The use of digital reports to support the visualization and identification of university dropout data

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Abstract. University dropout is a concern for educational institutions since it directly impacts management and academic results, as well as being directly related to social problems. The literature points out that analyzing this phenomenon is a positive factor for developing programs to combat dropout, in addition to planning interventional actions and academic monitoring, making it possible to identify students at risk of dropout through techniques that use Machine Learning, for example. This paper presents a panoramic study of a public university, in which the school data were analyzed and classified using Machine Learning. The analysis of the data allowed to obtain an overview of the dropout data of the studied university. In addition, the main stakeholders were interviewed to report their main difficulties to know statistics about dropout. Considering these different data sources, we created digital reports to professors, chiefs and academic assistants, with information and statistics to assist university managers in decision-making related. These reports were validated by stakeholders and we hope that the next decisions can minimize any problems related to mental health, thus improving the quality of life of students, as well as their academic trajectory.

Keywords: University Dropout · Mental Health · Machine Learning · Digital Reports · Validation · Public University.

1 Introduction

Students of higher education are exposed to several positive and negative events during the educational process. The successes often outweigh the efforts from the enrollment until the student effectively earns a degree, however adversities may lead to dropout [34, 32]. This phenomenon is common to public and private higher education, directly interfering in their management and in the results of education quality [27, 31], which consequently generates a necessary concern, as the students' departure from the study cycle induces several consequences [28, 18].

The costs associated with college attrition include hindering of future job prospects with impacts in the countries economy, the personal and professional costs for the former student, waste of institutional and federal resources, a potential damage to university reputation and demoralization of students still in the school [14, 3].

Several factors influence dropout, the main ones being related to financial and family reasons, unfulfilled expectations and lack of motivation [3]. Likewise, in a survey carried out by FONAPRACE [12], issues related to academic requirements are also discussed, which were also considered preponderant to dropout. Xenos, Pierrakeas and Pintelas [35] state that the identification of these factors is essential to provide special assistance to students, and categorizes them as follows: Internal factors - related to students' perception; Factors related to the course and professors and; Factors related to student demographic characteristics.

Studies point out that the prevalence of mental health problems in universities among students is high, with the majority being in university students subjected to relational stressors and with low social support [21, 9]. In a survey conducted at an American University, Eisenberg et al. [9] observed that the prevalence of depressive or anxiety disorders was 15.6 % for undergraduate students and 13.0 % for graduate students, and also, there is suicidal thought reported by 2 % of students. According to Leonhardt and Sahil [18], in American higher education, in 2018, about one in three students who enroll in college never earn a degree. They looked at 368 colleges arranged by what they would expect their graduation rates to be, based on the average for colleges with similar student bodies concluding that colleges with higher success rates study academic data and use it to remove hurdles for students, in addition, students' connection to other people, financial issues, and university structure also influence to increase success.

In Brazil, a special committee on dropout studies was established in 1995, from the Ministry of Education ordinance, with the purpose of evaluating the performance of Federal Higher Education Institutions (FHEI; IFES, in Portuguese). In 2002, this became a major concern with the significant increase in the number of places offered by IFES in Brazil [34].

Since this, data visualization techniques have been explored to prevent dropout in terms of providing management support in order to identify students at risk of dropping out [8, 26, 4, 10]. Some studies also see Data Mining (DM) and Machine Learning techniques (ML) to predict possible dropout [30, 23, 1, 20, 16, 5, 29, 15].

This paper presents the report of the panoramic study of a Brazilian public institution of higher education through the data visualization of its students and interviews with different stakeholders, seeking to identify students in a possible situation of risk of dropout and who may need support services due to emotional difficulties, financial, among others. We hope that this study can motivate other institutions to use the concepts and techniques proposed, to support students in vulnerable situations more effectively. We also highlight that this study went through the validation of the Brazilian ethical committee, CAAE number: 34343920.5.0000.5504.

The paper is structured as follows: Section 2 describes related works; Section 3 describes university data and techniques to collect data; Section 4 describes the prototype designed; Section 5 presents the validation carried out in prototype; Section 6 shows the metrics of the reports usage and, finally, Section 7 relates the final considerations and future work.

2 Related Works

Previous studies found that college attrition depend on the type of course [35, 6], student's year at college [6, 32, 18, 19], social issues such as parental background [2, 6], class-cultural discontinuities [17] and economic profile [25]; as well as quantitative academic data [23].

Lozano et al. [19] found the first and second years to be crucial when it comes to retention as it allows for more numerous and more intensive interventions. According to Casanova et al. [6], the first years are particularly difficult for students who enrolled in the course as a second option. The authors suggest improving motivation in students who have to adapt to this situation.

Hippel and Hofflinger [13] conducted a study to identify students at risk of dropping out at 8 Chilean public universities using Logistic Regression (LR). The authors used both personal/family data, e.g. parents' education, high school grades, and entrance exam scores, as well as academic data collected during college. They studied the effect of programs focused on helping students adapt to university life, develop study skills and manage anxiety. The assisting programs dictated a reduction of 30-40% in the chances of dropping out in 2 of 4 universities where such programs existed. They found the dropout risk to be inferior for older students, and also for those receiving scholarships. This makes it evident there is no clear consensus on the causes of dropout and also the variety of factors protecting against it.

Coutinho et al. [8] analyzed dropout data using related metrics and developed visualization interfaces covering: a) dropout index; b) the main factors that lead to this phenomenon and c) data related to teaching methodology, in order to support decision making. In the same methodology, Reino [26] carried out an analysis of the main causes of dropout in a distance undergraduate course and showed the results through statistical visualizations.

Already Barbosa et al. [4] performed the classification of students at risk of dropout using machine learning techniques and also performed an analysis of the results to support management.

Ferreira et al. [10] extracted and processed a dataset from a Brazilian institute using all courses and degrees since 2002. They analyzed applications for data visualization based on interactivity, client and API support, data modeling, multiple visualizations on a single screen and active community tutorials. After choosing the visualization tool, they applied eight different report pages, including monthly tracking and comparison, overall performance, achievement by profile and personal information, concluding that data visualization allows to detect and adopt measures to prevent dropout situations.

After identification of students that are prone to dropout college, interventions may be employed to assist students. Those may represent a positive approach to improve retention, as shown by the experience of a Brazilian public university, which points out a dropout decrease of 12.3% in 2018 when compared to 2017 [33]. This reduction was due to institutional interventions that increased the number of registered students, accounting for new admissions and the re-inclusion of students who had taken time off from college. In addition, the number of these students decreased from 10,686 (2017) to 1,142 (2018).

This paper describes the analysis of dropout in a higher education institution, as well as offering support decision-making by managers in order to decrease dropout rates and minimize the consequences and losses caused by it.

3 Data Collection Step

The data collecting step was carried out by using three different sources: (1) literature study (described above); (2) mining of university's data and; (3) analysis of stakeholders' questionnaire responses. These three sources allowed us to understand the context and also to propose some interventions for different stakeholders to consider.

The university where this study was carried out has several computational systems for managing institutional processes. They are separated by purpose for example: under-graduation; postgraduate studies; university restaurant; library, among others. The main systems used to manage academic and student data are integrated used in this study to collect data are: **Integrated Academic Management System**: responsible for the academic processes related to the student, lecturers and the main activities, such as course enrollments, registration of grades and frequencies, teaching plans, subjects, courses, among other activities; **Integrated University Management Support System**: general management of the university including registration of people, permissions, and applications student cards; **Dean of Extension**: management of outreach and extension courses, as well as postgraduate courses *lato sensu* e *stricto sensu*.

By considering source (2) to data collecting and, aiming to find out the relevant data to be collected to assess dropout risk, we follow the empirical evidence found by Pal [24], Hippel and Hofflinger [13]; and Souza [31], in which: personal data, academic information prior to college enrollment, academic information collected during college, as well as economic information, are sufficient to investigate college attrition and student dropout.

Note that, Brazilian federal universities have affirmative actions, so that the category of admission defines quotas of student places related to social/economic status of the student as well as race.

We obtained data from students who entered the university between 2008 and 2020, from all undergraduate courses offered by the institution during this period. In each year, between 2000 and 3000 students are admitted. In total, information was collected from 32.892 students, separated by course, year and period/semester.

Based on the data collected, the biggest problems related to dropout are found in the departments of exact sciences and, for the most part, occur in the 1st, 2nd and 3rd scholar semesters. There are other metrics that can be analyzed in the fight against dropout, for example: fees from academic centers and evasion by type of admission. These and other information were made available in the university's academic management system, actually validated by stakeholders and described in the following section.

Finally, in the source (3) of data collection, we analyzed the information obtained through an online questionnaire, which aimed to understand how the monitoring and combat dropout actions are carried out by teachers, heads and managers. In addition, we seek to understand the perception of these users regarding the dropout scenario, collecting the views of monitoring, combating and preventing dropout, which are not currently used and applied at the university.

The questionnaire was divided into 5 parts to assist in the planning and development of indicators/reports, those: 1) participant identification; 2) profile survey and activities performed at the university; 3) follow-ups performed with students and/or groups of students; 4) perception of dropout; 5) needs, ideas for data visualization in the systems and final suggestions.

Among the information collected from the 32 participants who answered the questionnaire, it was observed that individual and group monitoring of students is carried out according to the teacher's subjects. The coordinators of undergraduate courses, especially, also monitor the students by profile and characteristics, including: a) indigenous people; b) students with special needs; c) students with learning disabilities and d) scholarship holders.

The perception of school dropout by participants reflects the literature and reaffirms the different factors that influence this phenomenon, among them, difficulties in basic high school subjects, lack of motivation, lack of interest in classes and courses, financial difficulties and family problems. In addition to the literature, the data also included the lack of dialogue between teacher and student, difficulty with the Portuguese language (foreign and indigenous students), use of illicit drugs, immaturity, problems with gender identity and difficulty in self-regulation and planning.

Mental health conditions impact the conduct of basic actions, such as: getting out of bed to attend classes and staying in the classroom, with students having panic and anxiety attacks.

Issues related to gender identity highlight adaptation in courses — transgender people experience violence and discrimination. On the other hand, problems related to planning occur due to a difficulty in delineating academic life in the long and medium term, which directly affects the payment of credits.

As a preventive approach to dropout, interventions were suggested by the participants in the first semesters of the course, in order to introduce the student to higher education and equalize the knowledge of incoming students, through complementary high school teaching activities; psychological support to face the responsibilities and adaptations in the university; pedagogical tutoring; facilitate access to motivational assistance and smaller classes.

In addition, among the solutions cited to assist in these approaches, was mentioned the use of graphs, indicators, simulators of real data, extract from semiannual dropout and progress reports of each student, in a way that they are able to visualize the students who dropped out in semester, and the student data according to the monitoring groups.

In line with the actions suggested above by the main stakeholders, this group of researchers proposed the development of graphical reports to be inserted into the main management system for leaders and teachers, in order to give visibility to information related to students and dropout trends. The next section describes the design of these reports.

4 Reports - Graphical Interface Design Step

We followed four stages to design digital reports to support university managers: a) Identifying the main requirements from a survey with different stakeholders of university (described above); b) Definition of reports to be developed according the requirements and interested stakeholders; c) Prototyping graphic interfaces with relevant information (to be available in the university management system) and, d) Validating of the prototyped interface with a sample of stakeholders who participated from step a).

In step (b), among the stakeholders interested in viewing statistics and monitoring the dropout, stand out five user profiles that were defined for the purpose of this study, namely: 1) the undergraduate rectory managers, 2) academic centers heads, 3) departments heads, 4) coordinators of undergraduate courses and 5) professors. Each of these profiles should follows the visualization of the interesting data according to the organizational hierarchy, in this way, the profile with the highest visualization capacity (1) can also view information from the other profiles: **Undergraduate rectory managers**: It has an overview of the data without hierarchy restrictions, being able to also visualize the data of academic centers, departments, courses and professors; **Academic centers heads**: It is restricted to only viewing data related to the center, being only the departments, courses and professors that are under its management; **Departments heads**: It has the visualization of the data of the courses and professors that are related to the department; **Coordinators of undergraduate courses**: It is restricted to viewing data related to the course and professors who are under his/her coordination; **Professor**: Can view the data of the subjects and students, as well as the number of approvals and disapprovals related to them over the years.

In the (c) stage, we prototyped digital reports for data visualization based on the collection of data from the questionnaire, from the literature review [8, 26, 4] and data mining step. Ten reports, divided into 2 groups of profiles, were prototyped to be made validated. For the first group - profiles of undergraduate rectory managers, centers, department heads, and coordinators of undergraduate courses - these users can view: the history of dropout rates, dropout rates by academic center, general situation of students per semester and by type of admission; historical evasion by student profile; Number of credits enrolled, approved, disapproved per student. For the second group - the professors profile - they can view: failures, approvals and cancellations; subjects' failures; historical overview of semester data; general situation of students by subject.

The interface design followed all the system's interface and language standards. The person in charge of the UX/UI area of the university also analyzed the reports' interface.

Fig. 1 illustrates three different graphs that present an overview of dropout rates at the university, making it possible to verify the variations by period and which academic centers have the highest rates. Finally, the students' situations are shown according to the division already used by the university. The Fig. 2 illustrates the teacher's indicators, with the number of students, approvals and disapprovals, in order to provide performance data and subjects that need further monitoring. Finally, Fig. 3, illustrates the visualization of student credits in a table format and allows the identification and monitoring of groups of students (defined by the manager), as well as students who enrolled in a few credits in that semester, also being able to cross information of credits taken and final deadline for completion of the course.

Fig. 1. Visualization of dropout rate, dropout by academic center and student situation graphs.

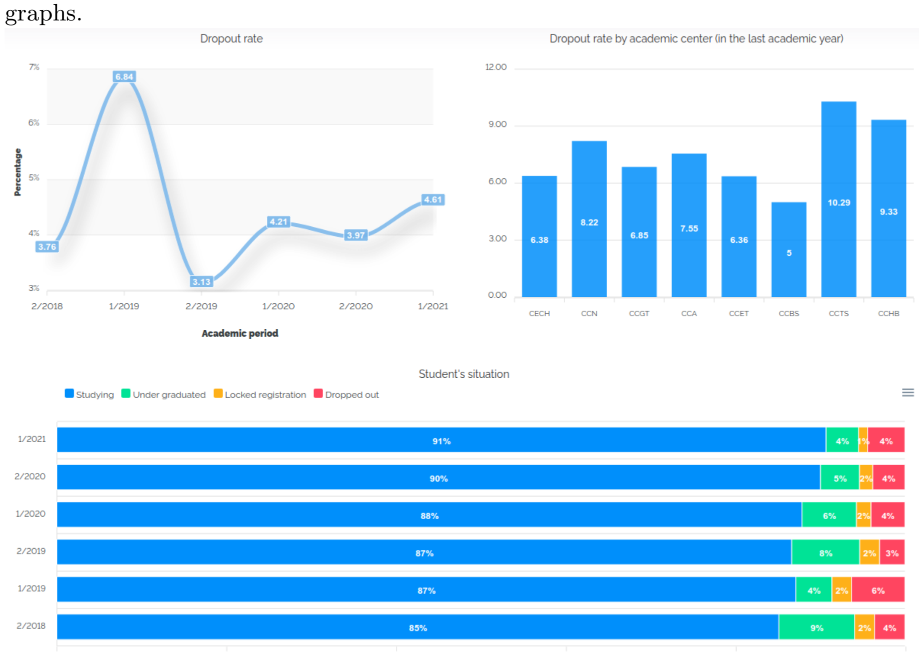
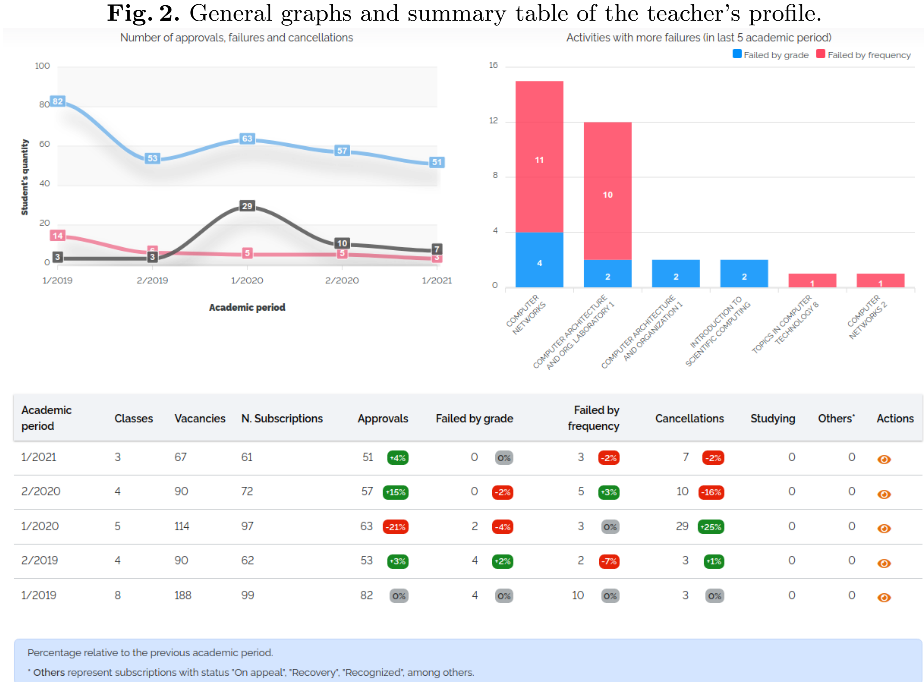


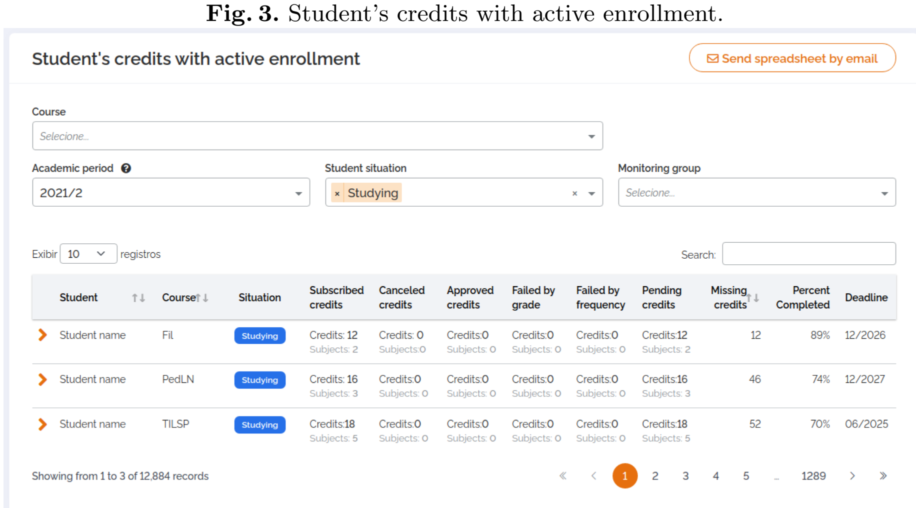
Fig. 2. General graphs and summary table of the teacher's profile.



Academic period	Classes	Vacancies	N. Subscriptions	Approvals	Failed by grade	Failed by frequency	Cancellations	Studying	Others*	Actions
1/2021	3	67	61	51 +4%	0 0%	3 -2%	7 -2%	0	0	
2/2020	4	90	72	57 +15%	0 -2%	5 +3%	10 -16%	0	0	
1/2020	5	114	97	63 -21%	2 -4%	3 0%	29 +25%	0	0	
2/2019	4	90	62	53 +3%	4 +2%	2 -7%	3 +1%	0	0	
1/2019	8	188	99	82 0%	4 0%	10 0%	3 0%	0	0	

Percentage relative to the previous academic period.
* Others represent subscriptions with status "On appeal", "Recovery", "Recognized", among others.

Fig. 3. Student's credits with active enrollment.



Student	Course	Situation	Subscribed credits	Canceled credits	Approved credits	Failed by grade	Failed by frequency	Pending credits	Missing credits	Percent Completed	Deadline
Student name	Fil	Studying	Credits: 12 Subjects: 2	Credits: 0 Subjects:0	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:12 Subjects: 2	12	89%	12/2026
Student name	PedLN	Studying	Credits: 16 Subjects: 3	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:16 Subjects: 3	46	74%	12/2027
Student name	TILSP	Studying	Credits:18 Subjects: 5	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:0 Subjects: 0	Credits:18 Subjects: 5	52	70%	06/2025

Finally, the last stage included the validation of the interface with stakeholders of different levels. This step is described in detail in the next section.

5 Validation Step

The validation of the requirements listed from different sources and made available in the reports interface is relevant to ensure that they have achieved the purpose for which they were created, as well as to ensure that target users are able to use the features, even with little knowledge of the system [11, 7].

Usability tests [22] are used to evaluate interfaces of computer systems under development. This was the technique used here.

To conduct the validation, high-fidelity prototypes of the reports were developed in the university's management system. Thus, the profile representatives (who answered the questionnaire to gather requirements) were able to access the prototype and provide feedback on the available data, and on the interface and interaction elements arranged in the reports. It should be noted that the data provided are fictitious data.

The profile that carried out the use test was the profile of the Dean of Undergraduate Studies - in the figures of the head of the sector and two administrative technicians of the academic and pedagogical monitoring coordination. They carried out 10 tasks via web conference, with a recorded screen, in which the researchers in charge were able to observe the user's interaction with the report screens available on the SAGUI system.

System logs were also being collected. It was observed the ease with which the user interacted and understood the actions of the system. In these tasks, the user should answer some associated questions to ensure that the correct information has been found. The following metrics were evaluated. a) Number of clicks; b) Time required to complete the task; c) Number of successfully executed interactions; d) Unexpected behaviors; e) Ease of learning.

The tasks carried out were made available in a questionnaire and it consist of: a) Logging in; b) Consult the avoidance reports; c) View the general dropout data of the university; d) Find the number of canceled credits for student 2; e) Find foreigners who made an external transfer of the physics course in 2020/1; f) Find indigenous students who locked the Environmental Engineering course in 2018/2; g) Finding students of the Administration course dropping out in 2018/1 who entered the University through the PcD PPi, modality with an income ≤ 1.5; h) Find out which department has the highest dropout rate considering the management and technology center; i) Find the course with the second highest dropout rate in the physics department; j) Find the subject with the most disapproval from any professor. The tasks to be carried out on the prototype should vary according to the stakeholder profile performing the validation.

Tables 1 and 2 illustrate the results obtained by this first stakeholder, comparing them to the data collected in the pilot test evaluation.

In general, participants showed ease in performing what was requested, with only partial difficulty being observed in some tasks, which did not prevent them from being carried out. Among the difficulties, there were efforts beyond what was expected to relate a requested task to the information presented in the interface, in addition to confusion between the data of the visualizations, which

Table 1. Results of the **amount of clicks** and unexpected behavior, comparing the values obtained and the expected value.

	Number of clicks				**Unexpected behaviors**		
	P1	P2	P3	Expected	P1	P2	P3
Task a	3	3	3	3	0	0	1
Task b	4	6	2	2	0	0	0
Task c	7	3	3	3	0	0	0
Task d	5	0	0	0	1	0	0
Task e	7	19	9	4	0	0	0
Task f	6	15	13	6	1	1	0
Task g	8	5	15	4	0	0	0
Task h	9	9	5	5	0	0	0
Task i	6	9	5	5	0	0	0
Task j	13	8	14	8	0	0	0

Table 2. Result of the **time** required to carry out the Tasks, comparing the values obtained and the expected value.

	Time			
	P1	P2	P3	Expected
Task a	15s	23s	21s	30s
Task b	40s	34s	23s	1min
Task c	2m3s	1m33s	1m06s	1min
Task d	1m40s	58s	48s	3min
Task e	1m25s	2m06s	1m32s	3min
Task f	42s	2m45ss	1m18s	1m30s
Task g	1m33s	1m42s	2m54s	2m30s
Task h	1m32s	1m47s	1m02s	1min
Task i	1m50s	2m01s	57s	1m30s
Task j	3m11s	2m04s	3m54s	2min

were overcome with a more careful analysis of the system. The participants, however, pointed out several doubts, needs and suggestions for availability in the interfaces of the reports:

1. Specification of the concepts used visually, detailing the meaning of the information;
2. List of students who fit the dropout factors (grade, attendance, credits enrolled, credits canceled);
3. Division of dropout rates into course dropout and institution dropout;
4. Add option to filter data by "Non-scholarship holders" and also select several items, such as: Foreign Scholars;
5. Change the chart of dropout by academic center due to the large amount of information;
6. Differentiate the courses by Graduation Degree (Bachelor's Degree/Bachelor's Degree) and Shift (Night/Afternoon/Day);
7. Correction of some of the used nomenclatures.

During the validation of the reports, it was possible to observe that they were relevant to assist managers in decision making through the different profiles. The collection of requirements through the online questionnaire confirmed the information found in the literature and in the university data mining stage, in addition to highlighting the evasion scenario in the university. The reports developed in prototypes were validated by the main representative of all profiles and had positive results with regard to acceptance, satisfaction and usability requirements.

6 Reports Implementation and Real Usage

After the validation stage, we implemented and made the reports available in the university's management system with minor adjustments, including the issues raised by the participants, which proved to be relevant and significant for the improvement of the system and the effectiveness of the reports.

The technology used in the implementation of the system was the Angular 12[1], a Javascript-based framework maintained by Google, and, for the development of reports, the libraries apexcharts[2] and datatable[3], which cover full chart implementation and table visualization, respectively.

Two formal presentations of the system were made to all stakeholders, including those who participated in data collection and usability tests. Also, during the presentations, new changes and functionalities were suggested, among them: a) List of disciplines and the number of students missing to take it; b) Information on the amount of credits allowed for a student to take in the semester and calculate if it is possible to take the missing credits until the end of the course; c) Expansion of the data view in more academic periods. Suggestion a) is intended to meet a managerial need for the planning of semesters and is indirectly related to dropout, while suggestions b) and c) are features directly linked to improving student monitoring and will be implemented with priority.

In order to collect information related to the use of reports, we implemented the features provided by Google Analytics and Google BigQuery, in order to identify, in practice, the profiles most interested in truancy and also the frequency of access to the system. Among the functionalities, we collect information related to the time spent on the page, information about the profile that requested the report and which report was requested.

The data was collected during the period of September 27, 2021 and January 21, 2022. Table 3 shows the number of page views, number of unique users, average queries per user and the average time spent on the page. Figure 4 shows the distribution of the users' profile, and finally, Figure 5 shows the relationship between the type of information and the number of times in which it was requested.

[1] https://angular.io/
[2] https:/ /apexcharts.com
[3] https://datatables.net

Table 3. Number of views, unique users, average queries per unique user, and average engagement time.

Views	Unique users	Average queries per unique user	Average engagement time
386	110	3,5	3 min 12s

Fig. 4. Unique users profile distribution.

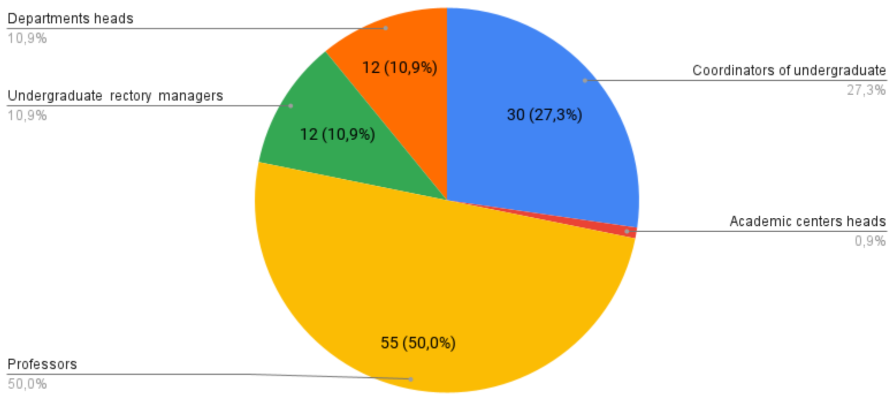
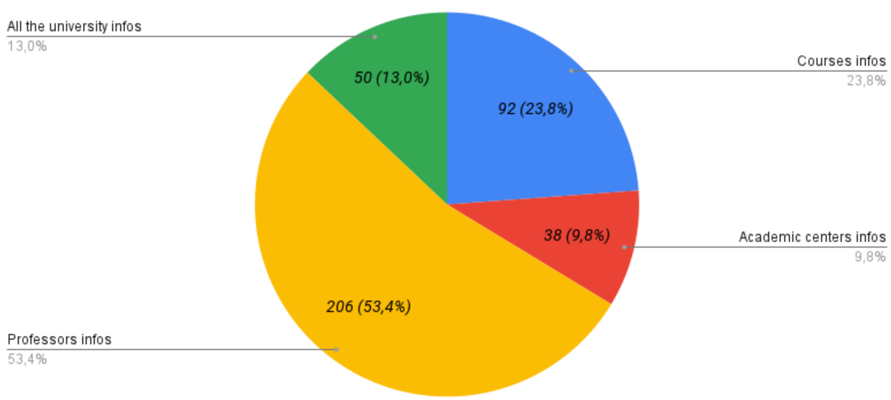


Fig. 5. List of the type of information and the number of queries carried out.



It is observed in Fig. 4 that of the 110 users who consulted the forms, 50% belonged to the professor profile, which was already expected, since this is the category with the largest number of representatives. We had, however, representatives of all categories accessing the reports.

Regarding the type of information researched, Fig 5 illustrates that information from professors was researched 53.4%, information about courses in 23.8% of the time, information from all the university in 13% of the time and information from academic centers in 9.8% of the time.

7 Final Remarks and Future Works

Obtaining, analyzing and providing data related to university dropout is an important step towards understanding the main causes and consequences of this phenomenon, especially to provide support in decision-making by managers of educational institutions.

In this article, issues related to dropout were explored using the collection of data from the academic systems of a public institution, and also, through an online questionnaire about the perception of this phenomenon *versus* the reality of the university. Then, ten reports with data visualizations were implemented to provide information to managers. Finally, a validation of the design of these reports was carried out with three participants who represent the undergraduate pro-rector profile.

We had positive perceptions regarding the use of reports in the dropout combat. That is, to make decisions and carry out more punctual interventions, managers and teachers need, in fact, to have access to information. Once they are available, monitoring becomes more feasible and viable.

Based on the results obtained, it was possible to confirm the empirical evidence from the literature, and the need to identify information on university dropout in the institution where this study was applied, to carry out interventions in all instances. The evaluation carried out encouraged us to continue with the study, considering that the evaluators highlighted the relevance of the work carried out, as well as the quality and importance of the reports made available.

In future works, we intend to analyze the effects of the use of reports in the fight against university dropout. A second stage, in progress, includes creating intervention models to be matched through a gamified computational solution. This solution should support students in the organization and planning of studies. Currently, at the studied university, these interventions are applied manually by an internal university program that welcomes students with difficulties in their academic life. The interventions have been designed and conducted with the support of the program's psychologists and will be evaluated together with the authors of this project.

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