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Research article

Academic-related stressors predict depressive symptoms in graduate students: A machine learning study

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ABSTRACT

Background: Graduate students face higher depression rates worldwide, which were further exacerbated during the COVID-19 pandemic. This study employed a machine learning approach to predict depressive symptoms using academic-related stressors.

Methods: We surveyed students across four graduate programs at a Federal University in Brazil between October 15, 2021, and March 26, 2022, when most activities were restricted to taking place online due to the pandemic. Through an online self-reported screening, participants rated ten academic stressors and completed the Patient Health Questionnaire (PHQ-9). Machine learning analysis tested whether the stressors would predict depressive symptoms. Gender, age, and race and ethnicity were used as covariates in the predictive model.

Results: Participants (n=172), 67.4 % women, mean age: 28.0 (SD: 4.53) fully completed the online questionnaires. The machine learning approach, employing an epsilon-insensitive support vector regression (Ɛ-SVR) with a k-fold (k=5) cross-validation strategy, effectively predicted depressive symptoms (r=0.51; R^2=0.26; NMSE=0.79; all p=0.001). Among the academic stressors, those that made the greatest contribution to the predictive model were "fear and worry about academic performance", "financial difficulties", "fear and worry about academic progress and plans", and "fear and worry about academic deadlines".

Conclusions: This study highlights the vulnerability of graduate students to depressive symptoms caused by academic-related stressors during the COVID-19 pandemic through an artificial intelligence methodology. These findings have the potential to guide policy development to create intervention programs and public health initiatives targeted towards graduate students.

1. Background

Graduate student population faces significant mental health challenges worldwide, raising great concern among the scientific community [1–5]. Apart from the psychological distress, mental health problems, like depression, substantially impact graduate students' productivity and impose financial burdens on institutions and research teams [6–9]. As daily routine, they face an extremely competitive environment filled with factors that possibly contribute to the development of mental health problems. These include long working hours, poor work-life balance, worries about deadlines, pressures for managing multiple responsibilities such as conducting research, teaching, and publishing, uncertainty about future job opportunities, strained relationships with supervisors, and financial hardship [10,11].

The COVID-19 pandemic led to a significant worsening of mental health problems globally [12,13]. According to the World Health Organization (WHO) [13], this increase primarily impacted populations from low-income countries, especially those most heavily affected by the

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pandemic, such as Brazil [14]. Regarding the academic environment, according to the United Nations [15], “the pandemic caused the largest disruption of education systems in history” around the world. The closure of schools and other educational spaces forced a shift to online academic activities and disrupted students’ social lives and support networks [15], exacerbating disparities and concerns.

Identifying vulnerability and protective factors in mental health poses a significant challenge within the field of psychiatry. Contemporary approaches using artificial intelligence, like machine learning, can be used to predict mental health vulnerabilities (e.g., [16,17]). During the COVID-19 pandemic, some studies applied a machine learning approach to predict depressive and anxiety symptoms based on psychometric variables related to the COVID-19 pandemic in several populations [18–22]. It is worth mentioning that, in the context of machine learning, the term "predict" implies that, once the model has learned a relationship between a set of patterns (e.g., multivariate patterns of psychometric data) and labels (e.g., a clinical score), it can forecast the label of a new pattern (e.g., psychometric data from a new subject). This is an innovative approach, whose advantages include the following: i) models are not constrained by traditional assumptions, such as a normal distribution of the data or an a priori model; ii) the method can assess relationships among many variables simultaneously; iii) it can identify patterns in complex datasets; and iv) the machine learning models can make predictions [23].

Despite the above cited advantages of the machine learning approach, to the best of our knowledge, no studies have investigated the contribution of academic-related stressors in the prediction of depressive symptoms in graduate students, through an artificial intelligence methodology. Previous studies examined the relationship between stress and mental health in undergraduate students using traditional analyses. For instance, Wang et al. [24] investigated academic concerns that contributed to increased stress levels on college students. O’Reilly et al. [25] described the relationship of the number of stressors, and Zhang et al. [26], the degree of perceived academic stress, with depressive symptoms. Their approach precludes the determination of the contribution of each stressor on the severity of depressive symptoms, aside from investigating undergraduate students. In fact, a press article by Denia Djokić and Sebastien Lounis [27] from the University of California at Berkeley calls attention to the paucity of data on this subject (see also Wang [28]). The present study aims to fill this gap. We surveyed a sample of graduate students from the Federal University of Rio de Janeiro (UFRJ) in Brazil, one of the largest and the most prestigious public universities in Latin America, during the period of remote activities of the COVID-19 pandemic. We employed a machine learning approach (pattern regression model) to predict depressive symptoms based on the participants’ ratings of stressors related to their lives and academic activities.

2. Methods

2.1. Participants

Participants were recruited from the student population of four graduate programs of UFRJ. The inclusion criteria were being a graduate student enrolled in one of the four graduate programs, and giving consent to participate in the study. Participants were excluded from the analysis if they did not provide answers for any reason, or if there were any errors in the questionnaires.

2.2. Setting and design

The study used an online survey that was designed and conducted during the period of remote activities at the UFRJ, due to COVID-19 pandemic restrictions. Data were collected from October 15, 2021, to March 26, 2022,[2] using the online platform Google Forms. From the starting point, the administrators of each graduate program sent weekly emails to the pool of 431 students from the four graduate programs, inviting them to participate in the study. From February 2022 until the end of data collection, a “virtual snowball” recruitment strategy [29] was also used. For this strategy, an initial group of students from the target population received the access link to participate, and were asked to indicate other students who met the inclusion criteria, to whom the questionnaire was sent, and so on.

All study procedures followed ethical guidelines regarding research with human subjects. All participants agreed to take part in the survey voluntarily and provided informed consent before accessing the questionnaires. The Research Ethics Committee of the Institute of Collective Health Studies of the Federal University of Rio de Janeiro approved the project, under opinion No. 4882,174 of August 3, 2021.

2.3. Outcome

Depressive symptoms were assessed using the Patient Health Questionnaire (PHQ-9) [32], translated to and validated for use with the Brazilian population [33]. This screening tool consists of nine symptoms of depression. The respondent is asked to indicate how often they have experienced them in the previous two weeks by responding on a 4-point Likert scale (0 - not at all, 1 - several days, 2 -more than half the days, 3 - nearly every day). The total score is the sum of each answer, and ranges from 0 to 27. A cut-off $\geq$ 9 presents 77.5 % sensitivity and 86.7 % specificity for diagnosing major depression disorder [33]. Thus, we considered a cut-off $\geq$ 9 as a ‘probable depression diagnosis’.

2.4. Variables and measurements

2.4.1. Assessment of sociodemographic data

Sociodemographic information included self-report of gender (women /men/ others), age, race, and ethnicity (white / black, mixed & others), and level of graduate course (master’s /doctorate).

2.4.2. Assessment of academic stressors/difficulties during the pandemic

Meo et al. [34] and Wang et al. [24] investigated the mental health of university students in Saudi Arabia and the United States, respectively, during the COVID-19 pandemic, and recorded a group of academic concerns that contributed to increased stress levels. Based on these studies, ten stressors/difficulties were applied here (see Table 2). Each stressor/difficulty was evaluated through a five-point Likert scale (0 = not al all, 1= very little, 2 = moderately, 3 = quite a bit, and 4 = extremely).

2.5. Data analysis

The online data was exported to Microsoft® Excel (Microsoft 365 MSO). To characterize the sample, we presented absolute and relative frequencies for sociodemographic data, and for the classification of ‘probable depression diagnosis’ (based on the established cut-off point of the PHQ-9). The total PHQ-9 score was reported as medians and

[2] It’s important to note that at the beginning of data collection, the cumulative deaths per 100,000 people during COVID-19, in Brazil was 69.50, reaching 305.04 at the end of data collection [30]. The first COVID-19 vaccine product introduction in Brazil was on January 17, 2021[31], and on October 14, 2021, 72 % of the population received at least one dose of the COVID-19 vaccine [30].

interquartile range (IQR).

The most prevalent stressors/difficulties were defined as those that most of the participants described as interfering "quite a bit" or "extremely" with their lives and academic activities, and were reported in absolute and relative frequencies.

These descriptive statistics were analyzed using Statistica software (v. 13.3, TIBCO Software Inc. (2017)).

2.5.1. Pattern regression analysis

Each participant's rating of the ten assessed stressors was included into the machine learning analysis to predict depressive symptoms (the participants' total PHQ-9 score). We trained a regression model using these ratings to assess each stressor's contribution to depressive symptoms.

The pattern regression analysis was performed through the open-source Pattern Recognition for Neuroimaging Toolbox (PRoNTo – version 3) [35], originally designed for neuroimaging analyses but further expanded to analyzing non-imaging data, such as psychometry (e.g., [19]). The development of pattern regression models is divided into two stages: training, where the relationship between stressors and labels (here, depressive symptoms, i.e., total PHQ-9 score) is learned, and testing, where this relationship is established to predict symptom scores. The linear epsilon-insensitive support vector regression (ε-SVR) (a non-kernel regression algorithm that uses an insensitive loss function for regularization parameters) was applied to predict depressive symptoms based on stressors in academic life, chosen for its robustness to outliers [36,37], and great performance, particularly for smaller samples [38–40]. Through testing various sets of hyperparameters, Portugal et al. [19] showed how the ε-SVR algorithm can better-fit models to data sets. We compared the performance of ε-SVR with Gaussian process regression (GPR), that is a kernel-based algorithm based on Gaussian probability distribution [41], and with kernel ridge regression (KRR), which is also based on kernel functions but it uses a squared error loss function for regularization parameter [42] – the detailed results of the GPR and KRR algorithms are present in supplementary material. The internal and exterior loops of PRoNTo used the same cross-validation method, and these hyperparameters were set automatically using a k-fold nested cross-validation approach. PRoNTo enables the automatic optimization of a few parameters that can be entered as a cell array of values and turned into a grid afterward. The values utilized for the parameters were 0.01, 0.1, 1, 10, 100, and 1000. The two distinct cross-validation procedures ($k = 2$; $k = 5$) were applied to demonstrate that the results were not dependent on a specific cross-validation scheme to evaluate the ε-SVR performance, compared with the other algorithms – the detailed description of learning rate batch sizes and epochs is presented in supplementary materials.

To address potential confounders like age and gender, which were linked to depressive symptoms [19,43], we balanced the proportion of data from potential confounders across all folds. There was no difference in depression symptoms scores by age, gender, and race and ethnicity across all cross-validation folds.

Model performance was evaluated using Pearson's correlation coefficient (r), which describes the strength of a linear relationship between two variables; the coefficient of determination (R^2), interpreted as the proportion of variance explained by the regression; and normalized mean squared error (NMSE), which represents the mean error between the predicted and actual scores, and is normalized by dividing the mean squared error by the variance in the target values. Significance was determined using permutation tests, with results considered significant if the model performed equally or better than the model without shuffling the labels at most 5 % of the time across 1000 permutations [44].

For model interpretation, the weights represent the contribution of each stressor/difficulty to the linear predictive function. Since each cross-validation fold yields a different weight vector, the final psychometric weight is the average across the folds divided by its Euclidean norm. Here, we presented the average and range (minimum and maximum) of weight values across folds. Only the two-fold cross-validation results are illustrated for brevity.

3. Results

3.1. Sample characteristics

Out of the 204 students who agreed to participate, data from 32 were excluded from the analysis. Nine participants had errors in their questionnaires, 21 failed to answer at least one question related to stressors, and two participants identified themselves as "other" gender. Thus, the final dataset comprised 172 participants, of whom 116 (67.4 %) were women, with ages ranging from 21 to 50 years (mean 28.0, SD 4.53). Seventy-one respondents were master's (41.3 %) and 101 were doctorate students (58.7 %) (Table 1).

The median total PHQ-9 score was 14 (IQR: 11). Based on the established cut-off point (i.e., PHQ-9 $\geq$ 9), 73.3 % (n= 126) met the criteria for a 'probable depression diagnosis'.

3.2. Academic life and stress

Among the ten stressors or difficulties interfering "quite a bit" or "extremely" with their lives and academic activities, the most prevalent was "fear and worry about academic progress and plans" reported by 155 participants, representing 90.1 % of the sample (see Table 2).

3.3. Machine learning applied to the prediction of depressive symptoms

Pattern regression analyses were performed for 172 participants, all of whom had valid responses to the ten stressors/difficulties affecting their lives and academic activities during the pandemic. After correction for multiple comparisons (since two different models were tested, the significance threshold was $0.05/2 = 0.025$, Bonferroni corrected), the ε-SVR regression models significantly predicted depressive symptoms from academic-related stressors during the COVID-19 pandemic. The performance of the regression model is presented in Table 3.

For reference: corrected p-value = 0.025.

Fig. 1 shows the scatter plots depicting the actual vs. predicted depressive symptoms (i.e., PHQ-9 total score), indicating that our models significantly decoded depression symptoms from the academic-related stressor questions. There were no significant differences in performance among the different kernel regression or non-kernel approaches. (see Supplementary Tables for consistency of results).

3.3.1. Contributions of academic-related stressors to the regression model

The relative contribution of each academic-related stressor to the ε-SVR is shown in Fig. 1. The weight of each question corresponds to its contribution to the predictive model. Notably, "fear and worry about academic progress and plans" (0.466; *range: 0.323–0.568*) was the academic-related stressor that made the greatest contribution to the depressive symptoms model, followed by "financial difficulties" (0.454;

Table 1
Sample characteristics (n=172). Rio de Janeiro, 2021–22.

Gender (n, %)		
Female	116	67.4 %
Male	56	32.6 %
Race and ethnicity (n, %)		
White	110	64.0 %
Black, mixed & others	62	36.0 %
Level of academic course (n, %)		
Master's	71	41.3 %
Doctorate	101	58.7 %
PHQ−9 (med, IQR)	14	11
Probable depression diagnosis (n, %)		
No	46	26.7 %
Yes	126	73.3 %

Table 2
The most prevalent stressors/difficulties, described as interfering "quite a bit" or "extremely" with their lives and academic activities (n=172). Rio de Janeiro, 2021–22.

Stressors/difficulties (n, %)		
Fear and worry about academic progress and plans	155	90.1 %
Fear and worry about academic performance	136	79.1 %
Fear and worry about academic deadlines	135	78.5 %
Financial difficulties	95	55.2 %
Social/interpersonal relationships	83	48.3 %
Family relationships	76	44.2 %
The need to perform housework	72	41.9 %
Difficulty adapting to distance learning	56	32.6 %
Relationship with supervisors	42	24.4 %
Difficulty in accessing study materials	27	15.7 %

Table 3
Measurements of agreement between the actual and predicted depressive symptoms based on academic-related stressors (n=172).

Regression Models	r	*p-value*	R^2	*p-value*	NMSE	*p-value*
ε-SVR (k = 5)	0.44	*0.001*	0.21	*0.001*	0.84	*0.001*
ε-SVR (k = 2)	0.47	*0.001*	0.22	*0.001*	0.78	*0.001*

range: 0.196–0.609), "family relationship" (0.428; *range: 0.349–0.460*), "social/interpersonal relationship" (0.411; *range: 0.318–0.435*), "fear and worry about academic deadlines" (0.339; *range: 0.283–0.355*) and "fear and worry about academic performance" (0.306; *range: 0.218–0.340*).

Other academic-related stressors with lower contributions to the predictive model were "relationship with the supervisor" (0.096; *range: −0.112–0.334*), "difficulty in accessing study materials" (0.058; *range: −0.0006–0.129*), "difficulty adapting to distance learning" (0.044; *range: −0.053–0.155*), and the "need to perform housework" (0.030; *range: −0.006–0.056*).

4. Discussion

To the best of our knowledge, this is the first study to investigate academic-related stressors as predictors of depressive symptoms through an artificial intelligence methodology. The pattern regression analyses significantly predicted depressive symptoms from academic-related stressors during the COVID-19 pandemic, with "fear and worry about academic progress and plans" as the academic-related stressor that made the greatest contribution to the predictive function. Previously, only a few studies have investigated the association of depressive symptoms using machine learning techniques, but with variables related to the COVID-19 pandemic and with different samples, such as college students from Egypt and Germany [18], and from China [22], Brazilian health workers [19], Brazilian general population [20], and Korean immigrants in the USA [21].

Participants' reports of the most frequent stressors was "fear and worry about academic progress and plans", the same stressor that made the greatest contribution to the predictive function. As reported earlier (e.g., [16,17], the machine learning approach can be used to predict mental health vulnerabilities, and offers several advantages, including it is not constrained by traditional assumptions, it can assess relationships among multiple variables simultaneously, and it can identify patterns in complex datasets [23]. The present result underscores the relevance of the assessment of academic-related stressors in graduate studies. It highlights the potential of machine learning as a valuable tool for identifying academic-related stressors associated with academic environments in graduate programs, aiming to guide actions at both promoting mental well-being and preventing mental health problems.

As stated previously, there are some studies which investigated the relationship between stressors and depressive symptoms in undergraduate students through different statistical analyses. For example, O'Reilly et al. [25] investigated the correlation between depressive symptoms and both the number and perceived impact of stressors among medical students. They categorized stressors into two groups: personal stressors, such as financial issues, marriage, and family matters, and academic stressors, such as exams, coursework, and hospital-related challenges. The analysis, conducted through linear regressions, included the sum of stressor events, but did not identify which specific events contributed most to the severity of depressive symptoms. Although not specifically associated with depressive symptoms, in O'Reilly et al. [25], one of the most impactful events experienced by a large proportion of their participants was related to "thoughts about future career possibilities", a concern similar to the stressor reported in our study (i.e., "fear and worry about academic progress and plans"). In another example, Wang et al. [24] investigated mental health of college students (including depressive symptoms) during the COVID-19 pandemic in a large university system in the United States. However, their analyses were presented as frequencies without assessing associations with the severity of depressive symptoms.

In graduate students, Kreger [45] observed a relationship between perceived stress, measured through a single question, and depressive symptoms in 29 graduate students. Hish et al. [46] reported a relationship between stress and depressive symptoms in 69 biomedical doctoral students. In this study, stress was assessed through the Graduate Stress Inventory–Revised, which measures academic stress, environmental stress, and family/ monetary stress. During the COVID-19 pandemic, Mansur-Alves et al. [47] investigated perceived stress in general and observed that perceived stress contributes to the intensification of depressive and anxiety symptoms. To investigate stress, the authors used the Perceived Stress Scale, which measures stress in general, not specifically related to academic activities. Wyatt and Oswalt [48] investigated perceived stress in a sample of 27,387 respondents, undergraduate (88.9 %) and graduate (11.1 %) students in the USA. The authors observed that graduate and undergraduate students reported similar levels of mental health problems (including being diagnosed with depression) and perceived stress, but the authors did not investigate the relationship between stress and mental health issues.

Our pioneer machine learning study investigated specific stressors related to graduate activities based on previous studies that identified academic concerns contributing to increased stress levels in university students [24,34]. In our study, participants reported "fear and worry about academic progress and plans" as the stressor/difficulty experienced during the pandemic that most affected their lives and academic activities, followed by "fear and worry about academic performance", "fear and worry about academic deadlines", and "financial difficulties". Entering university represents a challenge in respect to adapting to the study regime, having much greater independence, and dealing with new teaching dynamics and responsibilities, while at the same time having to integrate into a new social environment [49]. In the case of UFRJ, especially in recent years, because of cuts in funding, there has been a growing need for students to seek employment while pursuing their studies. Such a scenario imposes significant physical, intellectual, and emotional demands on the students. Moreover, for those who need to relocate from other cities, there are added challenges, including gaining independence and adjusting to life in a large urban center with high exposure to urban violence [50]. The influx of many social quota students from different social backgrounds has further contributed to an increase in the number of students with even more challenging conditions.

Our sample reported marked high levels of depressive symptoms, using a PHQ-9 cut-off point of ≥ 9, which was shown to present 77.5 % sensitivity and 86.7 % specificity for diagnosing major depression disorder in the Brazilian population [33]. Even with a higher cut-off (i.e., ≥ 10), still a high proportion (70.3 %, n= 121) met the criteria for a 'probable depression diagnosis'. Investigating a similar period (November 3, 2021, to March 21, 2022) using the PHQ-9 and a cut-off

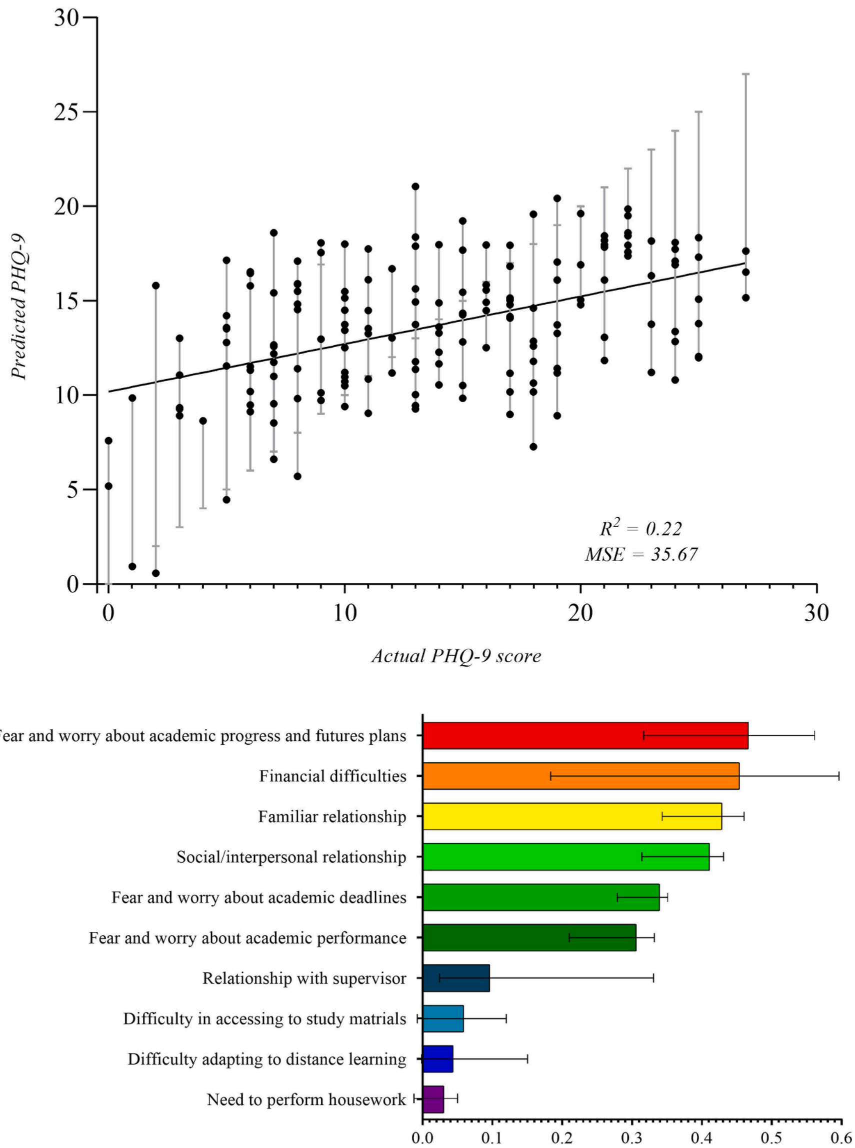

Fig. 1. Weight of stressors/difficulties for the prediction model of depressive symptoms. *Upper* - Scatter plots of actual *versus* predicted values applied to two-fold cross-validation schemes for the PHQ-9 symptoms model prediction (Ɛ-SVR); the gray bars representing the loss value to each participant (predicted *minus* actual values on the scale). *Bottom* - Plot showing the values of the weights for each question about academic-related stressors/difficulties for predicting depressive symptoms (Ɛ-SVR, k=2); the error bars show the lowest and maximum values achieved for each weight.

point of ≥ 10, Prado et al.'s study [51] found a prevalence of 61.1 % of participants reporting clinically relevant depressive symptoms among Brazilian graduate and undergraduate students.

The COVID-19 pandemic imposed several challenges to the academic environment, such as the new ways of working and learning (i.e., remote activities), social distancing, and increased financial hardships, which likely exacerbated mental health issues among graduate students [52]. Cacioppo & Cacioppo [53] emphasized that perceived social isolation is a strong risk factor for depressive symptomatology (but not vice-versa). Additionally, Sott et al. [54] highlighted that Brazilian public health faced several challenges during the pandemic. Despite the efforts of researchers and health professionals; political disputes and insufficient investment contributed to a widespread insecurity and uncertainty. Brazil's response to the COVID-19 pandemic was among the worst globally [55], with strong political deleterious effects over the mortality rate [56]. Together, these factors likely contributed to the high level of depressive symptoms observed in the present study.

The study has some limitations that need to be highlighted. First, the sample was not probabilistic and did not represent all the students from UFRJ. This is a common limitation of web surveys and may introduce self-selection bias, for instance, individuals presenting higher depressive symptoms could be more likely to agree to participate in the study. It is important to note that the gender and age composition of our sample correspond to the same distribution of the original population of graduate students from the four graduate programs investigated. Even though, the prevalence of such symptoms must be interpreted with caution. Second, the use of self-report measures did not enable us to verify the reliability of the responses or to ensure that participants correctly understood the questions. Third, although we used two cross-validation schemes (two-fold [or half split] cross-validation and five-fold cross-validation), predictive models should ideally be further validated with a truly independent sample. Finally, we obtained only two responses from participants who did not identify themselves as either woman or man, which precluded the inclusion of this data in our analysis. We opted not to describe these data to prevent a possible identification and exposure of the respondents. In future studies, we hope to have a more diverse and inclusive body of graduate students, which should include not only transgender and transexual people but also be more representative in respect to other social and ethnic groups.

5. Conclusions

To our knowledge, this is the first study that employed pattern regression analyses to predict depressive symptoms from academic-related stressors during the COVID-19 pandemic. The results are promising since they could provide significant models for predicting mental health symptoms from psychometric data. Moreover, the results highlight the importance of considering how students perceive the way the academic environment affects their lives. Notwithstanding our data were collected during the COVID-19 pandemic, results must be faced as evidence of the urgent need to investigate graduate students' life stressors and to promote actions directed to improve mental health and stress management in the research environment.

A comprehensive understanding of the underlying risk factors influencing students' mental health is pivotal for crafting interventions targeted to students' specific needs. Notably, the early identification of students in vulnerable situations presents a unique opportunity to proactively avert potential mental health crises through timely intervention, either before or during their graduate studies at the university [57].

Furthermore, it is essential to foster strategies within the academic and research space that promote inclusivity and encourage prosocial behaviors, such as offering mutual support to colleagues, and creating a welcoming and cooperative environment, which could act as a potent method to counteract the adverse impacts of everyday stressors on the emotional state of everyone in the academic team [7,58].

List of abbreviations

WHO – World Health Organization
UFRJ – Federal University of Rio de Janeiro
PHQ-9 – Patient Health Questionnaire
PRoNTo – Pattern Recognition for Neuroimaging Toolbox
ε-SVR – Linear epsilon-insensitive support vector regression
GPR – Gaussian process regression
KRR – Kernel ridge regression
r – Correlation coefficient
R^2 – Coefficient of determination
NMSE – Normalized mean squared error

Ethics approval and consent to participate

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and the 1975 Declaration of Helsinki, as revised in 2008. The study was approved by the Research Ethics Committee of the Institute of Collective Health Studies of the Federal University of Rio de Janeiro, opinion No. 4882,174 of August 3, 2021. All participants provided informed consent before the assessment. Additionally, participants were informed of their right to withdraw from the study at any time.

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CRediT authorship contribution statement

Raquel De Boni: Writing – review & editing, Methodology, Conceptualization. **Eliane Volchan:** Writing – review & editing, Methodology, Conceptualization. **Aline Bastos:** Writing – original draft, Visualization, Formal analysis, Data curation. **Mirtes Pereira:** Writing – review & editing, Methodology, Conceptualization. **Giovanni Lovisi:** Writing – review & editing, Methodology, Conceptualization. **Fatima Erthal:** Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Orlando Fernandes-Jr:** Writing – review & editing, Visualization, Formal analysis. **Suzana Liberal:** Investigation, Data curation. **Anna Júlia Pires:** Writing – review & editing, Investigation. **Aline Cardoso:** Writing – review & editing. **Leticia Oliveira:** Writing – review & editing, Methodology, Conceptualization. **Luisa Lage:** Writing – review & editing, Investigation. **Olga Grichtchouk:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no competing interests.

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Data Availability

Data will be made available on request.

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