Assessment academic performance in online courses: a multivariate model

Avaliação de desempenho acadêmico em cursos online: um modelo multivariado

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ABSTRACT

Grades and other student academic indicators are the most evaluated parameters in studies about teaching and learning. However, several authors point out that these indexes, alone, are not enough to explain the students' performance. To understand the predictors that facilitate or compromise learning in higher education, it is necessary to consider other variables related to students, teachers, and the teaching context. Thus, this paper presents a multivariate model for assessing student performance in online courses. The model was tested in the context of the COVID-19 pandemic with undergraduate students in Engineering. The course was Calculus 2. Data were analyzed using multivariate statistical analysis techniques. Among the 10 variables tested in the model. Three variables were significant and showed that the students' performance in Calculus 2 was impacted by: family income, cognitive and self-regulatory learning strategies, and teachers' instructional events. The main contribution of the study is the construction of a multivariate model that can be replicated in other contexts. In practices, professors and managers will have inputs to better plan the disciplines and avoid increasing retention and dropout rates.

Keywords: e-learning, learning assessment, higher education, academic performance.
RESUMO
As notas e outros indicadores acadêmicos dos alunos são os parâmetros mais avaliados nos estudos sobre ensino e aprendizagem. No entanto, vários autores apontam que esses índices, por si só, não são suficientes para explicar o desempenho dos estudantes. Para compreender os precursores que facilitam ou comprometem a aprendizagem no ensino superior, é necessário considerar outras variáveis relacionadas a alunos, professores e ao contexto docente. Assim, este artigo apresenta um modelo multivariado para avaliar o desempenho de alunos em cursos online. O modelo foi testado no contexto da pandemia de COVID-19 com estudantes de graduação em Engenharia. O curso foi Cálculo 2. Os dados foram analisados por meio de técnicas de análise estatística multivariada. Entre as 10 variáveis testadas no modelo. Três variáveis foram significativas e mostraram que o desempenho dos alunos em Cálculo 2 foi impactado por: renda familiar, estratégias cog-nitivas e autorregulatórias de aprendizagem e eventos instrucionais dos professores. A principal contribuição do estudo é a construção de um modelo multivariado que pode ser replicado em outros contextos. Na prática, professores e gestores terão insumos para planejar melhor as disciplinas e evitar o aumento das taxas de retenção e evasão.

Palavras-chave: e-learning, avaliação da aprendizagem, ensino superior, desempenho acadêmico.

1 INTRODUCTION
The debate about teaching modalities and the use of digital technologies in higher education has intensified worldwide over the past four years, particularly because of the outbreak of the COVID-19 pandemic in 2020 and the consequent deployment of “Emergency Remote Teaching” – ERT. Before the pandemic, studies on online education identified that variables such as students' satisfaction to teacher' instructional procedures (Deshwal, Trivedi & Himanshi, 2017; Kaizer et al., 2020) or students socioeconomic conditions (Hu & Hui, 2012; Park et al., 2014) predict learning in remote teaching context.

Chaka (2020) warns that, in ERT format, the specificities of the areas or disciplines cause the variables to behave in different ways. In students of Science, Technology, Engineering and Mathematics - STEM courses, variables related to learning influence these courses in a different way compared to other undergraduate areas. The main reason is: high failure rates in the initial years, in disciplines such as Calculus, for example, have been shown to be predictors of
a decaying academic trajectory that results in increased retention and dropout rates in these courses (Bergeron & Gordon, 2017). However, most of the studies that investigate learning in Calculus consider only grades or other academic indices as variables of interest (Anwar & Rani, 2021; Jiménez et al., 2015).

Although fragile and not very complex, grades are still the most usual mechanism adopted in educational institutions to measure student learning and are an important indicator (García-Pérez, Fraile & Panadero, 2021). However, in addition, researchers suggest the inclusion of latent variables (or constructs) and the application of multivariate models with multivariate statistical analysis to assess student performance and learning (Gonzalez et al., 2020; Martins & Zerbini, 2016). Computer simulation and artificial intelligence techniques can also be used to analyze the impact of predictor variables on a phenomenon under analysis, as done in Moreira et al. (2022).

For this, it is necessary to elect a theoretical and methodological referential that provides the basis for construction these models of evaluation and definition of its respective measures. The objective of this paper, then, is to present a multivariate model of learning assessment in an online teaching context, as well as the results of the first application made in undergraduate STEM/Engineering at a Brazilian federal public university. The discipline evaluated is Calculus 2. It was chosen because the increase in dropout and retention rates of university students in Science, Technology, Engineering and Mathematics areas is explained, in large part, by the constant failures in Calculus subjects (Hurdle & Mogilski, 2022; Ní Fhloinn & Fitzmaurice, 202).

Studying the learning variable in Calculus meets a research agenda of worldwide interest in the area of higher education assessment, especially in Engineering courses (Kramarski & Gutman, 2006; Silva et al., 2020). This is one of the highlights of this paper.

In this work, the referential chosen is Instructional Psychology, specifically, the area of Training, Development and Education of People - TD&E. The area has a recognized scientific contribution regarding conducting empirical research in education and has generated measurement instruments (scales), empirical
and conceptual models for understanding various social phenomena related to human learning (Bell et al., 2017, Salas et al., 2012).

The studies in TD&E are used to, first, identify the latent variables that could explain the educational phenomenon and, second, define the measurement criteria of these variables. The methodological approach of this study is explained later. In TD&E literature, each construct (for example, student satisfaction with a teaching platform, learning self-regulation) corresponds more to a complex set of phenomena than to a simple and directly observable phenomenon. To measure a construct, it is necessary to specify it in several indicators (which are the variables represented by the items of the psychometric scales) (Curado, Teles & Marôco, 2014).

However, we proposed this conceptual model, on Figure 1, composed of four constructs that have been shown to explain learning in online courses, according to the studies cited above.

![Figure 1 – Conceptual model multivariate.](source)

The first three constructs were measured using three psychometric scales that have already been validated in various studies on learning in higher and technical education. The Learning construct represents the grades obtained by students in Calculus 2. As mentioned, each construct comprises several variables, which are the items in the scales. Based on the Training, Development and Education (TD&E) literature, the meaning of each construct will be described in the following section. The aim is to identify which variables contributed most to the results obtained by the students in terms of grades, as well as the variables...
that hindered performance.

2 REVIEW LITERATURE

2.1 LEARNING STRATEGIES

Learning strategies comprise a set of cognitive, behavioral and self-regulatory skills that can be learned or improved in order to increase the effectiveness of learning in a given context. In this reasoning, there are no better or worse strategies, but strategies that are more or less appropriate for the type of activity to be learned (Umekawa & Zerbini, 2020).

According to Warr and Allan (1998), activities of different natures and degrees of complexity require different learning strategies. To better understand, the authors developed a classification of learning strategies into three major components according to Table 1.

<table>
<thead>
<tr>
<th>Table 1 – Learning Strategies Classification.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cognitive strategies</strong></td>
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<td></td>
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<tr>
<td><strong>Behavioral Strategies</strong></td>
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<tr>
<td></td>
</tr>
<tr>
<td><strong>Self-regulatory Strategies</strong></td>
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<td></td>
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<td></td>
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</tbody>
</table>

In brief, cognitive skills and behavioral skills are directly related to learning activities and concern student attitudes such as: selecting materials, organizing, preparing summaries, rereading notes. The self-regulatory skills exert indirect influence on learning processes and are closely linked to the regulation skills, such as control of motivation to learn, monitoring of understanding, control of anxiety in complex situations (Salas et al. 2012). Thus, the construct in question was measured by means of the Learning strategies scale (Umekawa & Zerbini, 2020). An 29-item scale, using a 7-point rating likert-type scale from 1 (never) to 7 (always), that measures the frequency with which the participants employed learning strategies.

2.2 REACTIONS TO INSTRUCTIONAL PROCEDURES

According to the TD&E literature, reaction are opinions or satisfaction levels of students on various aspects of subject with which they participate (Martins, Zerbini & Medina, 2018). In this paper, the participants' satisfaction is measured with respect to instructional procedures of the subject such as: quality of the teaching content, learning assessments, link between the content of the subject and the course objectives.

Gagné (1985) extends this concept of “instructional procedures” in his theory of “instructional events”. The author distinguishes between “internal events” and “external events” of learning. Internal events are the student's cognitive and emotional abilities and readiness to learn. External events are the conditions provided by the teacher for the student to achieve learning. They are closely linked to the teacher's attitudes, for example: get the student's attention; inform the course objectives; retrieve the student's previous knowledge; present stimuli to the student; provide feedback. Considering the relevance of the teacher's role in student learning, the impact of the teacher's planning was tested. For this, Reactions to instructional procedures scale (Zerbini & Abbad, 2009) was used. An 12-item scale, with response alternatives scored from 1 (very bad) to 7 (excellent).
2.3 STUDY ENVIRONMENT AND INTERACTION PROCEDURES

In this paper, environmental factor was evaluated from two perspectives, first, one’s personal study environment, which is related to aspects of a student's routine, physical space, and material. It also covers issues related to study context and personal costs from engaging in remote activities. The second perspective is related to the virtual study environment, or student interaction with online communication tools.

Naji et al. (2020), in a study with engineering students in Qatar, found that in the transition to ERT, one of the main difficulties pointed out by students was the “study context”, the simultaneous or shared use of computers with other family members, the lack of isolated space to study, and problems with internet signal.

Thus, Study environment and interaction procedures scale (Zerbini & Abbad, 2008) was used. It is composed of 14 items, it measured variables referring to the context or study conditions of the student at the time, as well as the interactions within the virtual environment. Items based on intensity levels, which ranged from 1 (Hindered my performance a lot) to 7 (Did not hinder my performance).

2.4 LEARNING

For Gagné (1985), learning refers to a student's ability to demonstrate mastery of the pedagogical objectives proposed in a course or discipline. The author add that in order to do so, it is necessary to consider both internal learning processes (the cognitive, behavioral, and emotional abilities of the students) and external processes, which are the attitudes of the teacher to facilitate learning. Also considered external processes are events or conditions particular to the student's life context.

The concept of learning in higher education is commonly associated with grades, which are the most widely adopted method for measuring if students have learned something or not. Bell et al. (2017), state that most research on evaluations tends to use grade indicators as a single reference for analyzing
educational results. In this paper, learning will be considered a response variable, measured through the grades obtained by students in Calculus 2. However, grades will not be considered in isolation, others variables will be associated to better explain the learning outcomes.

3 METHODOLOGY

The research was conducted at a federal public university in Brazil and covered 12 engineering courses. The data was collected in Google Forms, from December 2020 to March 2021. Students' academic data was collected, such as grades, social data through a questionnaire and data from the psychometric scales. Ethical Committee that approved this study was University Center Itajubá (Protocol: 40625420.5.0000.5094, Ethical Clearance Number: 4.464.666/2020).

3.1 PARTICIPANTS AND CONTEXT

Participants, chosen non-randomly and by convenience, were 507 undergraduate students in Engineering who took Calculus 2, in Emergencial Remote Learning – ERT modality, at a federal public university in Brazil. In this study, the participants accounted for more than 50% of the individuals who took Calculus 2. Thus, the sample is characterized as follows: 55% male, 44% female; 83% were between 18 and 24 years old; only 3% of the individuals had children; 87% attended the 2020 school year in their family homes, 28% combined work and study during 2020, and 74% had no previous experience with online learning.

3.2 INSTRUMENTS

All instruments were adapted considering their textual aspects (semantics, content), their distribution in factors, and their psychometric indexes (factor loadings, Cronbach's Alpha, number of scale points, etc.) presented in other studies. After adaptation and validation of the scales, the three scales together summed up to 45 items. In all, there were 480 valid respondents.
3.3 DATA ANALYSIS

To run the descriptive and multivariate analyses, the SPSS/AMOS 26.0, Minitab 18 and Factor 8.02 was used. The statistics analysis techniques were: Principal Component Analysis – PCA, Exploratory Factor Analysis – EFA, Multiple Regression – MR. Two factor retention techniques were used: the ACP in an exploratory method and the EFA in a confirmatory method. The criteria for factor retention were defined based on Tabachnick and Fidell (2013) and Hair et al. (2009) and will be explained later. The exploratory analysis steps and their requirements are shown in Figure 2.

Figure 2 – Steps exploratory analysis.

![Figure 2](image_url)

Source: The authors.

To define the number of factors of each scale, the following tests and criteria were adopted: Kaiser-Meyer-Olkin (KMO) for factorability analysis (>0.70), Bartlett’s sphericity (p>0.05) for significance, calculation of the Cronbach’s Alpha index of each factor to verify internal consistency, analysis of the factor loadings of each item within the factor to which it belongs (r>0.40), to verify stability (Hair et al, 2009). Subsequently, the factor scores were used for the Multiple Regression Analyses step.

4 RESULTS

First, all statistical criteria for factor retention were applied to each scale. Next, the theoretical aspects were considered to then find a factor structure for each construct. Table 2 shows the distribution of the factors of each scale and
their respective internal consistency reliability estimate.

### Table 2 – Constructs and factor structure.

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Factors</th>
<th>Variables or items</th>
<th>Cronbach’s Alpha (α)</th>
<th>Factorial weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning strategies (LS)</td>
<td>Self-regulatory and cognitive strategies – LS1</td>
<td>11</td>
<td>0.91</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>Emotional control – LS2</td>
<td>3</td>
<td>0.80</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>Practical application and monitoring understanding – LS3</td>
<td>3</td>
<td>0.80</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>Elaboration and association – LS4</td>
<td>4</td>
<td>0.88</td>
<td>0.46</td>
</tr>
<tr>
<td>Reaction to instructional procedures (IP)</td>
<td>Instruction planning – IP1</td>
<td>10</td>
<td>0.90</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>Instruction events – IP2</td>
<td>2</td>
<td>0.82</td>
<td>0.81</td>
</tr>
<tr>
<td>Study environment and interaction procedures (SE)</td>
<td>Study context – SE1</td>
<td>8</td>
<td>0.80</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>Personal costs – SE2</td>
<td>4</td>
<td>0.80</td>
<td>0.51</td>
</tr>
</tbody>
</table>

Source: The authors.

All indexes indicate good (>0.80) and excellent indicators (>0.90) (Hair et al., 2009). The “Self-regulatory and cognitive strategies – LS1” factor explained 35% of the total variance in “Learning Strategies”. In the construct “Reaction to instructional procedures”, the factor “Instruction planning - IP1” explained 49% of the total variance and had the following variables with the highest factor load: The “Instruction Events - IP2” was composed of two variables: "Link between course content and your course objectives" (0.81) and "Link between course content and your personal objectives" (0.83).

Thus, in the construct “Study environment and interaction procedures”, it was identified that the variables "Conciliation of the course with my family commitments" (0.74) and "Conciliation of the subject with other subjects or with other courses I was taking" (0.72) had the greatest influence on the student’s “Study Context – SE1” factor. SE1 explained 36% of the total variance. In “Personal costs” – SE2, "Financial cost to access the Internet" (0.78) and "Financial cost to maintain a computer" (0.71) were the measures with the highest factor loadings.
The variables that measured the interaction procedures in the virtual environment did not remain in the final empirical structure due to low factorial load (<0.4): "Volume of exposure time to the computer screen" (0.33) and "Use of e-mail to communicate with teachers and classmates" (0.37), for example, had little influence on the dynamics of student learning in the context evaluated.

Once the exploratory factor analyses were completed, it was calculated the Z scores of each factor to perform the Multiple Regressions – MR and analyzed Pearson's bivariate correlations. Among the 13 variables related to the student's socioeconomic and academic profile, the correlations of income and period were stronger with the learning variable. Thus, the prediction model was composed of 10 predictors variables as shown in Figure 3. Table 2 helps to understand the terms below. This model was tested using two MR techniques.

The first technique was standard multiple regression and the results are in Tables 3 and 4.
In order to find a better fit for this model, a stepwise backward multiple regression was tested. In this estimation format, all predictors are included at once in the equation and are eliminated by computational method until the best predictors remain (Tabachnick & Fidell, 2013). The result indicated a significant improvement in the $R^2$ (adj.) index and the three significant variables, highlighted in Table 3, were maintained, with changes in their contributions, according to data in Tables 5 and 6:

**Table 3 – Standard multiple regression analysis.**

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Learning</th>
<th>Income</th>
<th>Period</th>
<th>LS1</th>
<th>LS2</th>
<th>LS3</th>
<th>LS4</th>
<th>IP1</th>
<th>IP2</th>
<th>SE1</th>
<th>SE2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B$</td>
<td>-0.04</td>
<td>0.01</td>
<td>0.06</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-0.01</td>
<td>-0.05</td>
<td>0</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>-0.11</td>
<td>0.04</td>
<td>0.11</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-0.02</td>
<td>-0.12</td>
<td>0</td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td>$Sr^2$</td>
<td>0.93%</td>
<td>0.17%</td>
<td>0.78%</td>
<td>0.34%</td>
<td>0.18%</td>
<td>0.34%</td>
<td>1%</td>
<td>0.03%</td>
<td>0.37%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Constant= 8 $R^2=4\%$ $R^2(\text{adj.})=2.2\%$ R=20%

* $p<0.05$ ** $p<0.01$
Source: The authors.

**Table 4 – Analysis of Variance.**

<table>
<thead>
<tr>
<th>Analysis of Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Response variable</td>
</tr>
<tr>
<td>Learning</td>
</tr>
<tr>
<td>SS</td>
</tr>
<tr>
<td>DF</td>
</tr>
<tr>
<td>MS</td>
</tr>
<tr>
<td>F</td>
</tr>
<tr>
<td>$p$-value</td>
</tr>
</tbody>
</table>

Source: The authors.

**Table 5 – Stepwise multiple regression analysis.**

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Learning</th>
<th>Income</th>
<th>LS1</th>
<th>IP2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B$</td>
<td>-0.04</td>
<td>0.06</td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>-0.12</td>
<td>0.11</td>
<td>-0.14</td>
<td></td>
</tr>
<tr>
<td>$Sr^2$</td>
<td>1.49%</td>
<td>1%</td>
<td>1.62%</td>
<td></td>
</tr>
</tbody>
</table>

Constant= 8 $R^2=4\%$ $R^2(\text{adj.})=3.3\%$ R=20%

* $p<0.05$ ** $p<0.01$
Source: The authors.

**Table 6 – Analysis of Variance.**

<table>
<thead>
<tr>
<th>Analysis of Variance</th>
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<tbody>
<tr>
<td>Response variable</td>
</tr>
<tr>
<td>Learning</td>
</tr>
<tr>
<td>SS</td>
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<tr>
<td>DF</td>
</tr>
<tr>
<td>MS</td>
</tr>
<tr>
<td>F</td>
</tr>
<tr>
<td>$p$-value</td>
</tr>
</tbody>
</table>

Source: The authors.
The general results of the model are that low-income students performed better in Calculus 2, students who adopted cognitive and self-regulatory learning strategies (LS1) achieved better results more often, and students who negatively evaluated their teacher’s instruction events (RP2) had higher grades.

The results of the relationship between the variable "Income" ($\beta = -0.12$) and the learning variable indicate that the fact that lower-income students had higher grades may be, in part, a positive effect of the student support programs conducted by the institution during the year 2020. The variable "Income" should be under constant monitoring by the university. The indicators associated with it (dropout rates, number of scholars, shifts, age group, stay, etc.) should be surveyed and compared to support administrative decisions on commitment of financial resources for student support. This becomes more crucial if it is decided to offer courses that rely on home internet or any other materials that the student cannot afford.

The Learning Strategies – LS1 variable measured the frequency with which students adopted self-regulatory (regulation of motivation, attention, and comprehension) and cognitive (elaboration and association) strategies to learn Calculus 2. Given the pandemic context, we expected that self-regulatory strategies for anxiety and emotions, which were grouped into the Emotional control – LS2 factor, would explain some of the learning in Calculus in the regression model. However, this did not occur. The students in MAT002 developed new strategies to learn calculus more autonomously. Self-regulation of motivation and attention are also part of factor LS1. The fact that students used these strategies showed that, although affected by the emotions of the pandemic and the challenges of the remote learning format, they managed to regulate themselves, and this is very positive because it means improvement of skills such as resilience and self-discipline, so desired for performance in the labor market. Naji et al (2020) reached similar conclusions in their study with engineering students in Qatar during the ERE.

In variable Events of instruction – IP2 ($\beta = -0.14$), which was measured by means of the students' response to two items of the "Reaction to instructional
procedures" scale: 1) "Link between Calculus 2 content and the student's course objectives" and 2) "Link between the content and the student's personal objectives", the student evaluated from (1) very poor to (7) very good these two occurrences. The IP2 variable is directly related to the teacher's role in providing favorable external conditions for the subject to produce positive effects.

In the regression results, it was found that: students who negatively evaluated the teacher's instructional events (IP2) had better scores ($\beta = -0.14$). At first glance, this result seems inconsistent. However, in the theoretical and especially in the practical field of teaching Calculus 2, these findings make a lot of sense. It appears that students may not be provoked or motivated to make the "connections" mentioned in the two items of the scale, and therefore end up taking the subject with the sole objective of fulfilling the required credits, and not with the objective of acquiring the competences required by a future professional in their area. Thus, being or not stimulated to understand the applicability of Calculus 2 becomes indifferent to the student.

Moreover, the items show the discontent of students with the absence or poor quality of the teacher's initiatives in leading the student to understand the relationship of Calculus 2 with the other components of the undergraduate course in Engineering. In this case, it is important to highlight: beyond what is written in the teaching plan, students seem to need more clarification about how the contents of Calculus 2 interconnect, what connections they establish with the other disciplines yet to come, and how the concepts will apply to practice.

5 DISCUSSION

The low coefficients of determination of the multiple regression model found indicate the existence of other variables, not addressed in this study, that could explain a greater portion of the variability in learning, as for example, the self-efficacy in Calculus learning. Even if a student recognizes that completion of a Calculus subject is necessary to complete his degree requirements, it may still be difficult for the student to motivate himself without the confidence that he can learn Calculus.
In the experimental study of the Gonzalez et al. (2020), the authors identified that there was a positive effect of confinement on the learning strategies used by Engineering students. The University made several exercises available on the academic platform before the pandemic, but students accessed few of them. During the ERT, there was a significant increase in accesses to the platform.

Anais et al. (2012) evaluated the learning strategies of 339 students who took an in-person Introductory Calculus for Civil Engineering course in Chile. The results showed that for cognitive and self-regulatory learning strategies, Calculus students used cognitive strategies more, especially strategies related to elaborating e.g., taking notes, making summaries, and redoing exercises, as this article has demonstrated. They also used strategies for organizing their ideas e.g., making mind maps and diagrams.

With regard to the IP2 - teacher’s instructional events variable, the absence of clear information about the objectives of a subject and about the connection between it and the other contents and the students' field of action is detrimental at whatever stage of the course a student is in. The negative results that may befall students can be: a) demotivation (lack of connection between the student's personal objectives and the subject); b) loss of focus; c) little involvement with course activities. In the long run, it can cause increased retention and dropout or damage to mental health, because the accumulation of academic hang-ups can, in some cases, bring suffering and emotional distress (Danowitz & Beddoes, 2018).

Some surveys have assessed student reactions to online course within higher education institutions and found significant positive correlations between student satisfaction and variables like the course program (Alqurashi, 2019), teacher-student relationship during hybrid teaching (Alla, Yulia and Gabriela, 2022).

Therefore, the presence of Instructional events – IP2 alongside Self-regulatory and cognitive learning strategies – LS1 reinforces that the choice for one or another learning strategy is not only based on the nature or level of
complexity of a subject, but also on the learning conditions provided by the teacher to that student. When these conditions are not adequate, they modify the learning processes. As was observed in this study, the student will need to compensate, during his academic career, this mismatch in the relationship of Calculus 2 with the other components of his course. To achieve this, this student will need to employ several self-regulatory strategies for motivation, attention and understanding of the contents, even without interest in the subject.

6 CONCLUSIONS AND PRACTICES IMPLICATIONS

The results of this study allow us to conclude that the gains in learning through grades were mainly due to the students' efforts in the intensive and associated use of self-regulatory and cognitive strategies. The learning conditions provided by the teachers, although fragile, did not imply prejudice to the students' academic performance in Calculus 2.

Based on the theoretical frameworks studied, it is considered essential that the teacher, with the support of the administrative and pedagogical sectors, carry out a diagnosis of the profile of his classes at the beginning of the semester, in order to better direct the teaching strategies. The teacher will be able to provide better teaching conditions if he has information about his students such as: a) types and levels of prior knowledge that students have (regarding content, technology, use of tools); b) personal interests and goals; c) study habits; d) most commonly used learning strategies: consulting materials, problem solving, application, synthesis, conceptual or mental maps. The teacher would plan his or her course based on this information.

In parallel to the analysis of the final indicators of a subject, for example, one should analyze indicators that measure the learning process, the procedure adopted by the teacher in the planning of his or her subject, the teaching conditions, the needs of the students, as was done in this study.
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