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Modeling the Quantification of Engineering Students' Academic Performance and its Association to Dropout Rates*

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The academic performance of most engineering students has been unsatisfactory in math and physics courses. This work proposes the construction of a measurement for evaluating students' academic performance based on grades and numbers of failures, associating this performance measurement to dropout percentages. This performance measurement proposed in this study aims to identify and track students who perform poorly in the initial semesters in order to monitor them during the program. The performances of 1622 students in math and physics courses in the first two years of engineering programs were analyzed. Daytime programs analyzed were: Civil Engineering, Electrical Engineering, Mechanical Engineering, Mining Engineering, Chemical Engineering, and Sanitary and Environmental Engineering. Evening programs were: Production Engineering, Computer Engineering, and Control and Automation Engineering. Descriptive analyses of the data, Spearman correlation tests, Mann-Whitney tests and Poisson regression models were performed. Results obtained showed an association between the proposed performance measurement and the students' entrance and exit forms in the programs. It was found that the majority of students performance below median in mathematics and physics courses. There was an inversely proportional relationship between the performance measurement and dropout levels, and higher risks for dropout in the first two performance quartiles, which are the lowest. The analysis based on the Generalized Linear Model, using Poisson regression, presented consistent and statistically significant estimates of relative risk. These analyses indicate that students with the lowest performances in the Analytical Geometry, Calculus I, Calculus II, and General and Experimental Physics I E courses are twice as likely to drop out of engineering courses when compared to students with higher performances.

Keywords: performance measurement; dropout risk; basic cycle; Poisson regression

1. Introduction

Monitoring performance with a view to evaluating proposals and assisting in decision-making constitutes a useful approach in process evaluation initiatives. Indicators make it possible to monitor performance through established factors, permitting adjustments that allow control and improvement of the objectives specified by public or private institutions. In the United States and the United Kingdom, the allocation of resources to government departments is associated to sector performance within each department [1], even in the health area, where resources are allocated according to the risks attributed to each disease [2]. In some European countries, performance in various public service systems is assessed based on meritocracy, and studies have shown an association between meritocracy and development [3].

Regarding educational institutions, the discussion of academic performance evaluation through indicators has evolved considerably in the last decades, as it is seen that they can provide quality information with respect to both student qualification and institutional ability. Evaluating the performance of educational institutions serves to improve managerial and academic performance, enhancing the quality of institutional practices. In the United Kingdom, the education sector has been heavily monitored since the Education Reform Act of 1988. This monitoring is designed to provide information on each school's performance for the benefit of parents, based on tests done with students, and to create an incentive for improving the schools' educational levels [1]. In England, a public-school performance assessment system based on testing students and observing classroom instruction helps to rank well performing and poorly performing schools. The tests are applied during inspection, and after a time the inspectors return to apply new

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tests in order to check whether there has been any improvement in performance. The results of the schools' performance are reported on the internet [4]. In North Carolina, in the Charlotte-Mecklenburg district, the disclosure of public schools' performance evaluation test scores enables parents to choose higher performing schools for their children. Choosing schools with better results will allow economically disadvantaged students to improve their academic performance by attending schools with a higher academic performance. This method puts pressure on schools that are considered underperforming to adopt strategies in order not to lose their students, which would entail class closures [5]. The researchers found that students who attended a school with a higher performance score increased their own test scores.

2. Evaluation of Academic Performance in Higher Education

One of the higher education evaluation processes in Brazil, of nationwide scope, is the National Higher Education Evaluation System (NHEES), which was created to guide higher education institutions and to form a basis for public policies. NHEES analyzes various aspects of the institution, its programs and the performance of its students [6]. This system aggregates information from the National Student Performance Examination (NSPE), institutional assessments and programs. Average performance scores of incoming students and graduating students obtained from the results of the NSPE test are the direct indicators. It is assumed that students with good academic performance are more likely to perform well on the NSPE, which functions as an indicator for assessing federal Higher Education Institution (HEI). It has been found over time that indicators in Brazil are used to support the evaluation of HEIs that possess indicators based on the success of students.

Between 2006 and 2016, there was a 62.8% increase in enrollments in Brazilian HEIs. The increase was on the order of 66.8% in the private network and 59.0% in the public network [7]. However, these students have shown an unsatisfactory overall performance in their chosen programs. Due to this low performance, the graduation rate has dropped and retention and dropout rates have increased over time [8].

Different performance evaluation measurements are applied to higher education institutions inside and outside Brazil. In other countries, authors such as Ramsden [9] discuss the evaluation of quality in higher education, based on the opinions of students in different programs in Australia. These opinions are collected by means of a questionnaire with items relating to students' overall satisfaction with their classes, their teachers, or with the institution. According to the author, several instruments for evaluating faculty performance have been constructed by HEIs, but the difference between these instruments makes them incomparable. According to the author, in many HEIs the tests given to students often do not aim to evaluate student performance and satisfaction with the HEI, but rather to evaluate teacher performance. Ramsden proposed a new version of the Program Experience Questionnaire (CEQ), which was reduced from 80 to 57 items. He concluded that there is evidence for the questionnaire being a valid instrument for performance assessment, useful for diagnostic purposes within universities and colleges. The evaluation of an institution's performance based on student-related information was also observed in the work of Johnes [10], conducted in the United Kingdom. In his study, the author performs a survey of the work done in universities in the last decade, prior to his research, and verifies the possibility of new research studies being conducted based on this work. The survey considered studies dealing with three types of performance indicators for the institution: graduation quality (the percentage of students graduating with honors), student difficulty (academic difficulties, lack of interest in the program, among others) and research productivity. Johnes [10] also emphasizes the entrance form of qualified students as a measure of institutional performance. Draper and Gittoes [11], took a different approach from that of Johnes [10], comparing indicators through statistical analysis based on hierarchical modeling with fixed effects, used institutional and student-related variables. The authors report that the United Kingdom has invested in the creation of institutional performance indicators in the public sector, more intensely so in the areas of education and health, aiming in particular at enhancing the reliability of the data to be provided.

In the context of public higher education in the United States, mention is made of the study developed by Rutherford and Rutherford [12], who proposed to evaluate the efficiency of financing policy performance as a way to improve graduation rate, persistence and student success. The authors used data from five hundred institutions in fifty states, obtained from the database of the Integrated Postsecondary Education Data System (IPEDS), where the need for adjusting approaches to measuring and monitoring students' academic progress could be seen. They also report that policymakers for quality in higher education in the United States have required universities to be held accountable for their performance, formally linking institutional funding to indicators that track student success. This is due to the fact that in traditional budget arrangements, universities do not show much interest in students' results, prioritizing postgraduate programs, research productivity and the construction of new facilities.

In research on success or performance where student assessment is the main focus, and not part of an institutional evaluation, we can cite the works of Vogt [13], Carstens and Fletcher [14], Palmer [15], Freemana et al. [16], McCool et al. [17], Ayalp [18], Laugerman et al. [19], and Dukhan and Brenner [20]. In his study of data from four universities, Vogt [13] produced a paper measuring the achievement of academic integration or remoteness from faculty on self-efficacy, academic confidence, learning behaviors, critical thinking, seeking help, peer learning, and the Grade Point Average (GPA), which measures performance. The sample consisted of first-year students, with 30% of the sample drawn from campus engineering organizations such as the Institute of Electronic and Electrical Engineers (IEEE) and the Society of Engineers (SWE), and the remainder from four research universities on the West Coast. Vogt [13] cites works that hold that classroom dynamics can influence students' persistence or academic disposition, in the sense of supporting the effort required for these students to excel in the subjects taught. The results confirmed the effects of academic integration or distance from faculty on students' self-assessment, learning behaviors, and academic performance, with a better teacher-student relationship being required.

In the Carstens and Fletcher study [14], students in the second-year History program at University of Pretoria's Faculty of Human Sciences participated in an intervention project to improve writing skills over a period of 14 weeks. Students' academic writing skills were evaluated by means of tests, to which the students responded in a positive fashion. These tests were applied before and after the intervention, then compared, and a significant improvement in performance was observed. Palmer [15] conducted a study to assess the academic performance of engineering students enrolled in sophomore classes. The study was conducted on 132 students enrolled in an entirely online course offered by the Deakin University School of Engineering in Australia. The author used the binary logistic regression model to associate student success status to some possibly related factors. Student success status was determined from the final grade in the unit and was seen to be associated to the course enrollment modality, previous academic performance, and the date of first access to the system. A meta-analysis was performed by Freemana et al. [16] with data collected between June 1998 and January 2010, aggregating 225 studies that compared students' performance in traditional versus active learning subjects (when students construct their own comprehension). One hundred and fifty-eight studies that dealt with active learning and sixty-seven that dealt with traditional learning in undergraduate programs in Science, Technology, Engineering and Mathematics (STEM) were analyzed. Student performance in these studies was identified by scores on identical or equivalent exams, or by the failure rate. As a result, the authors found that, on average, students in subjects using traditional learning are 1.5 times more likely to fail than students in subjects using active learning. The average failure rates were 21.8% in active learning versus 33.8% in traditional classes, showing the importance of the active learning method. In Ireland, McCool et al. [17] conducted a study with students enrolled in engineering modules to analyze some possible factors that might interfere with their academic performance. A total of 1263 students enrolled in different disciplines at the Dundalk Institute of Technology between 2010 and 2014 were evaluated. The authors used descriptive statistical analysis and multiple regression models to examine the influence of age, class attendance, grades, class size, and semester and year of study on student performance. McCool et al. [17] found a statistically significant association between academic performance and age, modules with practical classes, and class attendance. In his work with undergraduate students of the Civil Engineering program, Ayalp [18] analyzed the relationships between student learning approaches and success in construction management courses. Third- and fourth-year Civil Engineering students participated in the study during the 2013–2014 academic period at the Universities of Zirve, Gaziantep and Çukurova, located in Turkey. In order to identify learning approaches, the author used the Revised Two-Factor Study Process Questionnaire (R-SPQ-2F). According to Ayalp [18], the study analyses indicated that a deeper approach and deeper strategies in the learning process were preferred by Civil Engineering students. Moderate correlations were found between the type of learning approach and age and the year of study, and a moderate correlation between the type of learning approach and success in the construction management course. Laugerman et al. [19] conducted a study on transfer students from Community College (CC) who completed the Basic Program (BP) in engineering. Two groups of students were assessed according to their university admission status: 10,441 were admitted directly from high school and 1,191 were transferred from state Community Colleges. The study took into consideration students who were admitted to the College of Engineering (CoE) of a large Midwestern University between 2002 and 2005. The study reports student achievement levels using academic variables, which maximize their chances of success in engineering. The authors found as a result that the two most influential predictors of graduation in engineering are the University's overall Grade Point Average (GPA) (after transferring) and the number of transferred CC credits, which were applied to the core courses (BP) in engineering. Even very small increases in GPA have significant effects on increasing graduation rates in engineering. In research carried out on the African continent, Dukhan and Brenner [20] performed a study whose objective was to compare, based on grades, the performance of first-year biology students at a South African university, some of whom had English as first language and some whose second language was English. Unsatisfactory performance of the latter is usually attributed to limited language proficiency and reading ability. Data was collected through the analysis of records of studies conducted in the English language – permitting an evaluation of students' comprehension and writing – and subsequent comparison of the grades obtained. After the intervention to improve the reading and writing of students whose second language is English was carried out, performance assessed through grades improved considerably, indicating the existing relationship between reading proficiency and grades.

From the works presented, it can be seen that there are currently several performance indicators that assess higher education institutions, and consequently their programs, but there is no standard indicator for assessing a student's performance over the duration of their program of study, nor is there a standard indicator for assessing institutional performance. Factors such as acceptance into their first-choice program and entrance exam score can help determine students' academic success in the program but are not sufficient. Once inserted in the institution, the student's performance in each period may be evaluated in the most common and traditional manner, which is through the grade obtained in the component studied, or by evaluating the student's mode of leaving the institution: either obtaining a diploma or dropping out. Students with low academic performance generally do not complete a program in the average time established and do not take all the courses required in each semester, when they do not fail in courses at least once.

Thus, assessing academic performance is a means of quantifying the student's degree of learning and can help determine the quality of programs and, consequently, of the institution [8]. Students' academic performance reflects directly on institutional performance evaluations, since it is always inserted in the various methods of HEI evaluation, being part of this process. The government of any country that values quality education wishes its HEIs to meet the standards necessary for achieving such an education. The academic performance of students in a program directly influences graduation and dropout rates, which in many countries are used to allocate resources to institutions. Thus, indicators that help to measure students' academic performance in order to identify those who are about to drop out are an important part of the process of students' remaining enrolled in the initial semesters. Thus, this paper aims to present a measurement for quantifying students' academic performance based on final grade and number of times the component was studied. The performance measurement proposed in this study aims to identify and track students who perform poorly in the initial semesters in order to monitor them during the program. Once student performance is quantified and given a value in the category representing a dropout risk, the at-risk students can be directed to receive monitoring, tutoring, learning support or other projects developed by the programs coordinators which aim to convey a better understanding of the component contents. This student monitoring would contribute to the increase in graduation rates and the consequent reduction in dropout rates in engineering programs, given that up to 40% of engineering students drop out in their first year of study [15].

In order to quantify performance, this work adopted 1st – and 2nd – semester courses of the basic cycle, as studies show that many students present learning difficulties in some courses in the initial semesters. In a study of several programs at the State University of South Africa, Dennis and Murray [21], discuss the need for an introductory mathematics class in first year in programs actuarial sciences, engineering and mathematics, in order to raise students' success rate in math courses.

3. Materials and Method

In order to analyze and validate the proposed performance measurement, we will use information from a database of engineering students in daytime and evening programs at the Polytechnic School of the Federal University of Bahia (UFBA). UFBA is a free public higher education institution which increased its enrollment starting in 2008, through a national policy of expanding public higher education in Brazil by making more openings available to students. Daytime programs analyzed were: Civil Engineering, Electrical Engineering, Mechanical Engineering, Mining Engineering, Chemical Engineering, and Sanitary and Environmental Engineering. Evening programs were: Production Engineering, Computer Engineering, and Control and Automation Engineering. Data on 1622 students who left their programs between 2009 and 2016 were examined, with exit forms classified as follows: Graduation (graduates or those awaiting graduation), Voluntary Abandonment (withdrawal or dropout, change of program or transfer) and Exclusion for Unsatisfactory Performance (overstaying the maximum duration of the program, denial of enrollment due to failure in all courses, and denial of enrollment due to failure in the same course more than four times). The dropout variable was constructed based on voluntary abandonment of the program and on exclusion owing to poor performance.

The data were obtained from the Academic System (SIAC) – UFBA's computerized enrollment management system. They were extracted from the lists of students classified by form of entrance and form of exit, and from school records. The data were treated using SPSS (Statistical Package for the Social Sciences), version 20, and R Studio, version 1.0.143. Descriptive analyses of the data, Spearman correlation tests, Mann-Whitney tests and Poisson regression models were performed. The quartiles chart was constructed based on the quartiles of the proposed academic performance measurement obtained in each program, analyzing the math and physics courses common to all the programs evaluated. In order to calculate the dropout probabilities showing performance in the quartile strata found, the Bayes theorem and 95% confidence intervals were used. Chen et al. [22] named the latter confidence intervals with guaranteed coverage probability, built for binomial distribution.

Studies show that calculus, physics are considered high predictors of failure in engineering programs [19, 23]. Thus, to calculate the proposed performance measurement, only the mathematics and physics courses were considered in this study, as they presented high failure rates in the basic cycle. In the first – and second-semester courses common to all the programs evaluated, a measurement was obtained from the arithmetic mean of the performance measurement of each course constructed in isolation. The mathematics and physics courses considered in the general measurement were: Analytical Geometry, Calculus I, Calculus II, and General and Experimental Physics I E.

The evaluated variables were the grades and failures in the courses, and the existing forms of entrance into and exit from programs in the evaluated period.

3.1 Measure of Proposed Academic Performance

There are a number of factors that can affect a student's performance, but when it comes to academic factors passing in the courses is an incentive for the student to remain in the program, mainly in the first two years. Measuring learning level is a way of evaluating student performance. The grades or GPA are important indicator of performance, often used to measure the degree of student knowledge in a course or program [13, 24]. Although grades are one of the most commonly used indicators for assessing student performance, other indicators such as classroom participation and number of failures in courses are also widely used. The number of failures in a course is an important indicator, since it turns out that the greater the number of failures, the greater the indication of poor performance. Students' learning level and degree of involvement with the program are considered factors that can affect their academic performance and lead them to abandon their program of study. Studies such as that done by Nicholls and Nolfe [25] show that students with better performance are more likely to complete their programs.

In terms of academic factors, although grades are an important indicator for measuring student performance, assessing academic performance based on grades alone may not reflect whether the student presented difficulties in learning the content of a given course, since they may have obtained a satisfactory grade only after one or more failures in the course. Failure can be an indication that the student experienced difficulties during the period in which they studied the course, which may have occurred due to a lack of understanding of classroom content, or to other factors.

In order to strengthen two important indicators, a measurement for academic performance is proposed here as a way to assist in monitoring and evaluating student performance during a program. This measurement is based on the final grade obtained in the component in the last semester attended and the number of times the student enrolled in the component. In order to use the formula, the final grade obtained in the component must range from zero to ten (Equation (1)). The measurement created indicates poor student performance in the course the closer its value is to zero, and good student performance in the course the closer its value is to one (Fig. 1). This formula can be applied to any course that has numerical information on grades and failures.

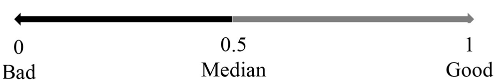

Fig. 1. Illustrative scale of performance measurement.

The performance measurement is given by Equation (1):

$$I_{CA} = \frac{\text{Nfinal}}{10 \times Rp_{CA}} \quad (1)$$

in which:

I_{CA}: is the measurement of performance in course A;

Nfinal: is the final grade obtained in component A, with absolute values between zero and ten;

Rp_{CA}: is the number of times the student studied component A.

A student may be monitored by the faculty member who teaches the component in each unit, based on the grades obtained by the student during the semester. The teacher may choose to intensify work on the component content with students who show poor grades in the units, in order to try to reverse possible failures. This individual monitoring in the classroom usually does not take place, however, due to the high demands on teachers. Thus, the college, which values the academic success of all students, can carry out this monitoring at the end of the semester, so as to follow the trajectory of students in the course. The performance measurement used in this work can assist program coordinators in this monitoring every semester, when it signals students who are in the low performance risk range. Knowing the semesters' average grades recorded in the academic system and the number of times the student attended each component, coordinators can easily calculate the performance measurement used in this work. Identifying underperforming students can prevent potential dropout, as program coordinators are able to refer students to activities that can improve the learning process, such as learning support, tutorials, and monitoring. Fig. 2 shows, through a spreadsheet, an example of how students can be monitored. The identification and monitoring of underperforming students in the 1st semester of the program (students 3, 4 and 7) could prevent new failures in the following semesters.

Fig. 3 shows the secondary axis graph of the ordinate, which presents values from two data groups in parallel. The figure presents an example of performance in the Experimental Physics I course for four Civil Engineering students (identified by the numbering 1 to 4 on the abscissa axis), and compares final grade information obtained by these students in physics (major axis of ordinate) with information on the performance measurement of these students in physics (secondary axis of the

1	A	B	C	D	E	F	G
2	**Name**	**1st semester**	**Ica**	**2nd semester**	**Ica**	**3rd semester**	**Ica**
3	Student 1	8.8	0.9	....		....	
4	Student 2	7.0	0.7	....		....	
5	Student 3	1.8	**0.2**	1.8	**0.1**	5.5	0.2
6	Student 4	1.5	**0.2**	0.0	**0.0**	7.0	0.2
7	Student 5	7.6	0.8	....		....	
8	Student 6	7.0	0.7	....		....	
9	Student 7	0.0	**0.0**	0.1	**0.0**	2.0	**0.1**

Fig. 2. Semester monitoring of student performance in calculus I.

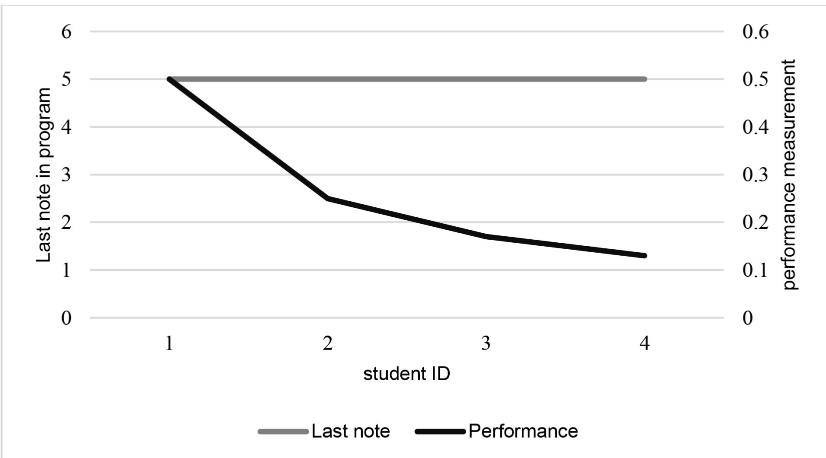

Fig. 3. Comparison between grades and the performance measurement.

ordinate). When considering only the final grade obtained in the course, it can be seen that the four students presented the same performance in Physics I, evaluated by the grade 5 which all of them obtained. Assessing the value of the performance measurement for each student, we find that their performance in Experimental Physics I is not the same. Student n° 1's degree of learning can be seen to be superior to that of the other students, because the content he assimilated in physics allowed him to be successful the first time he attended the course. The other students failed in the course at least once, which can serve as a discouraging factor in regard to remaining in the program.

3.2 Generalized Linear Model

The adjustment of the academic performance measurement associated to dropout will be realized through a Generalized Linear Model (GLM). GLMs are an extension of the classical regression models formed by the union of linear and nonlinear models. They present a random part of the model (response variable) belonging to the exponential family of distributions involving distributions such as normal, inverse normal, gamma, binomial, negative binomial, and Poisson, among others. The GLM's systematic part is formed by the explanatory variables. The model's link function is responsible for linking the random part and the systematic part [26, 27].

In the present study, a log-linear model involving the Poisson distribution was used. The log-linear model is applied in the analysis of count data in contingency tables, but studies show the efficiency of Poisson models for binary data in the consistent estimates of relative risks, through Poisson regression with a robust error variance, which guarantees validity in the presence or absence of heteroscedasticity [28].

Consider $x_i, i = 1, 2 \ldots, n$, assuming two possible values: 1, if exposed to the problem, and 0 if not exposed to the problem. Consider that individual i poses a risk that is a function of $x_i, \pi(x_i)$.

Since $\pi(x_i)$ is a positive value, the logarithm of the link function is a natural choice to model $\pi(x_i)$, given by Equation (2):

$$\log[\pi(x_i)] = \alpha + \beta x_i. \tag{2}$$

The exponential of $\beta(\exp(\beta))$ is Relative Risk (RR). Assuming that the response variable y_i has Poisson distribution, log-likelihood is given by Equation (3):

$$l(\alpha, \beta) = C \sum_{i=1}^{n} [y_i(\alpha + \beta x_i) - \exp(\alpha + \beta x_i)], \tag{3}$$

where C is a constant.

Applying the standard likelihood theory, we have the estimates Equation (4) and Equation (5):

$$\exp(\hat{\alpha}) = \frac{c}{n_0}, \tag{4}$$

$$\widehat{RR} = \exp(\hat{\beta}) = \frac{an_0}{cn_1}. \tag{5}$$

The variance of $\widehat{RR}$ consistently estimated after correction is given by Equation (6):

$$\widehat{var}(\widehat{RR}) = \frac{1}{a} - \frac{1}{n_1} + \frac{1}{c} - \frac{1}{n_0}. \tag{6}$$

in which a is the number of individuals where the event of interest occurred (dropout) and exposed to it (performance below Q_i), c is the number of individuals where the event of interest occurred (dropout) and not exposed (performance above Q_i), n_0 total number of individuals exposed to the problem and n_1 total of individuals not exposed to the problem. The Poisson regression model will help measure the impact that students' performance has on their decision to leave a program, considering their failure in basic-cycle courses.

4. Results and Discussion

A descriptive analysis of the performance measurements will be presented for each program, in order to show the variability in performance among students of the programs evaluated. The program showing lowest performance (Computer Engineering), the program showing highest performance (Chemical Engineering) and the program showing intermediate performance (Civil Engineering) were selected in order to prove the validity of the proposed performance measurement's probability estimates. This ensures heterogeneity in the validation database as regards student performance measurement values, avoiding bias in estimates. The Poisson regression model, which relates the performance quartiles to dropout, will consider the database unstratified by program, as student performance in the mathematics and physics courses did not vary significantly among students in the same program.

Table 1 shows the medians (Q2 or Md) of the performance measurement for each program, with the respective limits formed by quartiles 1 (Q1) and quartiles 3 (Q3). The proposed performance measurement was calculated based on first- and second-semester mathematics and physics courses common to all program evaluated. The figures presented include students who left programs through graduation, dropout or exclusion. In the point estimates of the quartiles whose values were zero, there were a large number of dropouts or excluded

Table 1. Performance measurement quartiles of the 1st- and 2nd-semester mathematics and physics courses common to all programs

Programs	Md	[Q1; Q3]	P-value*	P-value**
Day				
Civil Engineering	0.582	[0.220; 0.745]	0.014	–
Electrical Engineering	0.637	[0.198; 0.783]	0.028	–
Mechanical Engineering	0.688	[0.408; 0.799]	0.028	–
Mining Engineering	0.498	[0.024; 0.676]	0.029	0.023
Chemical Engineering	0.733	[0.608; 0.843]	–	–
Sanitary and Environmental Engineering	0.485	[0.121; 0.730]	0.042	–
Night				
Control Engineering and Automation	0.430	[0.000; 0.690]	0.035	–
Computing Engineering	0.290	[0.000; 0.592]	0.028	0.028
Production Engineering	0.566	[0.000; 0.740]	0.029	–

* Significance of the Mann-Whitney test for the Chemical Engineering program in relation to the other programs with a significance level of 5%.
** Significance of the Mann-Whitney test for the Production Engineering Program in relation to the other programs with a significance level of 5%.

students. In the case of these exit forms, the grades generally attributed to the courses are null because students usually drop out before the end of the semester, which results in performance measurement values equal to zero. The evening programs had the worst performances compared to daytime programs, with the exception of the Production Engineering program. One of the reasons for the underperformance of evening students is the need for these students to work during the day, which reduces their studying time. The Mann-Whitney test was applied in order to evaluate the equality of the performance measurement's medians among programs. There was a statistically significant difference of 5% between the Chemical Engineering program (which presented the highest performances) and all other programs. There was also a significant difference between the Production Engineering program and the Computing and Mining Engineering programs. The evaluation of the performance measurement among programs shows that there are different student learning levels in the programs. The results show that the Chemical Engineering students present the best performances of all the other evaluated programs. Candidates' demand for a spot in this program is high, which means that candidates with higher scores pass the entrance exam. Fig. 4 was constructed with the values of each quartile for all programs, with the left vertical bar being Q1, the points the median or Q2, and the right vertical bar Q3. Comparing the bars allows better apprehension of the differences and similarities between programs in relation to student performance in the basic-cycle mathematics and physics courses. There is great variability in student performance in almost all the programs with greater dispersion between Q1 and Q2, than between Q2 and Q3. We draw attention to the Chemical Engineering program, whose lowest performance quartile is above the median of the

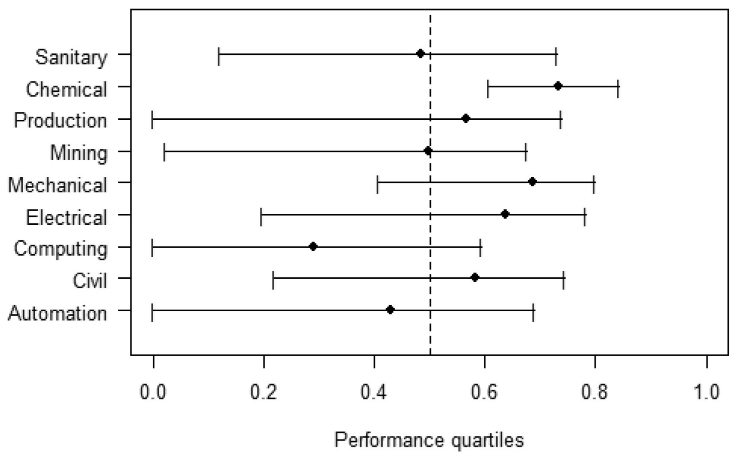

Fig. 4. Performance quartiles per programs.

Table 2. Percentage distribution of the students' exit forms, according to the intervals of the performance measurement quartiles

Quartiles Intervals	Automation (%)			Civil (%)			Computing (%)		
	G	A	E	G	A	E	G	A	E
< Q1	0.0	38.7	8.3	0.0	53.4	47.4	0.0	30.2	21.9
Q1 |- Q2	0.0	22.6	58.3	20.5	28.1	36.8	0.0	21.9	43.8
Q2 |- Q3	29.4	24.2	25.0	38.6	10.3	10.5	0.0	29.2	18.8
>= Q3	70.6	14.5	8.3	40.9	8.2	5.3	100.0	18.8	15.6
Quartiles Intervals	**Electrical (%)**			**Mechanical (%)**			**Mining (%)**		
	G	A	E	G	A	E	G	A	E
< Q1	0.0	38.4	41.5	0.9	48.2	46.2	0.0	35.6	16.7
Q1 |- Q2	7.1	37.5	29.3	18.9	30.6	34.6	5.9	27.8	58.3
Q2 |- Q3	42.4	15.2	14.6	37.7	11.8	15.4	35.3	23.3	8.3
>= Q3	50.6	8.9	14.6	42.5	9.4	3.8	58.8	13.3	16.7
Quartiles Intervals	**Production (%)**			**Chemical (%)**			**Sanitary (%)**		
	G	A	E	G	A	E	G	A	E
< Q1	0.0	64.3	25.0	6.4	45.8	52.4	0.0	34.7	45.5
Q1 |- Q2	12.1	17.9	45.0	25.5	23.6	28.6	6.2	32.0	45.5
Q2 |- Q3	37.9	12.5	25.0	34.5	15.3	14.3	39.6	21.3	4.5
>= Q3	50.0	5.4	5.0	33.6	15.3	4.8	54.2	12.0	4.5

G: graduated; A: abandonment; E: exclusion.

graphic axis and has much lower variability than the other programs. Evening programs, in addition to the Mining Engineering and Sanitary and Environmental Engineering programs, present greater variability in student performance, which shows that they have very heterogeneous students as regards the degree of learning.

The percentage distribution of student exit forms according to the intervals of the performance measurement quartiles is shown in Table 2. Quartile intervals were obtained according to the point values of the performance measure quartiles presented in Table 1 for each program. It is important to note that each quartile range contains about 25% of the students who left their programs, and that the percentages were obtained for each exit form separately. A direct relationship is seen between the performance quartile intervals and the percentage of graduates in all programs evaluated – in other words, the higher the performance, the higher the proportion of graduates. This relationship can be verified through the Spearman correlation test (not presented in the table), which showed a positive and significant correlation for all programs, at a significance level of 5%, between the courses' performance measurement quartiles and graduation. The proportion of graduated students performing below the 1st quartile value in the engineering programs evaluated is less than 1%, with the exception of the Chemical Engineering program. This indicates that students with performance values in the 1st quartile must be quickly identified so that the possibility of dropping out of the program is mitigated.

An inverse relationship can be observed between quartile intervals and the percentages of students who dropped out or were excluded for poor performance. The first two performance quartiles hold the highest percentages of these two forms of exit from programs. We see that in almost all the programs more than 60% of students who were excluded or left presented a performance inferior to the median performance measurement value for the program. The Spearman correlation test applied to the performance measurement quartiles and the exit forms of exit by abandonment and exclusion showed a negative and significant correlation, at a significance level of 5%, except for the Automation Engineering and Computer Engineering evening programs, where no statistical significance was observed. Projects to improve these students' learning in the Calculus and Physics courses in the initial years can reduce dropout and exclusion rates in engineering programs.

The overall dropout percentage, considering students who dropped out of programs on a voluntary basis and students who were excluded for poor performance, is presented in Fig. 5 with intervals at a confidence level of 95%. We find that the percentage of students who dropped out from programs with a performance measurement below the first quartile is almost 4 times higher than the percentage of students who dropped out with a

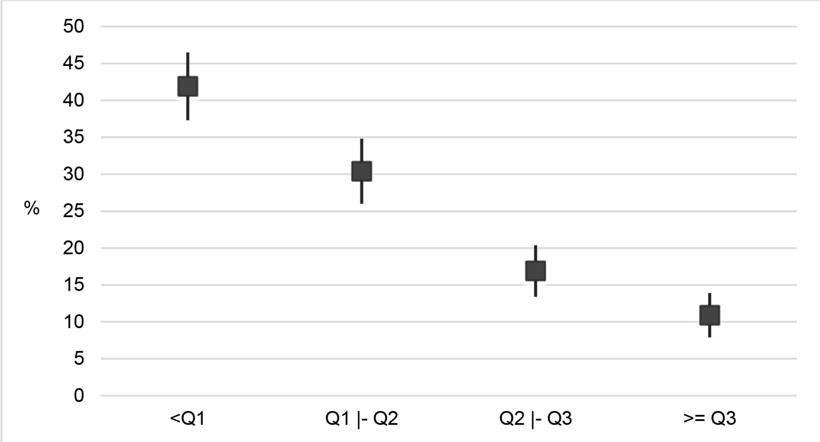

Fig. 5. Overall dropout percentage of student per quartile of performance measurement.

performance measurement greater than or equal to the third quartile. Between 37% and 47% of students who left without graduating presented very low performance in the mathematics and physics courses. An inverse and statistically significant relation (p-value <0.001 – Spearman Correlation) is found between the percentages of dropout and the quartiles of the performance measurement, ratifying the stratified data by program which were presented previously and the results found in other works. This indicates that for programs containing students with different levels of knowledge, the probability of dropout for students experiencing greater difficulty is much higher.

Three programs were selected in order to evaluate the estimated probabilities of student dropout according to the performances obtained through the proposed measurement. The total number of students in each program was divided into two samples, one containing between 65% and 70% of the students, that was used to calculate probabilities, and the other, varying between 30% and 35%, that was used for validation of the results obtained. Validation is performed in order to make sure that the results obtained through the estimates approximate the observed results, evaluating the results' statistical stability. Probabilities were estimated through the Bayes' theorem and the 95% confidence intervals by the formula for non-normal samples developed by Chen et al. [22], called a confidence interval with guaranteed coverage probability. Table 3 presents the results of the conditional probabilities of students dropping out, considering that performance is found in each quartile interval determined for the Automation Engineering, Civil Engineering and Chemical Engineering programs. In all programs, we see that the probabilities of dropout obtained in the validation banks, considering the quartiles of the performance measurement, are within the estimated 95% confidence intervals, with the exception of the third stratum for Civil Engineering and the fourth stratum for Chemical Engineering. This indicates consistent estimates of the estimated probabilities of dropout, considering the proposed performance measure. In the programs under consideration, the probability of students with above median performance (Q2 or Q3) is less than 0.2 (20%).

Table 3. Estimated (Pr) and observed (Pr*) probabilities of dropout levels considering the performance measurement quartiles

Condition	**Programs**					
	Automation		**Civil**		**Chemical**	
	Pr[IC95%]	**Pr***	**Pr[IC95%]**	**Pr***	**Pr[IC95%]**	**Pr***
< Q1 / Dropout	0.306 [0.193; 0.436]	0.273	0.541 [0.485; 0.596]	0.506	0.503 [0.434; 0.571]	0.458
Q1|-Q2 / Dropout	0.306 [0.193; 0.436]	0.318	0.314 [0.263; 0.367]	0.303	0.243 [0.188; 0.305]	0.208
Q2|-Q3 / Dropout	0.245 [0.143; 0.370]	0.273	0.081 [0.054; 0.115]	0.124	0.151 [0.107; 0.205]	0.167
> Q3 / Dropout	0.144 [0.066; 0.254]	0.136	0.065 [0.041; 0.096]	0.067	0.103 [0.066; 0.149]	0.167

* Probabilities of dropout in each quartile interval obtained in the validation bank.

Table 4. Poisson regression GLM of dropout according to performance measurement quartiles

Quartiles intervals	RR IC Wald 95%	Standard error	P-value
< Q1	2.084 [1.964; 2.212]	0.030	< 0.001
Q1 |- Q2	1.331 [1.236; 1.434]	0.038	< 0.001
Q2 |- Q3	0.610 [0.541; 0.688]	0.061	< 0.001
>= Q3	0.373 [0.317; 0.439]	0.082	< 0.001

Table 4 presents the Poisson regression GLMs applied in order to quantify the impact, through relative risk (RR), that students' performance in basic-cycle math and physics courses had on their decision to drop out. The proposed performance measurement was stratified into four intervals considering the quartiles for all programs. We decided to use a single model for all the programs put together, given that the general results were similar in the analysis of results by program, with greater risks for the first two performance quartiles. In analyzing each quartile interval separately, we can see that students with performance measurements lower than the first quartile present a 2.1 – fold greater risk of dropout than students with a performance above the first quartile. The risk decreases somewhat for students who had a performance measurement between the first and second quartiles, being 1.3 times higher than for the other students. For students with performance measurements above the second quartile, there was a 39% reduction in dropout risk for those performing between the second and third quartiles, and 63% for those performing above the third quartile. This indicates that the major concern of engineering programs administrators should be with students who achieve performance values in the first two quartiles. Underperforming students should be referred for follow-up monitoring or reinforcement in programs in order to correct possible learning disabilities.

5. Conclusion

The proposed academic performance measurement stratified by quartiles, created from the combination of the student's number of times attended the same course and final grade, proved to be efficient in identifying and quantification the risk ranges of students who have difficulty in assimilating the contents of the math and physics courses in the first semesters. The results found in this paper confirm statements made in other studies, relating the risk of dropout to poor performance. This study, however, adds the possibility of measuring the risk through the calculation of probabilities and RR measurements. This information enables programs administrators to immediately identify underperforming students, making it possible to referring them for monitoring in projects such as school reinforcement courses, tutoring by teachers or peer tutoring, aimed at correcting possible learning disabilities.

Dropout probabilities estimated according to performance, calculated using the Bayes theorem, proved to be effective through the validation of their estimates by the approximation to the observed probabilities, attesting to the statistical stability of the results. These results provide the estimated percentages of dropout that may occur in each programs, and students are ranked by performance quartile.

The analysis based on the Generalized Linear Model, using Poisson regression, presented consistent and statistically significant estimates of relative risk. These analyses indicate that students with the lowest performances in the Analytical Geometry, Calculus I, Calculus II, and General and Experimental Physics I E courses are twice as likely to drop out of engineering programs when compared to students with higher performances.

This proposed measurement of academic performance can also serve as an alert for the problem of students' length of stay in programs, as it was calculated based on grades and the number of times students studied the component. High percentages of underperforming students indicate that many of the students received low grades and/or failed at least once in the component, impacting programs completion time.

The measurement of performance academic of students proposed here does not invalidate researchers' use of grade and number of failures indicators, but increases the efficiency of these indicators in identifying students who are not succeeding, due to learning difficulties in specific courses. The process of early identifying students who are in the ranges at risk for dropout can help program coordinators to undertake more intensive monitoring. The early identification of probable dropouts can prevent their departure, raising the probability of graduating students in engineering programs.

The performance measurement proposed here is easy to calculate and understand, and its methodology can be applied to any course of any program.

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