satisfied with the way I use my time.	**0.708**	-0.241		
24 I find distractions to be very tempting.	-0.112	**0.605**	0.152	
25 I monitor progress towards my goals.	**0.582**		0.315	0.171
26 I have a hard time concentrating.	-0.253	**0.656**		0.351
27 I am hopeless at time management.	-0.382	**0.623**		0.385
28 I balance work, rest, and play.	**0.629**	-0.118	0.146	0.136

Table 2 Confusion matrix for validation data.

	High	Low	Medium
High	4	4	3
Low	1	1	2
Medium	4	1	5

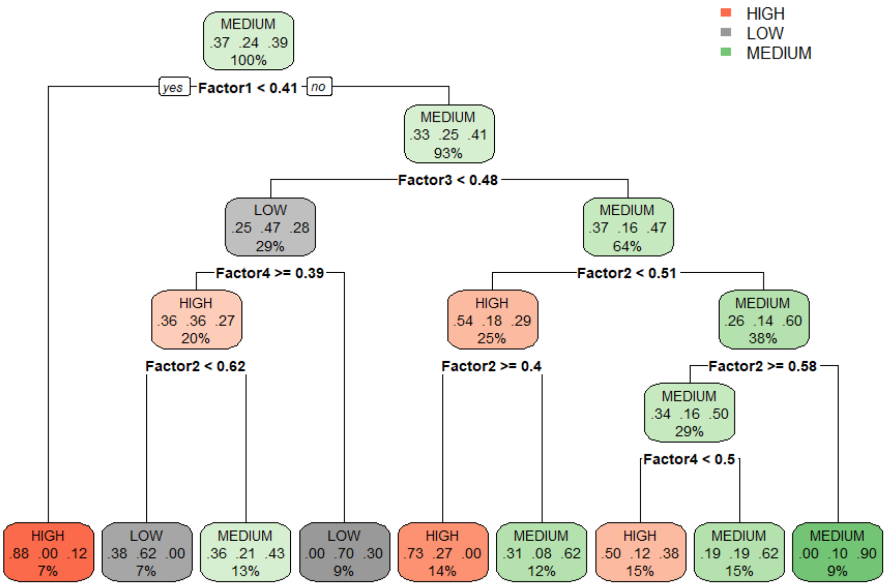

Figure 2 Final classification tree.

4. Conclusions

Poor class attendance is a problem that affects the university community. With the survey, four factors that define the temporary management of students have been identified. The elaboration of the taxonomy yields weak results in terms of precision but has allowed us to see the relationship between time management factors. It can be concluded from these weak results that there are other factors that affect attendance, and this cannot be fully explained by time management. Although, the tree taxonomy allows us to identify student profiles to orienteering them in order to improve their time management, increase their class attendance and decrease dropout rates. The study is limited by the protection of personal data of the students.

As future lines of work, it is intended to expand the survey to analyze other causes such as repetition of the course, the family environment, the perception of difficulty of the subject, or if the student does other activities that affect attendance. It is also intended to expand the sample with different subjects and degrees to enrich the results and make them more global.

Establishing a relationship between time management and dropout rates, this presents a challenging problem due to the difficulty involved in contacting students who have dropped out and having their willingness to complete the surveys.

Methodologically, several models will be compared, such as Ordinary Least Squares or Spline Regression.

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