Research Paper

Evaluation of COVID-19 Stress in University Students According to Their Socio-demographic Characteristics Based on Machine Learning Algorithms

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Citation Nooripour, R., Ilanloo, H., Naveshki, M., Naveshki, S., Amiri Majd, M., & Sikström, S., et al. (2024). Evaluation of COVID-19 Stress in University Students According to Their Socio-demographic Characteristics Based on Machine Learning Algorithms. *Journal of Practice in Clinical Psychology, 12*(1), 1-12. https://doi.org/10.32598/jpcp.12.1.288.1

doi https://doi.org/10.32598/jpcp.12.1.288.1

Article info:
Received: 02 Jun 2023
Accepted: 13 Aug 2023
Available Online: 01 Jan 2024

Keywords:
COVID-19, Machine learning, Psychological distress, Student, Stress

ABSTRACT

Objective: The coronavirus pandemic has presented a significant challenge and brought about dramatic changes for universities and their students. This study evaluated machine learning algorithms for estimating COVID-19 stress levels among Iranian university students.

Methods: We conducted an online survey from May 10th to November 20th, 2021, to determine how Iranian university students responded to the COVID-19 outbreak in Iran. The survey invitations were sent to Iranian university students via e-mail, forums, and social media platforms, such as internet advertisements. We collected data from 3490 university students, using sociodemographic characteristics and the COVID-19 Stress Scale (CSS; Nooripour et al. [2022]). The adaptive neuro-fuzzy inference system (ANFIS) network for prediction and fuzzy logic-based rules were used for analyzing the data. For classification, eight machine learning algorithms were employed: support vector machine (SVM), K-nearest neighbors (KNN), random forest, multilayer perceptron, decision tree, and passive-aggressive algorithm. These algorithms were selected based on their principles and suitability for stress detection in the desired category.

Results: Among the algorithms, the decision tree algorithm showed the best performance in accurately classifying the data into the correct stress intensity categories. Moreover, analyses revealed that gender, age group, and education significantly influenced stress intensity levels, with men experiencing less stress; stress intensity decreased with age, and higher education was associated with lower stress levels. The results indicated that education and marital status were the most influential parameters for all three top-performing algorithms (random forest, multi-layer perceptron, and decision tree).

Conclusion: Our research suggests that innovative methods such as machine learning algorithms can be used to evaluate psychological distress caused by the COVID-19 outbreak, such as stress. Evaluating stress levels can help prevent mental health problems and enhance students' coping capabilities.

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Highlights

• Machine learning is effective in assessing COVID-19-induced stress in Iranian college students.

• A decision tree algorithm can accurately classify the COVID-19-related stress levels among Iranian college students.

• Gender, age, and academic degree can significantly affect COVID-19-induced stress intensity, where older male students with higher academic degree have lower stress.

Plain Language Summary

This research explored the COVID-19-induced stress level of 3490 Iranian college students using machine-learning algorithms. We found that factors like age, gender, and academic degree significantly affected the stress level of college students. The decision tree algorithm was significantly more effective in identifying various stress levels. The results highlight the broader impact of the COVID-19 pandemic on mental health of young adults. It also demonstrates the potential of technology in understanding and addressing mental health problem. More support is needed for younger students, or those with lower academic degree who are more at risk for developing stress during the pandemic.

Introduction

The declaration of coronavirus disease 2019 (COVID-19) as a global pandemic by the World Health Organization (WHO) in March 2020 led to the imposition of widespread restrictions and lockdowns. This crisis has had far-reaching effects on health, economy, and society. Previous viral outbreaks, including the SARS virus, have been associated with various psychological disorders such as depression, anxiety, panic attacks, psychosis, stress, and even suicide (Zerbo et al., 2022).

Traditionally, university students have been considered to experience more stress and suffer from more severe health problems than primary and middle school students (Ge et al., 2020). Several studies have found that students' primary sources of stress include interpersonal relationships, financial difficulties, and meeting their responsibilities. Some universities have reduced the possibility of COVID-19 transmission among participants by moving resident students off-campus. In recent years, distance education has become more prevalent due to social changes in the education sector, such as the sharing of educational resources and advancements in communication technology. This change has resulted in communication patterns between teachers and students shifting, with students becoming more isolated and independent. Consequently, stress has become a major issue among university students (Hurst, Baranik, & Daniel, 2012).

This process has adversely impacted students who are pursuing a university education. According to research, COVID-19 stress negatively impacts academic performance and mental health (Ye et al., 2020). The Coronavirus disease caused psychological distress (Rehman et al., 2021), suicide (Galea, Merchant, & Lurie, 2020), confusion, and anger over the loss of life-sustaining resources (Nooripour, Hosseinian, et al., 2022), as well as stress (Nooripour, Ghanbari, et al., 2022). Several students could not access mental health care due to the closure of student health centers. According to anecdotal reports, students have difficulty adjusting to the ambiguities associated with the unprecedented open-ended COVID-19 pandemic.

Traditional models of stress and its treatment may need to be revised due to the worldwide prevalence and infrequency of the provoking event. Limitations, isolation, and changes in daily routines and education pose a risk of stress. For students, changing academic settings and contacting clinical settings, friends, university officials, instructors, and relatives can be stressful (Funkhouser, Klemballa, & Shankman, 2022). Identifying and measuring COVID-19 stress during sensitive periods could enhance our understanding of who is vulnerable to the adverse effects of coronavirus stress, the mechanisms linking stress exposure to health decline, and effective intervention strategies.

During the pandemic, maintaining good mental health is just as imperative as maintaining good physical health. As the coronavirus may adversely affect students' psychological health, it is essential to investigate psychological factors, such as stress, that affect mental health. In numerous countries, a mental health crisis is likely due to the COVID-19 pandemic. Interventions will likely be required on both an individual and societal level. Traditional models of stress and its treatment may not be adequate because of the prevalence and frequency of the provoking events worldwide (Xiang et al., 2020). We must evaluate the potential utility stress regarding COVID-19 in clinical practice and research to facilitate decisions about its use.

The COVID-19 pandemic, despite seemingly being resolved, has left a lasting impact on society. The lessons learned from this crisis underscore the ongoing necessity of research to comprehend and address the challenges posed by pandemics. While the goal is to prevent or effectively manage future pandemics, it is crucial to acknowledge the potential for similar global health emergencies. Consequently, conducting research that evaluates the stress and mental health implications on university students during pandemics remains paramount, as this knowledge can be applied to future outbreaks. Importantly, the significance of research in understanding and addressing pandemic-related challenges is further underscored by the incorporation of evaluation based on machine learning (ML) algorithms. By leveraging these advanced computational methods, researchers can analyze extensive datasets to identify patterns, risk factors, and effective coping mechanisms applicable in future crises. This approach enables a more comprehensive examination of the socio-demographic characteristics of students and their experiences during the COVID-19 pandemic, thereby enhancing the accuracy and reliability of the findings. The use of ML allowed us to identify nonlinear and relatively insignificant but vital factors that were difficult to identify using traditional approaches. We were able to quickly remove extensive data using machine learning methods and make predictions with greater accuracy. Our contribution to the current literature on stress and health is unique, as this is the first study to use machine learning algorithms to explore the stress levels of university students during the coronavirus outbreak. This research not only enables educational institutions to proactively prepare for and respond to potential future pandemics but also equips policymakers and healthcare professionals with evidence-based strategies for supporting the mental well-being of students during times of crisis. By recognizing the necessity of research on pandemic-related stress among university students, we can better protect and support the resilience of individuals and communities amidst uncertainty. Through thorough research, including the utilization of machine learning algorithms, we can enhance our understanding of the challenges faced by students during pandemics and develop effective strategies to address their mental health needs.

The incorporation of evaluation based on machine learning algorithms further emphasizes the importance and necessity of research to comprehend and address the challenges brought about by pandemics. By examining the experiences of university students and evaluating their mental health implications using advanced computational methods, we can gather valuable insights to aid future crisis management. This research enables educational institutions, policymakers, and healthcare professionals to proactively prepare for potential future pandemics and effectively support the well-being of students during such crises.

This research evaluated COVID-19 stress in university students according to their socio-demographic characteristics based on machine learning algorithms.

Materials and Methods

This study used a cross-sectional design for collecting data.

Setting and procedure

The study was conducted within a specific timeframe, spanning from May 10th to November 20th, 2021, to examine the impact of COVID-19 stress on Iranian university students. The statistical population of the study consisted of university students from various institutions across the country. Convenience sampling was employed to obtain a sample size of 3490 participants, who voluntarily agreed to take part in the study. Convenience sampling was chosen as the sampling method due to its practicality and feasibility within the given resources and time constraints. Participants were selected based on their availability and willingness to participate, allowing for a diverse representation of university students. It is important to note that while convenience sampling provides valuable insights, it may not guarantee the representativeness of the entire population of Iranian university students. To collect data, an online questionnaire was utilized as a convenient and efficient method. This approach offered several advantages, including a broader reach, faster data collection, and easier accessibility for participants. Invitations to participate in the study were sent out through various channels, such as email and social forums, including internet advertisements. The questionnaire itself was designed to be user-friendly and required approximately 5 minutes to complete. Participants had the opportunity to review their answers before submission. To ensure ethical considerations of the study, participants were assured of confidentiality, and the requirement to provide personal names was not obligatory. It is crucial to emphasize that while the sample included university students from various institutions in Iran, the study did not encompass all universities in the country. The focus was on obtaining a representative sample of Iranian university students through online convenience sampling. As a result, the specific number of universities included in the study was not explicitly reported.

Participants

To be eligible for participation in this study, individuals were required to be residents of Iran, have access to one platform, and have fluency in the Farsi language. A total of 3490 participants were included in this study, comprising 1542 women (44%) and 1948 men (56%) out of the total population. Data were classified according to age groups, which were assigned to three categories (1=20-30, 2=31-40, and 3=over 40), as well as gender, level of education, and marital status. The five levels of education were categorized as follows: 0=seminary education, 1=BA, 3=MA, 4=PhD., and 5=postdoctoral degree. The researcher collected all the data.

Measures

The sociodemographic characteristics comprised participants' marital status, level of education, gender, and age.

COVID-19 Stress Scale (CSS)

The 7-item COVID-19 stress scale (CSS) used in this study was developed by Nooripour et al. (2022) employing a Likert-type scale consisting of five levels, with a minimum score of one and a maximum score of five. The total score is calculated based on the item scores, which range from 7 to 35, with higher scores indicating more stress related to COVID-19. The Cronbach alpha coefficient for this scale was reported 0.76 among Iranian participants (Nooripour et al., 2021). In a study conducted among Iranian students, the Cronbach alpha coefficient was reported as 0.87 (Nooripour et al., 2021).

Data analysis

The collected data was analyzed using an ML model. The proposed ML-based model is described in the following paragraphs.

Machine learning algorithms

Artificial intelligence (AI) is one of the most significant accomplishments of modern times. AI can solve complex and intractable problems that were previously impossible to solve using classical methods. Intelligent models can be built using ML algorithms that learn a system's behavior and apply that knowledge to solve problems in various fields, including industry, social science, neuroscience, psychology, etc. Several studies in the neuroscience field have used ML-based methods, and in this paper, machine learning is employed to find an approximation model for evaluating stress based on psychological inputs (Nooripour et al., 2021).

We used the adaptive neuro-fuzzy inference system (ANFIS) network to make predictions. A neural network that employs a fuzzy inference system (FIS) is used to learn the underlying data's details. The fuzzy membership function parameters are adjusted by a dynamic environment. Networks can solve a wide range of complex and nonlinear problems. We considered a FIS with two inputs, x, and y, and one output, z. We presented two rules based on FIS using the first-order polynomial Sugo fuzzy model, as described by Güneri, Ertay, and Yücel (2011):

Rule 1: If X is A_1 and B1 then $f_1 = p_1x + q_1y + r_1$.

Rule 2: If X is A_2 and B_2 then $f_2 = p_2x + q_2y + r_2$.

Classification algorithms

Supervised algorithms are a common task for so-called intelligent systems. In recent years, various techniques based on artificial intelligence (such as logic-based and perceptron-based techniques) and statistics (such as Bayesian networks and sample-based techniques) have been developed. By analyzing the predictive properties of the distribution of class labels, supervised learning makes it possible to create a concise model of their distribution. The algorithm tests participants whose predictive features are known through class labels.

Various ML algorithms can predict issues related to stress detection in the desired category. In this study, we used and evaluated eight different algorithms to select the best one with the selected features. We used support vector machine (SVM), K-nearest neighbors (KNN) algorithm, random forest algorithm, multilayer perceptron (MLP), decision tree, and passive-aggressive algorithm. These eight algorithms represent different principles used in ML.

Results

Participants' profile

The survey included a total of 3490 participants, of which 1542 were female students (44%) and 1948 were male students (56%). In terms of education, 86 participants had a seminary education (2.46%), 1,298 had a BA (37.19%), 1342 had an MA (38.45%), 699 had a Ph.D. (20.02%), and 65 had a postdoctoral degree (1.86%). The participants were divided into three age groups: The first group consisted of 1745 people between 20 and 30 years old (50%), the second group consisted of 1709 people between 31 and 40 years old (48.96%), and the third group consisted of 36 people over 40 years old (1.03%). In addition, 2950 participants (84.52%) were married (or cohabiting), and 540 (15.47%) were single.

After classifying the data using various algorithms, we reported the accuracy values of each algorithm in Table 1. According to the accuracy levels obtained in this research, the decision tree, random forest, and MLP algorithms showed the best results. The accuracy values of each algorithm are presented in the first bar chart. We also evaluated the performance of the algorithms using a confusion matrix.

We categorized the data into four categories (1=no, 2=low, 3=moderate, and 4=severe). The accuracy of each algorithm was evaluated based on how accurately it classified the data into the correct class. The decision tree algorithm performed the best, and most of the data were predicted in the correct class.

Table 1 shows the accuracy values of each algorithm. The closer the value is to one, the higher the accuracy, indicating that the algorithm is suitable for use in the study.

In the following, we present the confusion matrix of each algorithm. A confusion matrix is a square matrix that demonstrates the predictions of each algorithm (Figure 1).

According to Figure 2, the RF algorithm correctly predicted 1332 participants in class 3 but incorrectly predicted 87 and 97 participants for classes 2 and 4, respectively. The Perceptron (P) algorithm had the weakest performance compared to the other algorithms as it predicted most of the data in only two classes while distributing the remaining data in different classes. The MLP algorithm had higher accuracy with larger diameter numbers, specifically correctly predicting 677 out of 915 participants in class 4 according to the matrix. Logistic regression also had good performance, correctly predicting 1326 out of 1520 participants. It is important to note that while the decision tree algorithm has the highest accuracy among the algorithms used in the study, it may not necessarily be the best algorithm for all situations. The choice of algorithm depends on various factors, such as the nature of the data, the problem being addressed, and the resources available. Therefore, it is essential to consider all these factors before deciding on the appropriate algorithm for a particular task. The passive-aggressive algorithm predicted most of the data into three classes, with 393 participants in class 2 being predicted as class 3. It is also important to note that these algorithms and their performance have implications for psychiatric illnesses, as they can help in accurately predicting and identifying patients who require treatment.

Pearson correlation coefficient

The Pearson correlation coefficient can be used to evaluate the mutual effect of two parameters on each other. The values in this matrix range between -1 and 1, where values closer to 1 indicate a stronger dependence between the two parameters. The sign (+ or -) indicates the direction of the relationship.

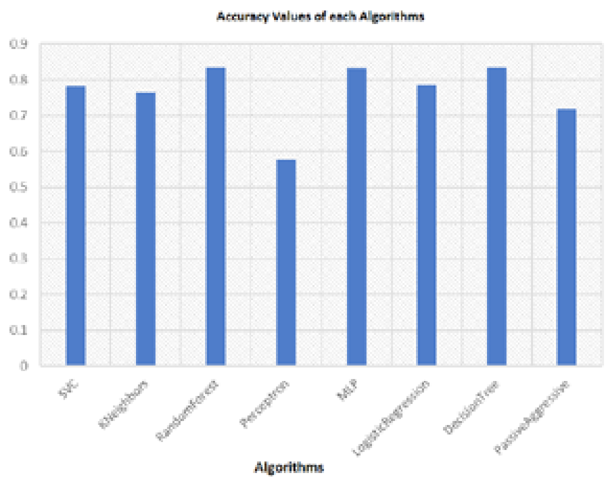

Figure 1. Accuracy values of algorithms

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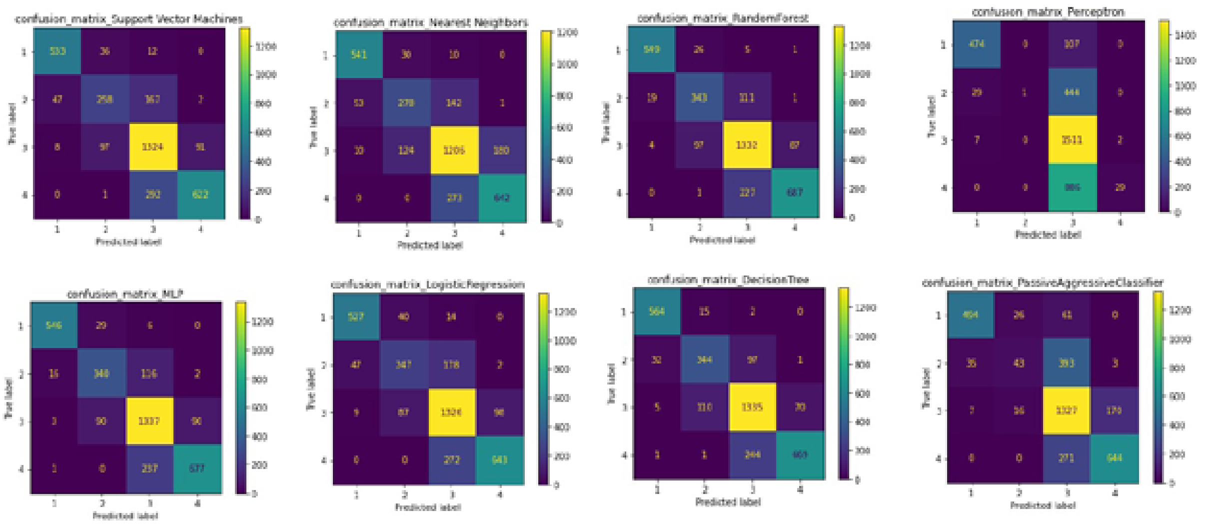

Figure 2. Random forest algorithm

Based on Figure 3, which presents the correlation coefficient using the Kendall method, we can observe that gender, age group, and education have a significant impact on stress intensity. A higher correlation coefficient indicates a stronger influence between the two parameters. In this case, men experience less stress than women, and stress intensity decreases with increasing age. Furthermore, an increase in education is associated with a decrease in stress levels.

The influence of parameters on the performance of algorithms

To identify the most important feature (parameter) among the input parameters, we analyzed the top three algorithms. Each parameter was systematically removed from person to person, and the accuracy was recalculated. The results are presented in Table 2. Across all three algorithms, education emerged as the most influential parameter, followed by marital status. However, there was a variation in the third most important parameter: Age group for RF and MLP, and family history of disorder for DT. The impact of education on the algorithm's performance is significant as it allows for a clearer division of data into distinct groups. Removing the education parameter led to a more substantial decrease in accuracy compared to the other parameters. The importance of marital status for the algorithms can be explained similarly.

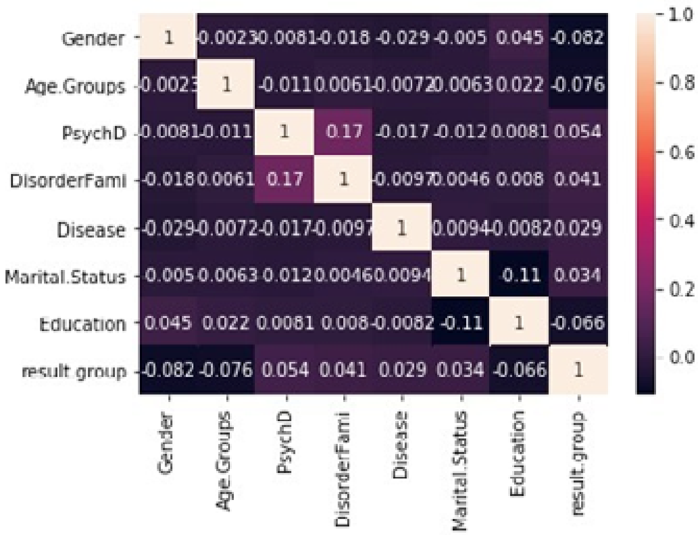

Figure 3. Correlation coefficient

Table 1. Accuracy values of each algorithm

Algorithm	Accuracy
SVM	0.7842
KNN	0.7641
RF	0.834
P	0.5773
MLP	0.8338
LP	0.7859
DT	0.8343
PA	0.7186

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Abbreviations: SVM: Used support vector machine; KNN: K-nearest neighbor; RF: Random forest; P: Perceptron; MLP: Multilayer perceptron; DT: Decision tree; PA: Passive-aggressive.

Table 2 shows that the top-performing algorithms are RF, MLP, and DT. We selected these algorithms for further analysis in Table 2. We removed each parameter one by one to determine the most critical parameter and then recalculated the algorithm's accuracy. The change in accuracy determined the importance of each parameter. For instance, when we removed education from the RF algorithm, the accuracy decreased from 0.834 to 0.8162. We repeated this process for all parameters and all three algorithms, and the resulting accuracy values are reported in Table 2.

Table 3 shows the most influential parameters for the three algorithms.

Discussion

In this study, we assessed the stress of COVID-19 using ML algorithms based on sociodemographic characteristics such as marital status, education level, gender, and age among Iranian university students. The COVID-19 pandemic not only poses a threat to individuals' physical well-being but also to their mental well-being (Cullen, Gulati, & Kelly, 2020; Dalila Talevi et al., 2020). Although some research has investigated psychological issues during COVID-19 (Lee, 2020), there has been no evaluation of COVID-19-related stress using ML algorithms.

We identified gender differences in the perception of stress among university students during the COVID-19 pandemic. Our findings indicate that female students reported higher levels of stress than male students. While the existing literature on COVID-19 is not specific to student populations, recent studies suggest that females are more likely to report high levels of stress during the pandemic (Aslan & Pekince, 2021; Pieh, Budimir, & Probst, 2020). Other studies have reported no association between gender and stress levels during COVID-19 (Li et al., 2020; Limcaoco, Mateos, Fernández, & Roncero, 2020; Wang et al., 2020). However, research has shown that females have experienced more psychological distress during the pandemic (Best, Law, Roach, & Wilbiks, 2021), possibly due to the stress of caring for family members (Balhara, Verma, & Gupta, 2012).

Table 2. The most influential parameters for random forest, multilayer perceptron, and decision tree algorithms

Algorithms	Gender	Age Groups	PsychD	Disorder Family	Disease	Marital Status	Education
RF	0.8245	0.8243	0.8274	0.8283	0.8268	0.8191	0.8162
MLP	0.8243	0.8241	0.8275	0.8286	0.8266	0.8189	0.8160
DT	0.8248	0.8246	0.8280	0.8291	0.8271	0.8194	0.8165

Abbreviations: RF: Random forest; MLP: Multilayer perceptron; DT: Decision tree.

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Table 3. The most significant parameters in RF, MLP, and DT algorithms

Algorithms	First	Second	Third
RF	Education	Marital Status	Age
MLP	Education	Marital Status	Age
DT	Education	Marital status	Disorder family

Abbreviations: RF: Random forest; MLP: Multilayer perceptron; DT: Decision tree.

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This study suggests that female university students experience higher stress levels than male students, potentially due to differences in stress responses related to their hormonal system and the multiple roles they are expected to fulfill. These gender differences in stress are not unique to the COVID-19 pandemic, but the pandemic may exacerbate them. While further research is needed to fully understand these gender differences in perceived and reported stress levels, these results can inform the development of guidance policies and teaching materials. It should be noted that the study only focused on samples within one country, so caution should be exercised when interpreting the results.

Additionally, we found that higher levels of education were associated with lower levels of COVID-19 stress. This research aligns with other studies demonstrating that certain subgroups of students experience significant distress during pandemics (Clabaugh, Duque, & Fields, 2021). Despite most university students experiencing stress related to COVID-19, increasing educational levels may help reduce this stress during the pandemic (Jarrett et al., 2021).

Another finding of our study is that older university students experienced less stress related to COVID-19. This is consistent with research conducted on a sample of quarantined individuals from 41 countries, where age and stress levels significantly correlated (Limcaoco et al., 2020). However, a study conducted on Chinese individuals found no correlation between stress and age (Wang et al., 2020). These findings are supported by other studies in the field (Scott, Sliwinski, & Blanchard-Fields, 2013; Stone, Schneider, & Broderick, 2017; Stone, Schwartz, Broderick, & Deaton, 2010).

Observing that older university students can avoid events that trigger negative emotions, being surrounded by close friends and family members, and having health problems effectively controlled by medication, may explain their lower susceptibility to stress. Age differences in chronic stress, such as the ongoing stress caused by COVID-19, could be attributed to the antecedent emotion regulation strategies predicted by socio-emotional selectivity theory (Carstensen, 1995). As university students with decreasing energy levels prioritize emotional goals, they tend to invest in valuable and rewarding social relationships (Carstensen, 2006).

Our study indicates that married or cohabiting individuals experience less stress compared to single people. Several previous studies have emphasized the benefits of intimate relationships (Braithwaite, Delevi, & Fincham, 2010). It is noteworthy that we did not find any significant differences in perceived stress based on marital status, which is in contrast to previous research (Wang et al., 2020).

Conclusion

In conclusion, our study demonstrates that incorporating ML algorithms into the evaluation of COVID-19 stress on university students and taking into account their socio-demographic characteristics provides valuable insights and tools for addressing this pressing issue. By recognizing the diversity of student backgrounds and circumstances, educational institutions can tailor their support efforts effectively and prioritize the mental health and well-being of their students.

The utilization of ML algorithms enables the analysis of vast datasets, revealing intricate patterns, correlations, and trends that might go unnoticed through traditional statistical methods. Through this approach, researchers gain a deeper understanding of the complex interplay between socio-demographic factors and the manifestation of COVID-19 stress among students.

Moreover, the application of ML algorithms empowers the development of personalized interventions and support systems. By considering individual socio-demographic characteristics such as age, gender, ethnicity, and socioeconomic status, these algorithms generate targeted recommendations and strategies to address specific stressors faced by each student. This personalized approach maximizes the effectiveness of interventions and ensures that resources are efficiently allocated based on individual needs.

Also, ML algorithms facilitate early detection and intervention for students who are at a higher risk of experiencing severe COVID-19 stress. By analyzing historical data and real-time information, these algorithms can identify warning signs and provide timely interventions, preventing the escalation of stress-related issues and ensuring timely access to support services.

In summary, integrating ML algorithms into the evaluation of COVID-19 stress among university students and considering their socio-demographic characteristics offers tremendous potential for enhancing student support and well-being. This comprehensive approach, powered by data analysis and predictive capabilities, enables educational institutions to develop evidence-based strategies that effectively address the unique challenges faced by students during these uncertain times. By prioritizing mental health, expanding consultation programs, and implementing targeted interventions, universities can support their students effectively and promote a positive learning environment even in the face of adversity.

Strengths and limitations

With further advancements in causality analysis, such as Bayesian networks, it will become possible to construct an intervention model. Machine learning methods enable us to process data more efficiently than conventional approaches, making it possible to quickly process large and complex datasets. Using a machine learning approach is faster and more reliable, producing better results. However, there are trade-offs in forecasting between precision and explainability. Therefore, this study optimized the feature selection process, and the interpretability of predictors needs to be addressed in detail.

Despite some limitations, this study contributes significant findings to the literature. Firstly, the study focused only on university students. This limitation could be overcome in future studies by collecting data from high school students and extending the age range of participants. Additionally, the use of observations and interviews alongside self-report scales could reduce the limitations associated with the exclusive use of self-report scales. Another limitation of this study is that it was conducted only on Iranian university students, which may limit the generalizability of the findings. To minimize this limitation, data from participants of different nationalities and ethnicities could be included in future studies. Lastly, the survey used in this study was voluntary, and therefore, selection bias could be a potential concern.

Ethical Considerations

Compliance with ethical guidelines

All human research was conducted according to the ethical standards established by the National Research Committee of the National Academy of Sciences, the Helsinki Declaration of 1964, and subsequent revisions, or equivalent ethical standards. Participants voluntarily completed all questionnaires anonymously and had the option to withdraw from the study at any time.

Funding

A personal financial budget was used to conduct this study.

Authors' contributions

Study concept and design: Roghieh Nooripour, Mohammad Naveshki, Saeid Naveshki, Sverker Sikström, Farnaz Jafari, and Mojtaba Amiri Majd; Acquisition of data: Roghieh Nooripour, Hossein Ilanloo, Mohammad Naveshki, Saeid Naveshki, Farnaz Jafari, and Mojtaba Amiri Majd; Analysis and interpretation of data: Roghieh Nooripour, Hossein Ilanloo, Mohammad Naveshki, Saeid Naveshki, Sverker Sikström, MH, and Mojtaba Amiri Majd; Drafting of the manuscript: Roghieh Nooripour, Hossein Ilanloo, Mohammad Naveshki, Sverker Sikström, Farnaz Jafari, and Mojtaba Amiri Majd; Critical revision of the manuscript for important intellectual content: Roghieh Nooripour, Mohammad Naveshki, Saeid Naveshki, Sverker Sikström, and Farnaz Jafari; Statistical analysis: Roghieh Nooripour, Hossein Ilanloo, Mohammad Naveshki, Saeid Naveshki, Sverker Sikström, and Mojtaba Amiri Majd; Administrative, technical, and material support: Roghieh Nooripour, Hossein Ilanloo, Sverker Sikström; Study supervision: Roghieh Nooripour, Sverker Sikström, and Mojtaba Amiri Majd.

Conflict of interest

The authors declared no conflict of interest.

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