




Using Discriminant Analysis to create a Dropout Prediction Thermometer for the Applied Social Sciences Field

Termômetro para previsão de evasão nas ciências sociais aplicadas utilizando a análise discriminante

 Maria Denise Nunes Rodrigues¹
 Monica Carvalho Alves Cappelle²
 Luiz Flávio Felizardo de Moraes³



Resumo

No Brasil existe uma vasta discussão no meio acadêmico, em que se busca entender/explicar os elementos que influenciam a evasão dos estudantes do ensino superior. Assim, o objetivo deste artigo é apresentar um “termômetro de evasão” com intuito de indicar quão próximo de evadir ou não o aluno possa estar. Aplicou-se a técnica da análise discriminante, utilizando-se dos dados acadêmicos presentes no banco de dados da instituição, para sugerir que elementos contribuem para a possível evasão dos estudantes. Como resultados do estudo, identificou-se uma função que discrimina quais elementos contribuem para a evasão do discente, de modo que ao conhecer previamente esses elementos, a instituição pode tomar as medidas cabíveis, para promover a permanência do aluno.

Palavras-chave: evasão, educação superior, análise discriminante

Abstract

In Brazil, there is a vast discussion in the academic environment that seeks to understand/explain the elements that influence the dropout of higher education students. Thus, this article presents an "evasion thermometer" to indicate how close to evading the student may be or not. The discriminant analysis technique was applied, using academic data in the institution's database to suggest which elements contribute to the possible dropout of students. As a result of the study, a function was identified that discriminates which elements contribute to student dropout so that by knowing these elements in advance, the institution can take appropriate measures to promote student permanence.

Keywords: evasion, college education, discriminant analysis

¹ e-mail, silviacb83@hotmail.com, Universidade de Coimbra - UC, Coimbra [Portugal]

² e-mail, silviacb83@hotmail.com, Instituto Federal de Educação, Ciência e Tecnologia de São Paulo - IFSP, Sertãozinho/SP [Brasil]

³ e-mail, silviacb83@hotmail.com, Universidade de Coimbra - UC, Coimbra [Portugal]

Recebido em: 27/07/2023

Aprovado em: 10/04/2023

Como citar este artigo

Rodrigues, M. D., Cappelle, M. C. A., & Moraes, L. F. F. (2023). Using Discriminant Analysis to create a Dropout Prediction Thermometer for the Applied Social Sciences Field. *Revista Administração em Diálogo - RAD*, 25(2), 64-79. <https://doi.org/10.23925/2178-0080.2023v25i2.58599>

Introduction

The National Institute of Educational Research and Studies Anísio Teixeira (INEP) shows that the Brazilian higher education system has experienced an expansion in the number of enrollments in recent years. In the Census for the year 2018, the most current on the date of this study, there was a growth of 44.6% in enrollments in the period between 2008 and 2018 (INEP, 2019). Concomitantly with the increase in admissions, the volume of dropouts in higher education is quite considerable. According to data from INEP (2015), which followed the trajectory of students entering in 2010, 55.6% did not graduate in the course they entered, with 84.4% referring to the private school system and 16.6% to the public.

Regarding this, there is a vast discussion in Brazil in the academic environment seeking to understand/explain factors that may favor dropout. According to Santos Junior and Real (2017), despite finding works on the subject in other countries from 1960 onwards, in Brazil, concerns about dropout effectively began in 1995. In this year, the Ministry of Education (MEC) held the “Seminar on dropout in Brazilian universities”, which made the topic part of the government agenda. For this Ministry, evasion refers to the definitive exit from the original course without completion, which can be measured by the difference between freshmen and graduates, after a complete training cycle (BRASIL, 2019).

As shown by Silva Filho et al. (2007) student dropout is a worldwide, multifactorial problem, common in Higher Education Institutions (HEIs), which occurs in all socioeconomic contexts, cultures and teaching modalities. And that, in addition, entails losses for the education systems, waste of public money and late training of professionals who may be in demand by society.

Oliveira and Barbosa (2016) point out that retention and evasion demonstrate nonconformities, on the one hand, institutional, in which the university’s role in promoting professional qualification is not configured, and, on the other hand, personal, due to dissatisfaction and insecurity of the withheld or evaded as to the course. The authors suggest that indicating retention and abandonment rates are not enough, and that it is necessary to identify the factors that culminate in the moment of abandonment or the failures that lead to retention.

There are not few empirical studies on dropout in higher education. Among these, there are several methodological approaches used to explore this phenomenon, from sophisticated methods such as structural equation modeling (Respondek et al., 2017) and logistic regressions (Contini, Cugnata & Scagni, 2018), to more modest calculations, such as comparison between means (Cunha, 2015). However, it is observed that there is no consensus on which factors are decisive for the student to abandon the training path, because the variables available for each study are only relevant to the reality studied.

On the other hand, it is known that these variables cover three dimensions: 1) personal factors, 2) institutional factors, and 3) sociocultural and economic factors external to HEIs (BRASIL, 1996). These factors have been addressed by international (Li & Carroll, 2019) and national (Santos Jr. & Real, 2017) researchers, associating them with investigative needs and observing the contexts in which they are used in view of the above, this article aims to present an “evasion thermometer” to indicate how

close the student may be to evading or not. Methodologically, this is a case study with a primarily quantitative approach, in which the discriminant analysis technique was applied to the academic data in the institution's database to distinguish which elements contribute to the possible dropout of students. The article is structured in five sections. The present introduction, followed by the theoretical foundation, in order to expose some discussions that have been carried out in the scientific literature on the subject; in the third section, the methodological course is presented, which contains the characterization of the research, the technical procedures; in the following section, the results are presented and, finally, the final considerations, highlighting the main aspects raised from the study, its limitations and possible complementation for future studies.

Theoretical foundation

Notably, the strong industrialization of the 19th and 20th centuries, and the so-called “knowledge society”, which gained notoriety from the mid-1970s onwards, brought new forms of social structure so that universities had to readjust to then form individuals capable of dealing with this new situation. In general, the incorporation of neoliberal logic into university policies has directed the focus of actions led by Brazilian Higher Education Institutions (HEIs), especially public ones, towards research and innovation (Silva Júnior, Schugurensky & Araújo, 2015).

Concomitantly with the social development and economic growth that has been taking place in the last four decades, and perhaps, on the one hand, being a support for this, or on the other hand, being pulled by market demand (Mancebo, Vales & Martins, 2015), the expansion of Brazilian higher education has become increasingly expressive since the late 1960s, and especially since the 1990s; so that Henriques (2018) points out that in the 1960s there were just over one hundred and six thousand students enrolled in on-site higher education courses, in public and private institutions throughout Brazil, in mid-2010, this number exceeded five million four hundred thousand students.

Data from the National Institute of Educational Studies and Research reinforce the findings of the author, demonstrating that in 2018 the last statistical synopsis of higher education available on the date of preparation of this study, there were almost eight and a half million students enrolled in presential and remote undergraduate courses throughout Brazil (INEP, 2019).

Faced with the gradual expansion of Brazilian higher education, adjacent phenomena were taking shape, as is the case of higher education evasion. It is known, on the one hand, that this phenomenon also occurs in graduate courses (Mccallin & Nayar, 2012), however, the discussions that are addressed in the present study focus on dropout in undergraduate courses, especially those which include the area of applied social sciences. Thus, here, the use of the term “dropout in higher education” refers to dropout in undergraduate courses.

Dropout in higher education has gained prominence in the national scientific literature in the last 20 years, mainly due to the gradual expansion in the number of public policies for access and permanence in higher education, which makes the topic attractive to the academic community (Oliveira & Barbosa, 2016). The study of the topic is relevant because there is still a theoretical gap in this area (Santos Jr. & Real,

2017). In other words, it is observed that the theme still has little theoretical support that helps to explain this phenomenon in a coherent way.

Among the concerns behind this phenomenon, some examples that can be highlighted are the economic/financial losses of institutions and governments (Cunha, 2015; Gallegos et al., 2018), interruption of family projects (Contini, Cugnata & Scagni, 2018) and failure to fulfill the teaching mission (Cunha et al. 2015; Souza, Sá & Castro, 2019).

Dropout in higher education afflicts all areas of knowledge but has different rates for each (Lobo & Silva Filho, 2017). Applied social science courses, especially business courses, such as accounting and administration, have high dropout rates, mainly because many of the students in these courses spend a good part of the day with work, which makes it difficult to reconcile studies and employment, often leading them to unsatisfactory performance in both activities (Cunha et al., 2015). Apparently, this reality occurs, including open and distance learning (the so-called ODL courses), due to the lack of policies to combat dropout in this type of education (Bittencourt & Mercado, 2014).

At the Federal University of Sergipe, for example, 90% of business students who dropped out tried to reconcile their studies with work activities (work and internship) (Oliveira & Barbosa, 2016). Furthermore, the specificities of the Business Administration course led to the observance of other factors that contribute to dropout. Additionally, at the Federal University of Alagoas (UFAL), Bittencourt and Mercado (2014) observed that in the Business Administration course, in the distance learning modality, most of the students who dropped out of that institution did so due to factors related to the HEI, such as problems with tutors, structural, and didactic-pedagogical problems.

Data from an empirical study carried out at a federal university in the state of Paraíba showed that the time required to complete the course contributes to dropout, so that a course with a greater number of semesters available for completion of the course implies in lower dropout rates (Costa, Bispo & Pereira, 2018). There are also cases in which some students choose to drop out of the morning course and enter an evening course, so that they can continue their work, others interrupt their studies due to maternity/paternity, or health problems that require time for treatment, and, finally, some students drop out because they do not identify with the previously chosen course, and end up abandoning their studies before finishing them (Thompson, 2017).

These are just a few examples of the countless factors that contribute to dropping out of studies, covering, for the most part, aspects that cannot be controlled by higher education institutions, so that they feel motivated to continue their studies, from the initial semesters.

Methodology

In the present study, the research problem was approached quantitatively. Data were organized, tabulated and subjected to statistical techniques and tests, which guided the analysis and interpretation of results (Martins & Theóphilo, 2016). As for the objective, it was descriptive research (Kauark, Manhães & Medeiros, 2010), as it sought to trace and identify the variables that most influenced the dropout of students from Applied Social Sciences courses, namely: Economic Sciences, Accounting

Sciences and Business Administration of a Federal Public University in the State of Minas Gerais.

Regarding the sample, this was composed of students who entered the institution using the Unified Selection System (SISU) from 2014, the year in which the institution fully adopted the SISU. This resulted in a sample composed of 1033 individuals. The time frame was necessary, since the students' scores on the National High School Exam (ENEM) were some of the variables used.

Regarding the collection and organization of data, a query was made to the institution's database, using Structured Query Language (SQL). This query was necessary since many of the variables are arranged in different tables in the database, requiring statements like LeftOuterJoin, to cross information from tables. The initial consultation covered all the institution's courses, and some information was filtered and removed. The data were organized to group the variables by student, regardless of whether the student was enrolled or not at the institution. The variables collected were classified between metrics and non-metrics, to be used in accordance with the assumptions of the statistical techniques used.

It is also noteworthy that, despite the collection having been carried out in October 2019, no data from the first or second semester of the current year was considered. This is because, due to the school year not having been concluded, the analyzes could be harmed. Thus, all data refer to a database backup performed immediately before the beginning of the 1st semester of 2019.

For data analysis, the Statistical Package for the Social Sciences (SPSS) software was used. Regarding the techniques used in the work, initially the Crosstabs analysis was used between dropout and all non-metric variables (sociodemographic categories). To achieve the main objective of the work, discriminant analysis was used, using all the metric variables (prior knowledge, internal variables to the organization and temporal issues) as foreseen by the technique.

Table 1 presents the statistical parameters that guarantee the adequacy of the function obtained by the discriminant analysis and of the variables that compose it.

Table 1
Discriminant Analysis Parameter

Step	Parameter	Meaning	Opinion
1	Explained variance	Explained variance Percentage at which the function explains the variance between groups.	Not applicable.
2	Canonical Correlation Index	Canonical Correlation Index Ratio between the variation between groups and the total variation.	The closer to 1 the better.
3	Test F	Significance level of the difference between the means.	If less than 0.05, significant at 5%.
4	Degree of precision	Significance level of the difference between the means.	Not applicable.
5	Coefficients of the discriminant function.	Degree of Precision Shows how accurate the model was in discriminating individuals between groups. In the case of the present study, the percentage in which individuals were correctly classified between dropouts and non-dropouts based on the variables.	Not applicable.

Note: Prepared by the authors based on Hintze (1998) and Marôco (2007)

As for the variables used in the study, Table 2 shows, in addition to the categories to which they belong, their meaning.

Table 2
 Variables tested in the study

Category	Variable	Meaning
Sociodemographic	Course Code	Course code determined by the university, represents the course with the shift in which the student was or is still enrolled.
	Sex	Gender, with F for female and M for male.
	Marital status	Shows whether the student is married or in a stable union, single, divorced or separated, fits in other cases, or has not reported his marital status.
	Entry with Affirmative Action	Separates students by admissions using affirmative action or not.
Previous Knowledge	Enem_Redaction	Grade obtained by the student in the ENEM Writing test.
	Enem_Languages	Grade obtained by the student in the ENEM test in Languages, Codes and their Technologies. It involves curricular components such as Portuguese Language, Foreign Language, and others.
	Enem_Social	Grade obtained by the student in the ENEM test in Human Sciences and its Technologies. It refers to curricular components such as History, Geography, Philosophy, and Sociology.
	Enem_Nature	Grade obtained by the student in the ENEM test in Natural Sciences and its Technologies. It involves curricular components such as Chemistry, Physics, and Biology.
	Enem_Math	Grade obtained by the student in the ENEM test in Mathematics and its Technologies.
	Enem_Placing_Course	Placement that each student obtained in the selection process in which he was selected for the course.
	Enem_Average_Simple	Simple arithmetic average of all 5 ENEM scores mentioned above.
	Enem_Weighted	Weighted average of 5 ENEM exam scores. As the courses emphasized are in the same area, the weights are the same for all: Writing (1); Natural Sciences and its Technologies (1); Human Sciences and their Technologies (3); Languages, Codes and their Technologies (3); Mathematics and its Technologies (3).
Internal Organizational Variables	Qtd_Locking	Number of semesters that the student has taken during the course.
	Coefficient_Yeld	Student achievement level: performance coefficient (sum of the products of the grade obtained by the workload of each course unit taken, divided by the total hours taken)
	Average_Presence	Average attendance of the student in the subjects taken.
	Qtd_Subjects	Total courses taken, regardless of approval.
	Approval_Percentage	Percentage of subjects that each student passed (60% of the grade and 75% of attendance).
	Concept_Evaluation_teacher	Average of the grades that students give to each teacher they had classes with during the previous semester. Grades are awarded through a mandatory-response questionnaire administered before the next enrollment.
Time matters	Year	Age (years) of the student on the date immediately before the start of the first semester of 2019.
	Years_Dif_High_School	Period (years) between the completion of high school and the student's entry into higher education.
	Year_Admission	Year of entry of the student at the institution, ranging from 2014 to 2018.

Note: Prepared by the authors

As auxiliary software, Excel was also used, especially in the elaboration of the graphs. It is worth mentioning that the evasion thermometer presented was prepared based on the Bankruptcy Thermometer proposed by Kanitz, proposed in December 1974 in Exame Magazine, which aimed to predict the failure of companies based on the insolvency rate.

Analysis and Results

Initially, the quantitative and descriptive statistics referring to the sample are presented. From Figure 1, it is possible to see that, of the 1033 students involved in the analysis, 364 dropped out and 669 had not dropped out until the beginning of the 2019 school year, which represents a dropout rate of 35.2%.

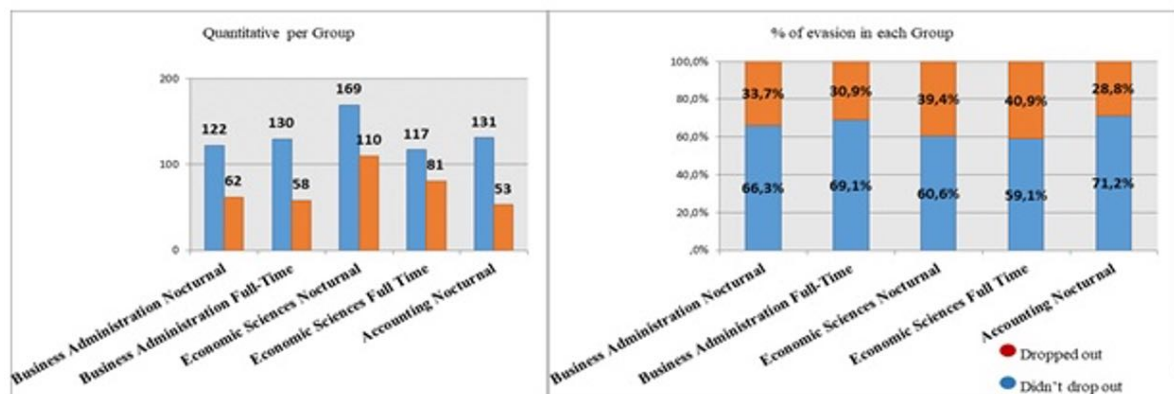
Figure 1
 Number of dropout and no-dropout students



Note: Prepared by the authors

Figure 2 below shows the number of dropouts and non-dropouts and dropout rates per course and shift. It is possible to notice that these rates were relatively different. The results indicate that there was a higher level of dropout in economic science courses, both evening and full-time, which percentage was approximately 40%. Next, the percentage of dropouts in business administration courses stands out, around 32%; and finally, in the accounting sciences course (28.8%).

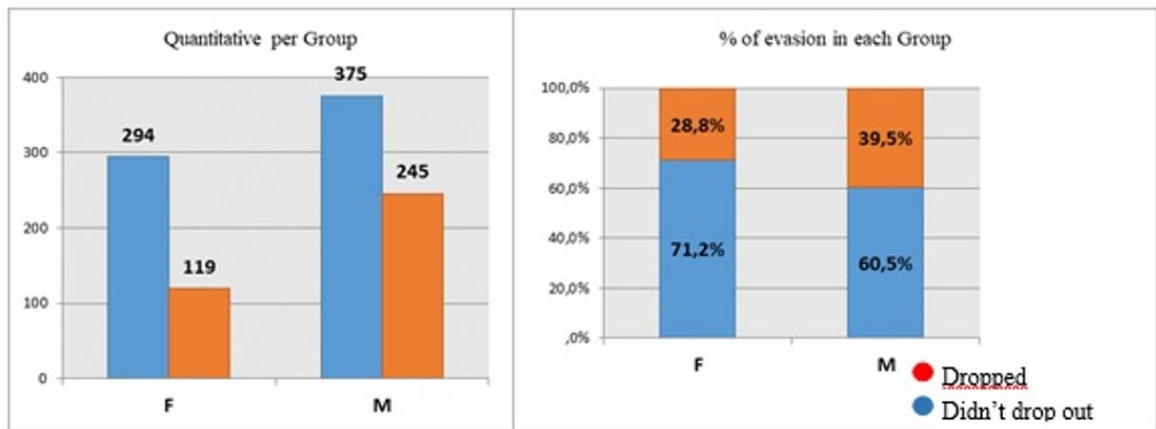
Figure 2
 Ratio of dropout and non-dropouts by course



Note: Prepared by the authors

Figure 3, in turn, presents the ratio of dropouts and non-dropouts by sex. In view of this, a greater representativeness of dropout was identified among men.

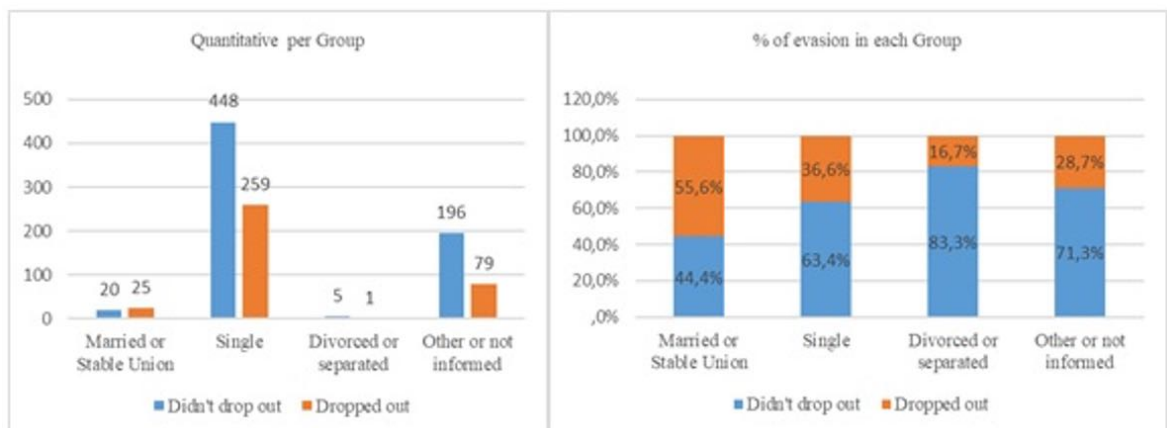
Figure 3
 Relationship of dropout and non-dropout by sex



Note: Prepared by the authors

About marital status, although many students are classified as other or not informed, the sample is mostly composed of single students.

Figure 4
 List of dropout and non-dropouts by marital status

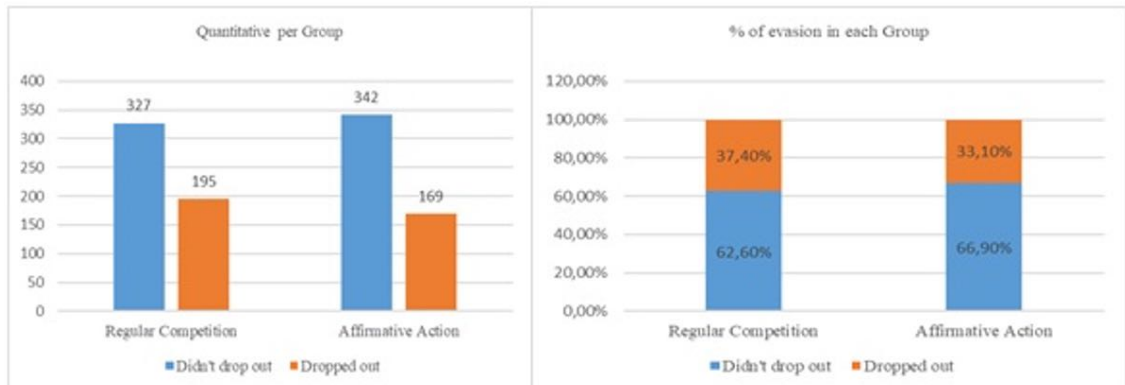


Note: Prepared by the authors

Figure 4 shows that, despite representing a small portion of the sample, the group composed of students who were married or in a stable relationship had the highest percentage of dropouts.

Dropout and non-dropout students were further discriminated between admitted with or without affirmative action. Figure 5 shows that freshmen who accesses through regular means had a higher dropout rate when compared to students from affirmative action.

Figure 5
 List of dropouts and non-dropouts by affirmative action



Note: Prepared by the authors

After characterizing the sample through the relationship between the variables that make up the sociodemographic category, then the technique of discriminant analysis was applied, the main technique for the construction of the evasion thermometer.

When performing the discriminant analysis, it was initially verified the adequacy of the tests and values referring to the discriminant function. The first verified value concerns the variance explained by the function, whose value was 100%, which means that, statistically, the function obtained explains 100% of the differences between the groups.

Then, the canonical correlation was evaluated, that is, the ratio between the variation between the groups and the total variation. The results showed a canonical correlation of 0.875. If the closer to 1 the better, it can be said that the value was acceptable (Hintze, 1998).

After this analysis, the significance of the function was also checked. For this, the level of significance expressed by the F Test was verified. The model also passed this test by presenting a significance of 0.000, that is, significant at 1%. Thus, it was shown that the means are significantly different from each other, and that is why the function is significant when discriminating the groups (MAROCO, 2007). In addition, it is important to verify the accuracy of the model regarding the classification of individuals in relation to the groups, which is shown in Table 3.

Table 3
 Classification of Discriminant Results

Original situation	By method		Total
	Non-dropout	Dropout	
Non-Dropout (amount)	662.0	7.0	669
Non-Dropout (%)	99.0	1.0	100
Dropout (amount)	32	332	364
Dropout (%)	8.8	91.2	100

Note: Prepared by the authors

It is possible to notice that of the 669 students who did not drop out, the model correctly classified 662 (99%) as non-dropouts and only 7 as dropouts, because they have strong dropout characteristics. Regarding dropouts, the model classified 332

students as dropouts (91.2%) and 32 as non-dropouts out of a total of 364 who dropped out. Thus, the precision or accuracy of the model was established at 96%, 994 correct answers from 1033 students.

To show the weight of the variables that make up the discriminant function, that is, how much they discriminate between dropouts and non-dropouts, the coefficients of the standardized discriminant function are presented (Table 4).

When considering the categories to which the variables belong, it is noted that the variables referring to prior knowledge were responsible for 10% (gray) of the discrimination between the groups. While the institution's internal variables were responsible for 60% (blue) and the one related to temporal issues 30% (yellow).

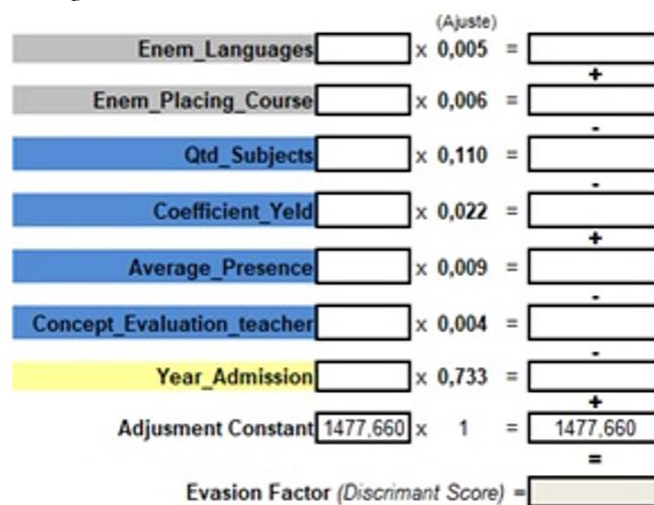
Table 4
 Standardized discriminant function coefficients

Category	Variable Name	Value	%	Category Total (%)
Previous Knowledge	Enem_Languages	-0.203	6	10
	Enem_Placing_Course	-0.139	4	
Variables internal to the organization	Qtd_Subjects	1.244	37	60
	Coefficient_Yeld	0.477	14	
	Average_Presence	-0.189	6	
	Concept_Evaluation_teacher	0.089	3	
Temporal issues	Year_Admission	1.011	30	30

Note: Prepared by the authors

It is important to note that, although the standardized function presents the weight of each variable in the evasion calculation, another function, called the canonical function, is responsible for calculating the evasion factor, since the data are not standardized and need of weight adjustments and a constant. Thus, with the canonical discriminant function it is possible to calculate the dropout factor of any student. As shown in Figure 6, the value of each variable is multiplied by the adjustment and then added or subtracted with the next result (product between the value of the next variable and its respective adjustment), until it results in the value referring to the evasion factor or Discriminant Score of the function.

Figure 6
 Evasion discriminating function



Note: Prepared by the authors

The dropout factor is represented by a number that, among the individuals present in the analyzed sample, can vary from -3.7 to 5.3. Thus, the higher this value, the higher the level of characterization of the student as dropout. Figure 7 presents two simulations based on data from two students. The first was identified as a non-dropout and did not really drop out, while the second is a student who dropped out and was identified as such by the model.

Figure 7
 Example of using discriminant function

Student 1			Student 2		
Enem_Languages	655	$\times 0,005 = 3,459088634$	Enem_Languages	610	$\times 0,005 = 3,221441323$
Enem_Placing_Course	4	$\times 0,006 = 0,023914931$	Enem_Placing_Course	1	$\times 0,006 = 0,005978733$
Qtd_Subjects	52	$\times 0,110 = 5,724835553$	Qtd_Subjects	9	$\times 0,110 = 0,990836923$
Coefficient_Yield	78	$\times 0,022 = 1,741989483$	Coefficient_Yield	35	$\times 0,022 = 0,781661947$
Average_Presence	92	$\times 0,009 = 0,830458075$	Average_Presence	56	$\times 0,009 = 0,50549622$
Concept_Evaluation_teacher	95	$\times 0,004 = 0,335068236$	Concept_Evaluation_teacher	85	$\times 0,004 = 0,299797896$
Year_Admission	2014	$\times 0,733 = 1476,10323$	Year_Admission	2017	$\times 0,733 = 1478,301993$
Adjusment Constant	1477,660	$\times 1 = 1477,660$	Adjusment Constant	1477,660	$\times 1 = 1477,660$
Evasion Factor (Discrimant Score) = -1,932			Evasion Factor (Discrimant Score) = 1,018		

Note: Prepared by the authors

Finally, as proposed by the present work, an evasion thermometer was created (Figure 8). This thermometer makes it possible to represent each of the students to verify how close they are to dropping out, according to the characteristics presented by them and the discriminant function generated.

On the left side of the thermometer, represented by the Y axis, the Dropout Factors or Discriminant Score are informed, and each point represents a student. Like a mercury column thermometer to measure body temperature, the higher the factor, the more likely the student is to drop out.

The gray band, called the twilight, is the one where the model has the most difficulty in distinguishing students efficiently. It groups individuals with between 1% (-0.480 evasion factor) and 50% (0.720 evasion factor) chance of evading.

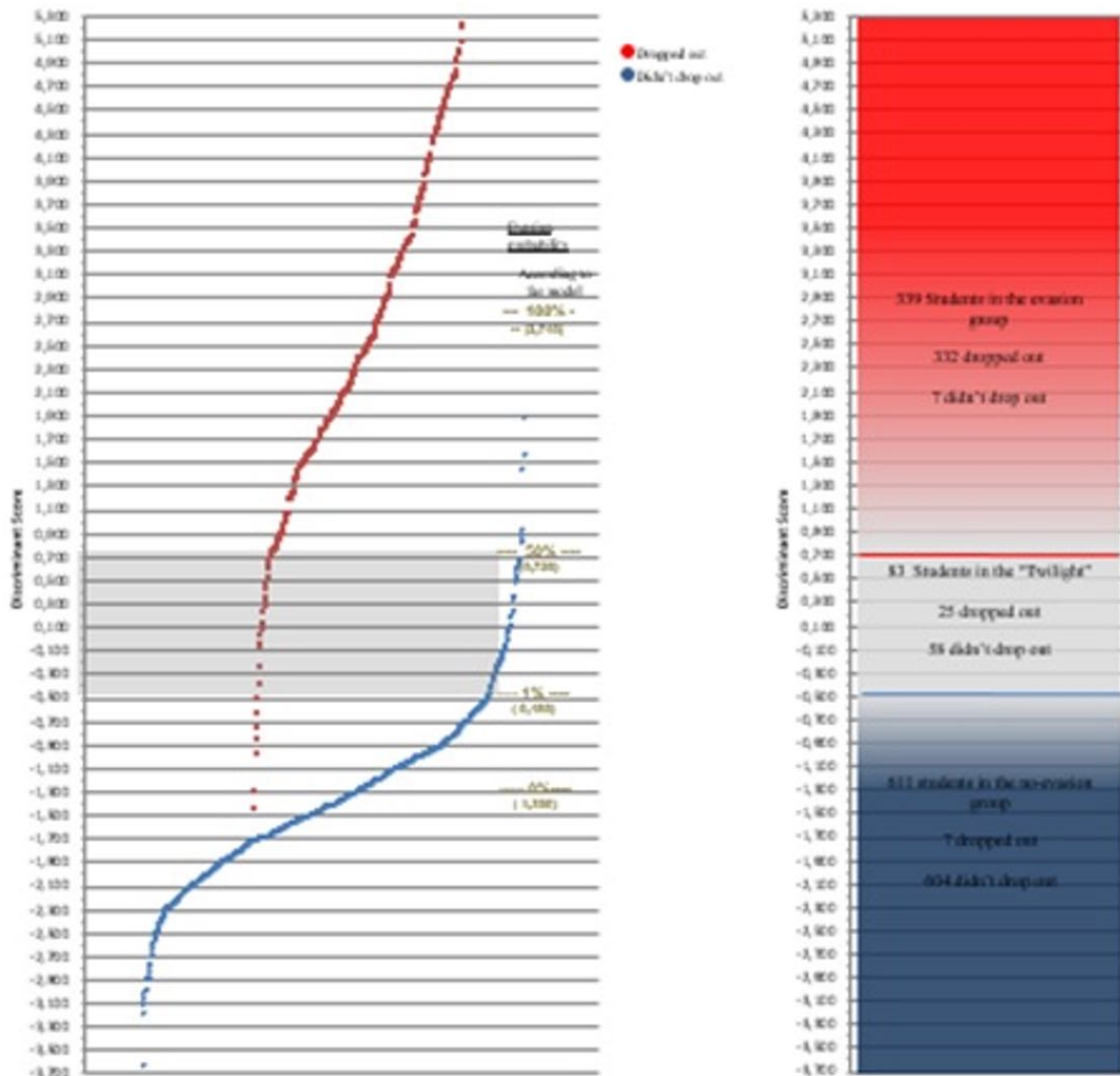
Above the twilight are students with more than 50% of characteristics aimed at dropping out and who, therefore, are potential dropouts. Below this range are grouped individuals who have less than 1% chance of evading.

Two other levels to be verified refer to students with more than 100% or less than 0% dropout characteristics, whose Discriminant Scores are between 2.740 and -1.300, respectively. Figure 8 also shows the number of individuals in the sample classified in each of the three thermometer ranges: above 50%, below 1% and in the twilight.

In Figure 8, it is also possible to identify among the individuals still enrolled, that is, who did not drop out, and how many students would have more than a 50% chance of dropping out, which in the sample is only 7. The same can be applied to

students who have more than 1% chance, whose total was 65 students (58 in the twilight plus 7). And yet, to students who did not drop out with less than 1% of dropout characteristics, which in the sample regards 604 individuals. This is important when considering what actions can be taken to keep students in higher education, and mainly directed according to the probability of dropout.

Figure 8
 Evasion thermometer

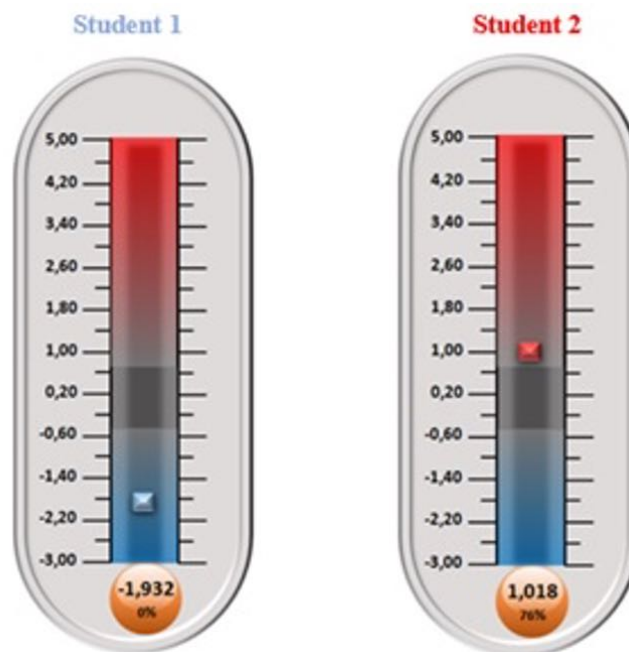


Note: Prepared by the authors

Finally, to demonstrate the application of the thermometer obtained by the present work, Figure 9 is presented, in which it is possible to locate the two individuals already taken as an example previously and point them on the thermometer based on their factor of evasion.

Additionally, Figure 9 shows the dropout factor and the probability that this will occur, for each of the two students in accordance with the results obtained by the model.

Figure 9
 Evasion thermometer



Note: Prepared by the authors

Final Considerations

The objective of this article was to present a “dropout thermometer”, to indicate how close, the student may be to dropping out.

It was observed, through the Crosstabs statistical technique, that the Economic Sciences course had the highest dropout percentage, and that the highest representation in terms of dropouts was related to males. Results of this type can help in the analysis and performance of managers and administrators of educational institutions, by exposing patterns in the face of the phenomenon under analysis. In addition, this can instigate these professionals to seek explanations for the occurrence of dropout, and thus the delimitation of more effective strategies that mitigate the abandonment of undergraduate courses.

As for the use of discriminant analysis, a function was identified based on data extracted from the institution’s database, more specifically from Applied Social Sciences courses. It was possible to evaluate, according to an index measured from the function, the student’s propensity to drop out or not. This gave rise to the Evasion Thermometer. It is worth mentioning that, despite not being subject to generalizations between educational institutions, the built thermometer can be replicated, from its restructuring based on variables specific to each institution. The results allow us to state that, in view of the sample used, the variable of the function with the greatest capacity for discrimination in terms of dropout is the number of subjects taken. In addition, it was possible to track students with evasive characteristics.

These results, arising from the application of the Thermometer, can be used by managers or coordinators of the courses involved in the present study, and thus help to

reduce dropout rates. A possible way of acting based on the results is the direct observation or even the delimitation and application of measures aimed at students who were more likely to drop out of the course. In this way, the Thermometer can be used as a system to automate the control over evasion, and still favor the generation of reports to managers.

As limitations of the study, the strictly quantitative analysis is pointed out, which makes it impossible to identify the causes for which the variables were considered to discriminate between dropouts and non-dropouts. It is also understood that the limitation of the model is the fact that it does not consider variables arising from student permanence policies, issues of race and university infrastructure (such as university restaurant, student reception center such as psychologists/pedagogues, among others) and difficulty in reconciling studies and work (raised in the literature review and not considered in the model). These variables are important to improve the model's indicators and would clarify the "twilight" of results not explained by the model.

It is suggested as future investigations the application of the same technique to other areas, as well as in other institutions, to identify potential determinants of dropout in multiple contexts. In addition to carrying out qualitative research with students with greater possibility of evasion. Finally, a future verification regarding the students identified by the present study as potential dropouts is considered valid, to verify if these students really dropped out.

References

- Associação Nacional dos Dirigentes das Instituições Federais de Ensino Superior [ANDIFES]. (1996). *Comissão Especial de Estudos Sobre a Evasão nas Universidades Públicas Brasileiras*. Brasília, DF. http://www.andifes.org.br/wp-content/files_flutter/Diplomacao_Retencao_Evasao_Graduacao_em_IES_Publicas-1996.pdf.
- Bittencourt, I., & Mercado, L. (2014). Evasão nos cursos na modalidade de educação a distância: estudo de caso do Curso Piloto de Administração da UFAL/UAB. *Ensaio: Avaliação e Políticas Públicas em Educação*, 22(83), 465-504. <https://doi.org/10.1590/S0104-40362014000200009>.
- Brasil. (1996). *Comissão Especial de Estudos sobre a Evasão nas Universidades Públicas Brasileiras*. ANDIFES/ABRUEM, SESu, MEC, Brasília. <https://bit.ly/34fHmdl>.
- Céspedes, J., Minhoto, M., Oliveira, S., & Rosa, A. (2021). Avaliação de Impacto do Programa de Permanência Estudantil da Universidade Federal de São Paulo. *Ensaio: Avaliação e Políticas Públicas em Educação*. 29(113), 1067-1091. <https://doi.org/10.1590/S0104-403620210002902418>.
- Contini, D., Cugnata, F., & Scagni, A. (2018). Social selection in higher education. Enrolment, dropout and timely degree attainment in Italy. *Higher Education*, 75(5), 785-808. <https://doi.org/10.1007/s10734-017-0170-9>.
- Costa, F., Bispo, M., & Pereira, R. (2018). Dropout and retention of undergraduate students in management: a study at a Brazilian Federal University. *RAUSP*

- Management Journal*, 53(1), 74–85. <https://doi.org/10.1016/j.rauspm.2017.12.007>.
- Cunha, J. (2015). Quem está ficando para trás? Uma Década de Evasão nos Cursos Brasileiros de Graduação em Administração de Empresas e Ciências Contábeis. *Revista de Educação e Pesquisa em Contabilidade*, 9(2), 124-142. <https://doi.org/10.17524/repec.v9i2.1141>.
- Gallegos, J. A., Campos, N. A., Canales, K. A., & González, E. N. (2018). Factores determinantes en la deserción universitaria. caso facultad de ciencias económicas y administrativas de la Universidad Católica de la Santísima Concepción (Chile). *Formación Universitaria*, 11(3), 11-18, 2018. <http://dx.doi.org/10.4067/S0718-50062018000300011>.
- Henriques, F. (2018). Evolução histórica, expansão e financiamento da educação superior no Brasil: das primeiras faculdades à expansão do início do século XXI. *Comunicologia*, 11(2), 124-145. <http://dx.doi.org/10.31501/comunicologia.v11i2.10058>.
- Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira [INEP]. (2019). *Sinopse estatística da educação superior 2018*. Brasília: INEP. <https://bit.ly/2UiKofT>
- Kanitz, S. (1974, dezembro). Como prever a falência de empresas. *Revista Exame*. <https://pt.scribd.com/document/61123852/EXAME-ComoPreverFalenciaEmpresa-Kanitz>.
- Li, L., & Carrol, D. (2019). Factors influencing dropout and academic performance: an Australian higher education equity perspective. *Journal of Higher Education Policy and Management*, 42(1), 14-30. <https://doi.org/10.1080/1360080X.2019.1649993>.
- Lobo, R., & Silva F. (2017). A Evasão No Ensino Superior Brasileiro – Novos Dados. Instituto Lobo. <https://bit.ly/2XGVytl>.
- Mancebo, D., Vale, A., & Martins, T. (2015). Políticas de expansão da educação superior no Brasil 1995-2010. *Revista Brasileira de Educação*, 20(60), 31-50. <https://doi.org/10.1590/S1413-24782015206003>.
- Martins, G., & Théophilo, G. (2016). *Metodologia da investigação científica para ciências sociais aplicadas*. 3 ed. Atlas.
- McCallin, A., & Nayar, S. (2012). Postgraduate research supervision: a critical review of current practice. *Teaching in Higher Education*, 17 (1), 63-74. <https://doi.org/10.1080/13562517.2011.590979>
- Oliveira, R., & Barbosa, J. (2016). Retenção os discentes de administração da UFS: fatores condicionantes e ações da gestão acadêmica. *Administração: Ensino e Pesquisa*, 17 (2), 355-380. <https://doi.org/10.13058/raep.2016.v17n2.428>.
- Respondek, L., Seufert, T., Stupnisky, R., & Nett, U. E. (2017). Perceived Academic Control and Academic Emotions Predict Undergraduate University Student Success: Examining Effectson Dropout Intention and Achievement. *Frontiers in Psychology*, 243 (8), 1-18. <https://doi.org/10.3389/fpsyg.2017.00243>.

- Santos Júnior, J., & Real, G. (2017). A evasão da educação superior: o estado da arte das pesquisas no Brasil a partir de 1990. *Avaliação* (Campinas), 22 (2), 385-402. <https://doi.org/10.1590/S1414-40772017000200007>.
- Silva Filho, R., Montejunas, P., Hipólito, O., & Lobo, M. (2007). A evasão no ensino superior brasileiro. *Cadernos de Pesquisa*, São Paulo, 37 (132), 641-659. <https://doi.org/10.1590/S0100-15742007000300007>.
- Silva Júnior, J., Schugurensky, D., & Araújo, J. (2015). Ciencia académica, intelectuales y el trabajo del professor universitario em Brasil: convergencia y hegemonia. *Revista de la Educación Superior*, 44 (173), 157-179. <https://doi.org/10.1016/j.resu.2015.04.006>.
- Souza, T., & Sá, S. (2019). Evasão escolar no ensino superior: um estudo qualitativo via mapeamento de licenciaturas. *Revista Lusófona de Educação*, 44 (44), 63-82. <https://doi.org/10.24140/issn.1645-7250.rle44.04>.
- Thompson, P. (2017). Deserción universitaria. Análisis de los egresados de la carrera de Administración. Cohorte 2011-2016. *Población y Desarrollo*, 23 (45), 107-112. [https://doi.org/10.18004/pdfce/2076-054x/2017.023\(45\).107-112](https://doi.org/10.18004/pdfce/2076-054x/2017.023(45).107-112).