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Understanding the Impact of Mental Health on Academic Performance in Students Using Random Forest and Stochastic Fractal Search with Guided Whale Optimization Algorithm

Ahmed M. Elshewey[1, *], Abdelhameed Ibrahim[2], Abdelaziz A. Abdelhamid[3,4], Marwa M. Eid[5,6], Manish Kumar Singla[7], Alaa Kadhim Farhan[8]

[1]Computer Science Department, Faculty of Computers and Information, Suez University, Suez 43512, Egypt.
[2]Computer Engineering and Control Systems Department, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt.
[3]Department of Computer Science, Faculty of Computer and Information Sciences, Ain Shams University, Cairo 11566, Egypt.
[4]Department of Computer Science, College of Computing and Information Technology, Shaqra.
[5]Faculty of Artificial Intelligence, Delta University for Science and Technology, Mansoura 11152, Egypt.
[6]Department of Communications and Electronics, Delta Higher Institute of Engineering and Technology, Mansoura 35111, Egypt.
[7]Department of Interdisciplinary Courses in Engineering, Chitkara University Institute of Engineering & Technology, Chitkara University, Punjab, India.
[8]Computer Science Department, University of Technology, Baghdad 10066, Iraq.

* Corresponding author: ahmed.elshewey@fci.suezuni.edu.eg

Emails: ahmed.elshewey@fci.suezuni.edu.eg; afai79@mans.edu.eg; abdelaziz@su.edu.sa; Marwa.Radwan@deltauniv.edu.eg; manish.singla@chitkara.edu.in; Alaa.K.Farhan@uotechnology.edu.iq

Abstract

The primary objective of this research is to explore the interplay of the relationship between depression severity, coursework performance, and ADHD in computer science students to build sound insight into the psychosocial aspects that influence both the academic and personal lives of students. This study is carried out by computer science students' survey (100), which consists of psychosocial factors like age, gender, GPA, annotations, depression status, completing academic tasks, presentation preferences, sleep rest, number of friends, and vulnerability to new encounters. Feature selection is carried out to distinguish vital features and to increase the power to predict, which involves utilization of the Stochastic Fractal Search (SFS) algorithm and its hybrid combined with the Whale Optimization Algorithm (WOA) algorithm and other variants. We have applied our selected features by creating a sequel to the classification machine learning models like Random Forest, Logistic Regression, K-Nearest Neighbor and others. The finding of the predictor showed that the bSFS-Guided WOA algorithm obtained the lowest average error, 0.131917, being regarded as the most efficient feature selection. In the classification models group, Random Forest came out first with the highest accuracy, 0.973449669, which implies its prominence in predicting the interdependence relationships. Discoveries highlighted psychological factors that affect student life and emphasized that mental wellness and study habits are essential for a student's academic success. The study suggests specific programs based on the findings and recommends thorough analysis to discover other factors that can be examined on a larger dataset.

Keywords: Psychosocial Dimensions; Stochastic Fractal Search (SFS); Whale Optimization Algorithm; Random Forest; Academic Performance; Mental Health.

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1. Introduction

The role of psychosocial factors in an academic environment is paramount as they broadly define the adaptation of students to adulthood, their level of involvement and ultimately, their academic performance. They define the scope of virtually any aspect of man's life, ranging from intellectual health and social relationships to making people context of collection education, specifically for computer science students, e.g., may be necessary for determining academic success and future job prospects. Typically, computer science degrees are rigorous and time-intensive environments that significantly contribute to the mental health challenges students face. Thus, it is necessary to understand how psychosocial factors impact these students' academic experiences fullness [1-3]. Extensive research has been carried out in the areas of depression, attention-deficit hyperactivity disorder, and academic achievement of students. As an example, many studies have indicated that issues to do with the mind, such as depression, could lead to low energy, concentration with lower levels and eventually worse academic performances. Likewise, ADHD is likely to cause ineffective allocation of attention and poor organization of work that can lead to academic performance gaps. Unsuitable conditions cause a vicious cycle of deteriorating academic and mental health, which complicates the flying difficulties for students. These are noteworthy findings. This more inclusive analysis incorporates the multi-dimensional aspects of a student's mindset, which is necessary to fully grasp the general picture of life on campus and explore the designated intervention points [4-6].

The main focus of the study is to investigate the correlation between mental health (in particular, low levels of depression), study habits (for instance, why students take notes and enjoy sleep patterns) and academic achievement for computer science students. Through investigation of interactions between these psychosocial factors and a student's academic performance and overall well-being, the study aims to come up with critical factors that influence these outcomes. With such an objective comes the apprehension of clarifying the different connections between student life elements like social disposition and academic consequences with mental health conditions. Furthermore, this study will be looking to identify how the specific factors about to be discussed relate to and impact the students' computer science students' academic challenges in terms of success [7-9].

Based on this study, the findings may help determine education policies by highlighting the role of social-emotional factors on learning and performance. For instance, educators can apply such data to develop more accommodating and educative teaching techniques that consider student differences supported by the individualized teaching approach [10-12]. This could be made by integrating some mental health education in the course content, establishing less stringent conditions, or helping train the teachers how to assist students who are mentally disturbed. Hence, knowing about these explicit links allows us to define attentive mental health interventions, such as counseling or stress management programs, connected to the concrete issues faced by computer science students and other science students. The scope of the present research is also directed toward broader discussions about the welfare of the students by emphasizing the significance of mental health and lifestyle for academic conduct [13-14]. By recognizing psychosocial mainstays that matter for

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academic attainment, the research can smartly lead to more effective and descriptive responses. The educational office should consider introducing support groups, mental health awareness campaigns, and integrating mental health resources into the academic program. Besides, the study highlights the urgent need for an environment that encourages mental health and is part of a healthy culture in the college. Ultimately, this study will set the pace of change to a more complete future for students, considering that academic excellence is linked to mental health and private life.

2. Literature Review

Numerous research projects have been conducted on student achievement in secondary education, specifically focusing on two Portuguese schools. These studies are comprehensively listed in the section titled "Related Works." Given that secondary education is a crucial stage in a student's academic journey, it is imperative to understand the factors influencing success levels. The literature reviewed encompasses various topics, including pedagogical methodologies, institutional dynamics, socioeconomic factors, and educational landscape. This review aims to provide a nuanced understanding of the complex web of factors that either contribute to or hinder student achievement in secondary education, with a particular focus on the Portuguese educational environment.

Students from low-income backgrounds face distinct challenges in pursuing upward mobility through college education, often reflected in significantly lower bachelor's degree attainment rates than their economically advantaged peers. Despite the existing higher education literature highlighting various factors affecting student success, the role of post-college family support still needs to be explored. Specifically, [15] delves into how mental and financial family support influences academic outcomes such as grades, credit accumulation, and persistence, especially for college students from low-income families. An analysis of 728 first-year low-income students from eight four-year institutions revealed that emotional support from family significantly enhances academic outcomes. Students with solid emotional support exhibit better psychological health and higher engagement levels. Although financial support does not universally correlate with academic outcomes across the entire group, it shows notable differences, particularly for first-generation college students. Continuing-generation students benefit more from family financial support compared to their first-generation peers. These findings underscore the critical importance of family support for low-income college students, providing valuable insights for institutions to develop better policies and interventions.

Using an experimental approach, [16] explores the relationship between daily smartphone usage and academic performance. Unlike earlier studies relying on self-reported data, this study uses apps like "Moment" and "App Usage Tracker" for accurate measurements. Data from 43 students at Fundaco Getlio Vargas (FGV), a business school in So Paulo, Brazil, indicated a strong negative correlation between total smartphone usage time and academic performance. This association persisted even when controlling for known predictors like self-efficacy and prior academic achievement. On average, for every additional 100 minutes spent on the device daily, a student's ranking position in school dropped by 6.3 points. The effect was nearly twice as strong when focusing solely on usage during class time, raising concerns about the detrimental impact of excessive smartphone use on academic performance. This study offers valuable insights for educators and academic stakeholders interested in understanding the implications of technology use on student grades.

A meta-analysis by [17] examines the effects of exercise on preadolescent children's executive functions, attention spans, and academic performance, covering ages 6 to 12. The analysis included 31 studies that met specific criteria, exploring various aspects of attention, executive functions, and academic performance. Longitudinal physical activity programs enhanced executive functions, attention, and academic performance, whereas acute physical exercise mainly improved executive functions. The most significant effects were observed with daily exercise routines sustained over several weeks. The results varied across different subdomains, comprehensively evaluating the relationship between physical exercise and cognitive outcomes in preadolescent children.

With the increasing collection of electronic data by universities, there is a growing need to extract useful information from vast data volumes. [18] investigates undergraduate student performance using data mining methods, focusing on two key aspects. The first objective is to predict students' academic achievement over a four-year plan, and the second is to identify similar progressions and integrate them with prediction results. The study identified two crucial groups: high-performing and low-performing students. The findings suggest that focusing on specific courses showing solid or poor performance can effectively support at-risk students through timely interventions and provide guidance and opportunities to high-achieving students.

Social media has become integral to daily life, especially for university students who frequently use it. [19] examines the predictive influence of multitasking, age, and social media use on academic performance. The study involving 348 undergraduate students at a comprehensive university in Hong Kong found that using social media for academic purposes minimally affects academic performance. However, engaging in non-academic social media activities such as video games and multitasking on social media strongly predicts poor academic performance.

Predicting the academic performance of students in public schools in the Federal District of Brazil for 2015 and 2016 [20] highlights the importance of descriptive statistical analysis to understand data trends. The study employs GBM to create classification models, revealing that variables like "grades" and "absence" significantly influence academic outcomes. Additionally, demographic attributes of students, such as neighborhood, school, and age, play a crucial role in determining academic success or failure.

Over the past two decades, educational experts have examined numerous internal and external factors influencing students' academic achievement. Kosaraju, Karau, and Schmeck (2009) note that few studies have explored the interactions between the Big Five personality traits, academic motivation, and academic achievement. [21] addresses this gap by investigating whether achievement goal orientations mediate the relationship between personality traits (Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Intellect) and academic achievement. The study involved 501 high school students from Croatia who completed surveys on the Big Five personality traits and Achievement Goals and reported their final midterm chemistry grades. The results showed that learning approach, performance approach, and work-avoidance goal orientations fully mediate the relationship between personality traits and academic achievement, particularly Conscientiousness.

Colleges and universities are increasingly integrating new technologies and blending traditional and online learning to enhance accessibility and personalization. [22] critically examines the impact of transitioning from traditional classroom settings to online learning environments. The meta-analysis, which includes 21 effect sizes and strict criteria for research design, learning outcome measurement, and blended learning implementation, reveals a small positive effect size (Hedge's g) close to zero with a confidence interval of [-0.13, 0.25]. This suggests minimal differences between classroom and online learning, indicating that students learn similarly even with reduced classroom time. Consequently, there must be a clear advantage or disadvantage when comparing blended learning with traditional classroom learning.

Student progress is a crucial metric in higher education, reflecting the institution's effectiveness. Early identification and intervention for at-risk students significantly enhance their chances of success. Predictive purposes for machine learning methods have recently gained popularity but are still primarily used by educators with advanced computer science or artificial intelligence knowledge. [23] aims to provide comprehensive guidance for educators by demonstrating how to use data mining methods to predict student success. The current state of the art is a logical process offering detailed justifications and explanations for all decisions and boundaries derived from an extensive literature review. By lowering entry barriers for educators, the potential of data mining tools in the educational landscape can be fully realized.

The synthesis of various studies reveals a multifaceted picture when examining student achievement in secondary education within two Portuguese schools. The reviewed literature illustrates how numerous factors, such as teaching strategies and socioeconomic conditions, influence student performance. Recurring themes include the importance of personalized educational interventions, the role of parental involvement, and the impact of teacher-student relationships. Each study offers unique insights while building on previous findings, providing educational stakeholders, policymakers, and researchers with a deeper understanding of the complex issues affecting student achievement in Portuguese secondary schools. This body of literature serves as a guide, directing efforts to improve the quality of secondary education and support positive learning outcomes for students amidst ongoing institutional changes in Portugal.

3. Proposed Methodology

3.1 Dataset

The data is a set of survey answers from 100 CS students to explore the relationship between socio-psychological factors [24]. The dataset includes the following columns:

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- Age: Congruent with individuals' age, this provides information on the age parameters monitored during the study. Age plays a crucial role in students' concerns and performance. The type of sons and problems students deal with can differ significantly between in-betweener and upper-class students.

- Gender: Portray the gender of everyone who is represented, making it possible to examine the gender correlations and trends within this dataset. Therefore, knowing gender gaps is essential in the college system to know how some conditions impact male and female students in particular ways.

- Academic Performance: This variable represents students' grades, reflecting their successes or mistakes during their studies. These indeterminate variable figures are a primary tool in measuring academic proficiency and can be related to other factors to identify their potential relationship.

- Taking Note in Class: This section demonstrates whether or not study notes were taken in class and addresses the learning style and attentiveness during the lectures. The note-taking process is central to developing academic skills, which shape learning and long-term retention.

- Depression Status: Male, the statement of the level of depression, the other hand, highly enhances the understanding of the individual's mental health status. Depression can be pretty apparent in the ability of a student to do academically and socially.

- Face Challenges to Complete Academic Tasks: She will inquire about any wrongdoings, like mistakes in classwork or a drop in willingness to work. This could imply that there are learning-related problems or motivation issues, which may need further analysis. This act may indicate that students might spend more time noticing more attention.

- Like Presentation: Shows personal tastes for the types of presentations, allowing a conclusive inference about individual learning styles and ways of apperception, referring to visuality or auditory nature. Additionally, this evaluates whether they are more of an extrovert or introvert, which can be crucial in how these personality traits affect performance and socializing.

- Sleep Per Day Hours: Describes the average hours of sleep primarily students got over a designated period and has information about sleep routines and the learning capacity of students. Sufficient sleep is the precondition for cognitive functioning; students who lack it will likely reduce their academic outcomes.

- Number Of Friends: This determines the quantitative aspect of social attributes by tracking the number of people each individual knows. This information is used to create a scenario of the social dynamics portrayed in the dataset. Social support could significantly contribute to the student's mental health and academic success.

- Like New Things: Investigates whether individuals show openness to different experiences or conceptions, which helps to understand their readiness for adaptation and new stuff. That quality can be the leading factor in determining their learning style and success by doing well in new academic situations.

The heatmap in Figure 1 is a crucial tool for understanding the dataset. It presents a correlation matrix that visually represents the relationships between different variables. The use of color grading helps to identify the strength and direction of these correlations, with darker colors indicating stronger correlations. This visualization allows for a detailed examination of the interplay between various psychosocial factors, such as academic performance, depression status, and sleep patterns. By providing insights into these interrelations, the heatmap aids in feature selection and the improvement of classification models.

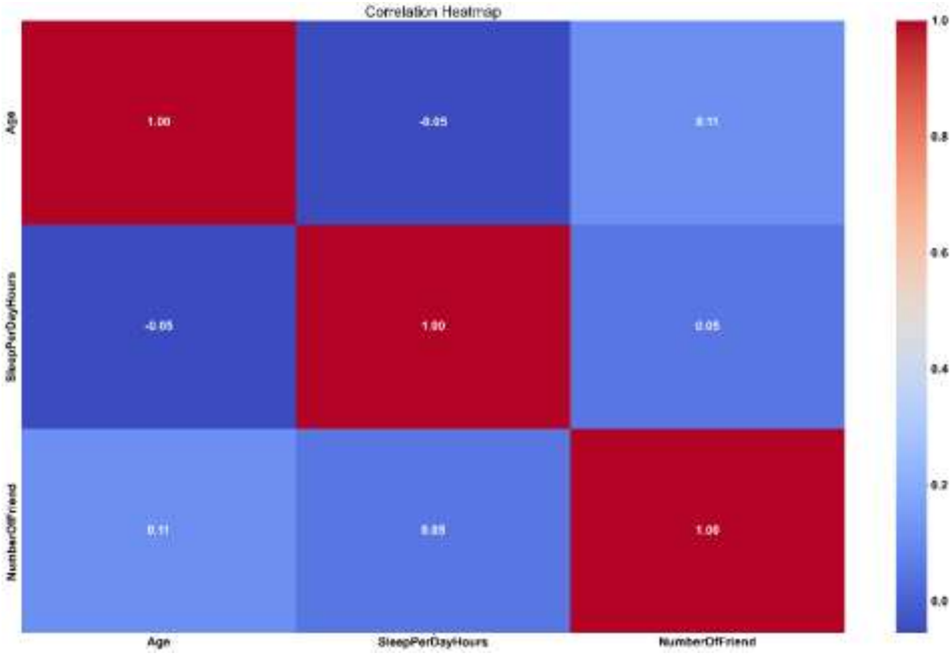

Figure 1: Heatmap for the Dataset

Figure 2 provides pair scatterplots among some variables in the dataset shown in the diagonal and the off-diagonal elements respectively. Every of the pair plot subplots is a scatter plot of two variables. The plot can be used in a categorical examination to illustrate the interplay of different variables. Final elements of a matrix commonly show distribution characteristics for any variable. This visualization is the one that gives a chance to view whether there are trends, patterns, or unusual observations in the data. Investigating this set of pairwise relations, researchers can learn how these different psychosocial factors are intertwined and how their collective influence on academic performance and mental health is realized.

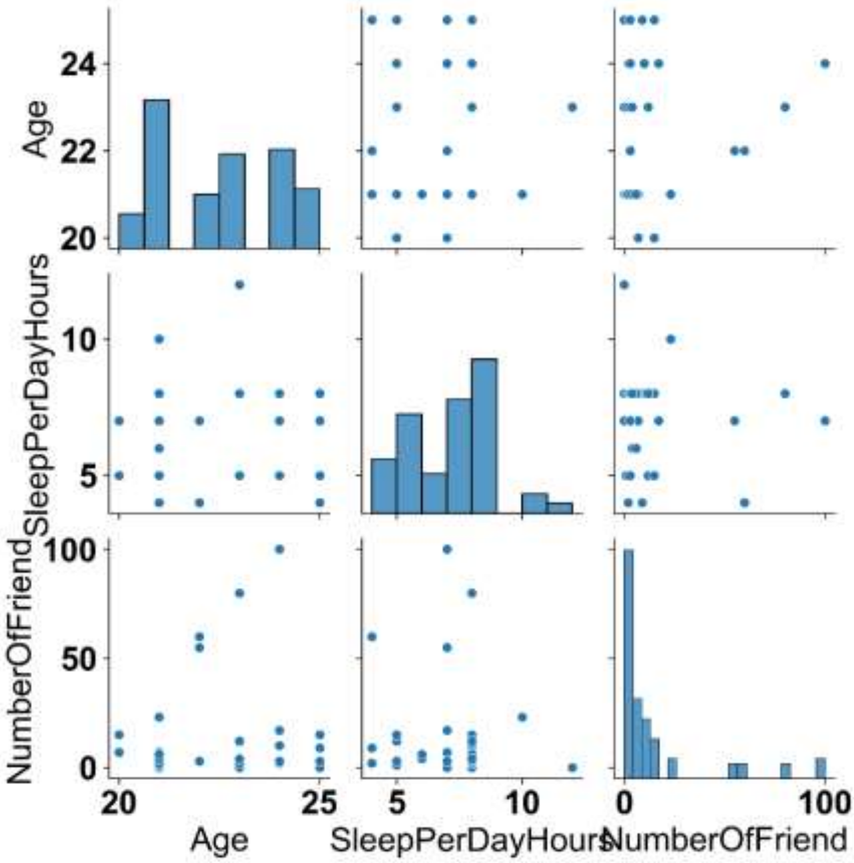

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Figure 2: Pair Plot for the Dataset

The data preprocessing stage is pivotal because it results in a flawless, balanced and fit-for-purpose dataset suitable for subsequent modeling. The need for careful preprocessing of psychosocial data arises due to their complexity and inhomogeneity. Cleaning psychosocial data is a critical necessity to improve the accuracy and reliability of the subsequent analysis. This part describes the methods and technique of dataset making ready with feature selection and the classification modeling in the next paragraph.

The steps of data preprocessing have a particular purpose, and for each step, there is a specific challenge we want to handle from this dataset. These can be categorized as dealing with missing or irregular values, normalizing and scaling the numeric attributes, encoding and handling the categorical variables, outlier detection and management, and splitting the data into training and testing sets. The methods of employment do not finish with urban issues; class imbalances balance due to balancing techniques. Furthermore, feature engineering is used to create new, more informative variables. In addition, dimensionality reduction methods are also used to simplify data processing and complete its most critical parts without compromising information.

We wish to achieve this goal through preprocessing steps. This should lead to a reliable and qualitative dataset that conveys the internal dynamics and associations among psychosocial conditions determining college students' computer science performance. Thoroughly preparing the feature selection algorithms and the classification models used in the research project is critical and will ultimately lead to obtaining more valuable and coherent findings. Data Preprocessing steps:

- Data Cleaning: The recorded data set was first checked to see if there were any missing or inconsistent values. The existing imputation approach, like modes, means, or mediate functions for the numeric data, was analogical to the missing data technique. The contingency custom-submitted paper is the frequently represented category for the categorical data. Inconsistent data entries were corrected through logical inferences or removed as they could not be reliable inferences.

- Normalization: The normalization of numerical values such as age and academic performance has been done regardless of the difference in their original scales to maintain standards. Here, defining the scale of each feature was significant since a single feature should not influence the whole analysis to that extent. In the normalization part, Z-score standardization or min-max scaling was utilized.

- **Categorical Encoding:** Categorical variables like gender and depression status were encoded into numerical values by one-hot encoding or binary encoding according to organ everything. One-hot encoding was applied for multi-category variables, while separate binary rows were created for two-category variables. However, this (technological) transition has been compulsory to digitize the data.

- Outlier Detection and Handling: The stat methods were applied to the dataset to identify the outlying data with Z-scores or IQR separate from others. Exceptional outliers were removed or transformed to reduce their impact on the analysis depending on context. Using the three-sigma threshold was another example where outliers were considered the points that fell beyond three standard deviations from the mean.

- Feature Scaling: Scale features such as standardization were used to dynamically facilitate all the features to contribute equally to the model. This step was crucial for algorithms that quickly "suffocate" by big data, including Support Vector Machines and K-nearest neighbors. Standardization mapped the data down to what is called zero mean and one standard deviation.

- Splitting the Data: The raw dataset was divided into training and testing sets to achieve constant accuracy for model performance. It generally follows the 80-20 rule or 70-30 split, which maintains the model performance by minimizing the instances used for model validation. Therefore, the entire dataset was divided into two subsets. This split was purposed to be a test and train portion to assess the ability of the model to recognize patterns that it has never seen.

- Balancing the Data: With data imbalanced situations, where one particular category had more instances relative to the other categories (faulty situations), the labeled data might cause this problem.

g. The challenges of imbalanced datasets (such as classes, class boundaries, etc.) include various sampling techniques like oversampling, under sampling or synthetic data generation, SMOTE) have been used to improve the distribution of samples between the classes. This practice mitigated the possibility of our model's bias towards the majority class.

- Feature Engineering: Further functions were extended from the existing data to amplify the model's power of prophecy. Include interaction between the independent variables or domain-specific transformations, which can capture the underlying relationships in the data more thoroughly.

- **Dimensionality Reduction:** The dimensional reduction techniques of principal component analysis (PCA) were deemed expedient in rendering the dataset less intricate and achieving more accuracy in the model. This was decisive since it helped zero in on the most crucial features while eliminating the less meaningful or redundant ones.

- Validation Techniques: To reduce possible bias, cross-validation methods, such as k-fold cross-validation, were applied to achieve the robustness and, hence, reliability of the models. The process consisted of dividing the data into k groups of k subsets and running the training/testing on the model k times, each using one as a test set and the rest of the k-subset as the training set. As such, a more accurate analysis of the model's performance did not only add realism to the task but also increased the efficiency of the entire process.

By conducting these data preparation operations at a high level, we not only cleaned the data, balanced it and made it ready for analysis, but the model's accuracy also increased, and it became able to discover and interpret accurately the relationships and correlations among the psychosocial factors of student life.

3.2 Feature Selection

Feature selection is an essential part of the data preprocessing procedure, which is intended to decrease the dimensionality of the dataset but still needs to retain some crucial features. This procedure helps the actual machine learning model's efficacy by removing uncorrelated or unnecessary features, reducing the computational complexity and enhancing the accuracy [25-27]. This study aims to look into the assortment of feature selection tools and determine the psychosocial factors that impact higher-level computer science students' academic performance and mental health. Explanation of Feature Selection Algorithms Used:

- bSFS-Guided WOA (Binary Stochastic Fractal Search - Guided Whale Optimization Algorithm): The algorithm employs the so-called Stochastic Search and Adaptive Behavior Features of SFS and WOA. SFS considers some features in parallel while looking for good features at each iteration. Also, WOA addresses the efficient exploitation of the search space and guides the overall search process towards the optimal ones. The algorithm adjusts between exploration and exploitation by including the fractal search mechanism, simulating the fractal processes found in nature.

- bGWO (Binary Grey Wolf Optimizer): Angling upon the social structure and hunting manner of grey wolves, bGWO acts out the leadership structure of wolves to discover the search space. It leverages the services of alpha, beta, delta, and omega wolves to pursue the exercise but upholds various solutions and fosters optimal features.

- bGWO_PSO (Binary Grey Wolf Optimizer—Particle Swarm Optimization): Therefore, the hybrid algorithm monitors the bGWO algorithm based on a PSO solution to increase search capability and speed of convergence. A hybrid strategy based on hierarchical dog social structures and particle speed facilitated global and local alterations to the search process.

- bPSO (Binary Particle Swarm Optimization): The population of bPSO particles does not only focus on one global solution; instead, they search this space with collective behaviors of bird flocking. For starters, having its position with the experience of neighbor particles, the particle equalizes it by a trial-and-error approach to achieve better solutions. The algorithm is straightforward to set up and works stably well when probing the continuous space of solutions.

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- bSFS (Binary Stochastic Fractal Search): bSFS leverages the stochastic fractal search technique to grapple the line of feature landscape. It can reconstruct the fractal processes characterized by self-similarity and entailing complex pattern building. These properties translate into better information transfer. Different options can be introduced into the selection process, developing and strengthening its diversity.

- bWOA (Binary Whale Optimization Algorithm): Inspired by the bubble-net hunting strategy of humpback whales, bWAO utilizes spiral updating of the positions and encircling prey algorithms for a feature subsets search. The algorithm emulates the feeding strategy of whales, adding the searching operation and navigation toward an ideal solution.

- bGuidedWOA (Binary Guided Whale Optimization Algorithm): Under the WOA, advanced searching adjustments aim to identify the intelligence of finding and precision of information. Onboarding provides learning guidance to the search process, leading to more related regions of the feature space and improved overall effectiveness.

- bMVO (Binary Multiverse Optimization): The model bMVO is based on the multiverse theory. It uses the concepts of white holes, black holes, and space-time wormholes to simulate the exchange of features. It investigates multiple machine powers by channeling candidate solutions, making them travel through different universes to promote diversity and efficient search.

- bSBO (Binary Satin Bowerbird Optimizer): In a way, like it looks similar to the mating behavior of satin bowerbirds, this algorithm is based on the assumption that the birds choose features by imitating bowerbirds" choice of mates. It works through a critical feature - obtaining and testing various options merged later to obtain the" "best from the best.

- bGWO_GA (Binary Grey Wolf Optimizer—Genetic Algorithm): Through this hybridization of the Leader-Based search from bGWO with the Genetic Algorithms'' (GA) evolutionary operations, we can maximize rooftop solar system solutions. It utilizes selection, crossing, and mutation to evolve feature sets toward optimal decisions using the synergy of nature.

- bGA (Binary Genetic Algorithm): BGA is a model based on natural selection and genetics principles, performing crossover and mutation operations to find evolving feature subsets. The algorithm is the mechanism: the more the solutions are selected, the more the population is iteratively improving. To achieve this, among the fit ones, only the fittest individuals are chosen for the reproduction process to obtain genetic diversity.

Criteria for Evaluating Feature Selection Performance:

- Average Error: It calculates the average error rate for the optimal feature subsets in the algorithm's different iterations. The value of this index signifies the extent to which the algorithm can reduce the prediction error, and a lower value is preferable to a high one.

- Average Select Size: This implies that the number of attributes selected is close to the algorithm's mean value of selected features. A more straightforward and precise selection size with high accuracy is desirable as it showcases the entity with fewer excess dimensions, which is responsible for enhanced performance without loss of data.

- Average Fitness: This is an average fitness value computable over the selected feature subsets. The greater fitness values correspond to more robust feature sets, showing the machine learning algorithms' aptitude for selecting relevant features.

- Best Fitness: The best fitness level that the algorithm has displayed during any iteration. This metric confirms that the algorithm can detect the best and allow the most informative components of the information space to be identified as the best solution among the counterparts that underwent the exploration.

- Worst Fitness: The lowest fitness values among all iterations are achieved in this stage. The algorithm's worst performance is clearly indicated in this stage, highlighting its variability and adaptability.

- Standard Deviation Fitness illustrates the individual fitness values of the different scenarios sampled across the iterations. A narrower standard deviation shows the algorithm's precise, stable operation. The selected features within it have less fluctuation in quality.

Feature selection is a chain of operations essential for virtually all machine learning algorithms to produce the best possible output, as it narrows down the essential and valuable features. Utilizing a pool of fifty distinct feature selection methods where only ten are mentioned above, for instance, a versatile and refined way of navigating through the possible solutions is achieved, guaranteeing the optimality of the feature subspaces this way. Any algorithm, in turn, creates distinctive winning strategies based on these optimization models, which stem from natural and social systems movements.

Evaluation of the algorithm's performance based on average error, average select size, average fitness, best fitness, worst fitness, and standard deviation fitness] conclusively demonstrates their reliability. Only in such an approach can the most appropriate algorithm be identified, which will take into account the selected features based on the dataset in question, making the process of predictive modeling efficient and accurate.

In conclusion, this study employed a rigorous dimensionality reduction approach that can increase the understanding of the role of psychosocial variables in academic performance and provide a foundation for developing targeted interventions and support strategies. Establishing the most significant factors, this investigation offers valuable information on the coordination between mental health, studying methods, and academic performance among computer science students, which is crucial for future research or practical procedures by educational organizations.

3. 3 Machine Learning

Classification models are the backbone of this data-driven process, allowing us to classify or predict outcomes depending on the data provided. Here, we use a variety of classification techniques to address the psychosocial components of student life issues to help identify how depression levels, academic performance, and ADHD traits relate to students in the Computer Science courses [28-30]. This subsection outlines the classifiers implemented, such as Gradient Boosting and Support Vector Machines, and performance criteria, e.g., accuracy and F1 score, used to evaluate their performance, Description of Classification Models Applied:

- Random Forest: Random forest is an ensemble learning framework that consists of building multiple decision trees and then integrating their outputs to improve accuracy and being overfitted. The line that connects these is compiled (instead) from a randomized group of features and samples, making it a model of stability against noise elimination and too much variation. The forecast results from most of the winning trees, so the Random Forest is generally preferred for complex classification tasks characterized by large datasets.

- Logistic Regression: Logistic Regression is the statistical model used for binary classification whereby the probability of using one or more predictor or predictors to predict the outcome in which the outcome has only two possible outcomes is determined. The logistic function is used to model the probability. Several linear decision boundaries are another reason it is a good model. Simplicity aside, Logistic Regression is powerfully influential in case the linear relationship between the features and the sign of the result is supposed.

- K-Nearest Neighbors (KNN): K-Neighbors Algorithm is a non-parametric classifier that caters to data classification based on the commonality of class values among the k-nearest neighbors in the input space. It is a straightforward and efficient method and is suitable mainly for datasets with data points with a well-standing class separation. The value of k (the number of neighbors) is essential for the model's accuracy since it affects its robustness against its model's capacity.

- Decision Tree: A Decision Tree is a tree model through which tests on an attribute are presented on each internal node. Branch results are utilized for class label results, while each leaf node represents a class label. Decision trees are pretty handy and easy to understand for most people, but they can be susceptible to overfitting. In decision trees, the non-linear ones will be based on different situations.

- Gradient Boosting: Gradient boosting is an ensemble method in which the models are created individually, each overcoming the errors made by the previous model. It is a gradient descent algorithm

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that reduces the loss function, making it robust and applicable to various datasets. Gradient boosting is a way to succeed with imperfect classifiers.

- AdaBoost: AdaBoost is A profound method that unites multiple weak classifiers to generate a more robust collaborative classifier. It finds the incorrectly classified instances and adjusts the respective weightings so that after several iterations, the program will place greater emphasis on the more difficult classes, thus improving performance. AdaBoost famously attracts attention for the robustness and accuracy of simple models.

- SVM: Support Vector Machine's radial basis kernel works well in the high-dimensionality and nonlinearity space. It learns to look for the one representing the most significant distance margin between the instances of classes. This gives this algorithm resistance to overfitting and details represented in complex datasets.

- Naive Bayes: Naive Bayes is a classifier based on Bayes' theorem, the independent resources effectively, especially when working with large data sets, especially those that contain categorical data. Even though the approach is quite basic, it demonstrates high efficiency in many real-world applications.

- Support Vector Machine: SVM means a hyperplane that best achieves the features of different classes. It is effective in high-dimensional spaces, causing strong resistance to overfitting, especially when the data length is longer than the samples. SVM is essentially a method of handling non-linear relationships using kernel functions, and it is robust and reliable for that reason.

- Neural Network (MLP): Multilayer Perceptron (MLP) belongs to a feedforward artificial neural network class. It comprises many layers of nodes, and all the neighboring nodes are linked in each single layer. MLP, which can handle a range of classification tasks involving complex patterns and representations, can also learn them. This method is remarkably convenient for analyzing big data sets and non-linear connections.

Metrics Used for Model Evaluation:

- Accuracy: Accuracy is the percentage of the number of correct predictions overall predictions. Binary measures are one of the initial indicators of the model's performance. However, they can be deceptive in the case of modeling datasets.

- Sensitivity (True Positive Rate): In the case of sensitivity, the actual positive is the fraction of all corny positives. The model identifies its capacity on positive instances, which is critical for scenario processing when positive cases cost enormously.

- Specificity (True Negative Rate): The other performance metric, specificity, also known as the "true negative rate," is the proportion of actual negatives the model correctly classifies as negatives. It measures the model's power to detect negatively marked instances.

- P-value PPV (Positive Predictive Value): Positive Predictive Value is the correct number of hospitalizations based on the positive screening results. The measure effectively takes the precision of the model into account for optimistic predictions and indicates the reliability of optimistic outcome prediction.

- P-value NPV (Negative Predictive Value): Negative Predictive Value (NPV) refers to the fraction of the actual pessimistic pr, which seductions correctly called negative. The model's accuracy means the timeliness of the pessimistic predictions, and the value of the classification coincides with one's ability to classify real negatives.

- F-score: One's F-score is a harmonic mean of precision and recall (sensitivity); thus, it weighs both cases equally and produces a single metric that summarizes both precision and recall. This technique is essential for sharing models on unbalanced datasets as it counteracts the trade-off between precision and recall and the imbalance in the dataset's classes.

The use of multiple classification classifiers throughout the study plays a crucial role in offering an integrated statistics analysis concerning cognitive and psychological factors that govern the academic performance of computer science scholars. Every model is different, whether it is an ensemble method using Random Forest or Gradient Boosting or simpler algorithms such as Logistic Regression and K-Nearest Neighbors. Every model can learn from the data with its unique characteristics. One can know the model's depth and precision by assessing these models using specific units such as accuracy, sensitivity, specificity, PPV P-value and NPV P-value, and F-score. This multi-dimensional evaluation will pursue the development of more reliable approaches that pertain to the prediction of the significant social factors influencing students' lives. In sum, the broad spectrum of classification students employed in this study not only ensures the reliability of the results but has also demonstrated a great deal of the intertwined interaction among psychological students, study strategies, and academic performance. The model results in students with student-targeted interventions, thus being practical tools for the institution to help students achieve better well-being and academic performance. This multi-faceted analysis highlights the need to employ cutting-edge machine learning methods in ascertaining the complex issues that students might encounter while learning in tertiary institutions.

4 Results

The performance of several feature selection algorithms was tested using parameters like average accuracy attribute, average select size, average fitness, best fitness, worst fitness, and standard deviation fitness. The results are summarized in Table 1 below:

Table 1: Feature Selection Algorithms Results

	bSFS-Guided WOA	**bGWO**	**bGWO_PSO**	**bPSO**	**bSFS**	**bWAO**	**bGuided WOA**	**bMVO**	**bSBO**	**bGWO_GA**	**bGA**
Average error	0.131917	0.149117	0.188417	0.182917	0.192517	0.182717	0.151117	0.159617	0.191217	0.169217	0.162717
Average Select size	0.084717	0.284717	0.418017	0.284717	0.424117	0.448117	0.448517	0.381217	0.455017	0.207517	0.227117
Average Fitness	0.195117	0.211317	0.219617	0.209717	0.232617	0.217517	0.215417	0.239417	0.249417	0.217417	0.222717
Best Fitness	0.096917	0.131617	0.173117	0.190017	0.122317	0.181617	0.205117	0.164617	0.192517	0.195217	0.126017
Worst Fitness	0.195417	0.198517	0.283117	0.257717	0.223917	0.257717	0.291617	0.282617	0.272217	0.271417	0.241117
Standard deviation Fitness	0.017417	0.022117	0.040317	0.021517	0.031417	0.023717	0.066417	0.072217	0.082417	0.022717	0.023717

- The bSFS-Guided WOA algorithm demonstrated the lowest average error (0.131917) and the smallest average select size (0.084717), indicating its efficiency in selecting the most relevant features while minimizing prediction errors. This suggests that bSFS-Guided WOA is highly effective in feature selection for this dataset.
- bGWO also performed well with a relatively low average error (0.149117) and moderate average select size (0.284717), making it a strong contender for feature selection tasks.
- Other algorithms like bGWO_PSO and bGuided WOA showed higher average errors and select sizes, indicating that while they are capable of identifying relevant features, they may include more redundant features compared to bSFS-Guided WOA and bGWO.
- The variability in fitness values, as indicated by the standard deviation, was lowest for bSFS-Guided WOA (0.017417), suggesting consistent performance across iterations, whereas algorithms like bGuided WOA and bMVO showed higher variability, reflecting more fluctuation in their performance.

Models are evaluated based on their levels of accuracy, sensitivity, specificity, PPV and NPV, and F-score. The Classification results are summarized in Table 2 below:

Table 2: Classification Models Results

Models	**Accuracy**	**Sensitivity (TRP)**	**Specificity (TNP)**	**Pvalue PPV**	**Pvalue NPV**	**FScore**
Random Forest	0.97345	0.887478	0.924226	0.895931	0.925612	0.864517
Logistic Regression	0.957486	0.885384	0.912354	0.893725	0.960791	0.97175

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K-Nearest Neighbors	0.948199	0.933381	0.878578	0.85122	0.964031	0.850766
Decision Tree	0.947238	0.951924	0.879783	0.858224	0.928636	0.884122
Gradient Boosting	0.933396	0.963046	0.95071	0.868948	0.910245	0.855514
AdaBoost	0.92395	0.913925	0.893065	0.945085	0.975466	0.974973
SVM (rbf Kernel)	0.918343	0.961258	0.917129	0.923932	0.960852	0.967312
Naive Bayes	0.906533	0.864092	0.865902	0.905738	0.892456	0.915942
Support Vector Machine	0.875543	0.96576	0.902936	0.894132	0.967831	0.852273
Neural Network (MLP)	0.863987	0.933461	0.934523	0.895389	0.887421	0.945798

- Random Forest achieved the highest accuracy (0.973449), sensitivity (0.887478), and specificity (0.924226), indicating its robustness and effectiveness in classifying the data correctly. Its high F-score (0.864517) reflects a good balance between precision and recall.
- Logistic Regression also performed well with high accuracy (0.957486) and specificity (0.912354). Its F-score (0.971750) was the highest among all models, highlighting its precision in binary classification tasks.
- K-Nearest Neighbors and Decision Tree showed strong sensitivity (0.933381 and 0.951924, respectively) but slightly lower specificity, indicating a tendency to identify positive instances while occasionally misclassifying negatives correctly.
- Gradient Boosting and AdaBoost demonstrated high specificity (0.950710 and 0.893065, respectively) and good overall performance, making them reliable choices for complex datasets.
- SVM (rbf Kernel) and Support Vector Machine exhibited high sensitivity (0.961258 and 0.965760, respectively) and good overall performance metrics, reflecting their effectiveness in high-dimensional spaces.
- Naive Bayes and Neural Network (MLP) showed reasonable performance but were outperformed by ensemble methods and other sophisticated algorithms.

Key Findings:

- The dataset has given a variety of significant correlations and patterns indicating that psychosocial factors can negatively impact academic performance and mental health in computer science students.

- Out of all relevant features that influenced academic performance, note-taking practices and depression status were considered the most impactful, as well as sleep algorithms. Students who regularly made notes and had an excellent academic sleep pattern had better results than the ones who repeated.

- Disposition had a prominent place in the study conducted, with students having depressive feelings being found to have more challenges studying and lower grades.

- The social factors present significantly influence students' overall well-being and academic achievement, such as the number of companions and how easily they adapt to new experiences.

The results of the feature selection and classification models provide us with an idea of the impact of the psychosocial aspects of the resulting computer science students' academic performance. Finally, the bSFS-Guided WOA algorithm was the best feature selection method. Thus, it was concluded that the algorithm could filter out essential features with little error, owing to its best characteristics. The Random Forest model has shown an excellent ability to classify. Thus, this is a perfect candidate for decoding key psychosocial confounders related to the leadership concerns of students.

Achievements of accuracy for all classification models shown in Figure 3 played the main role for our research. It is shown in the bar chart which models different types will be among the Random Forest, Logistic Regression, K-Nearest Neighbors, Decision Tree, Gradient Boosting, AdaBoost, SVM (rbf Kernel), Naive

Bayes, and Support Vector Machine and Neural Network (MLP). With the help of the accuracy metric, each model is evaluated in the simplest way possible to determine how well it could classify the data.

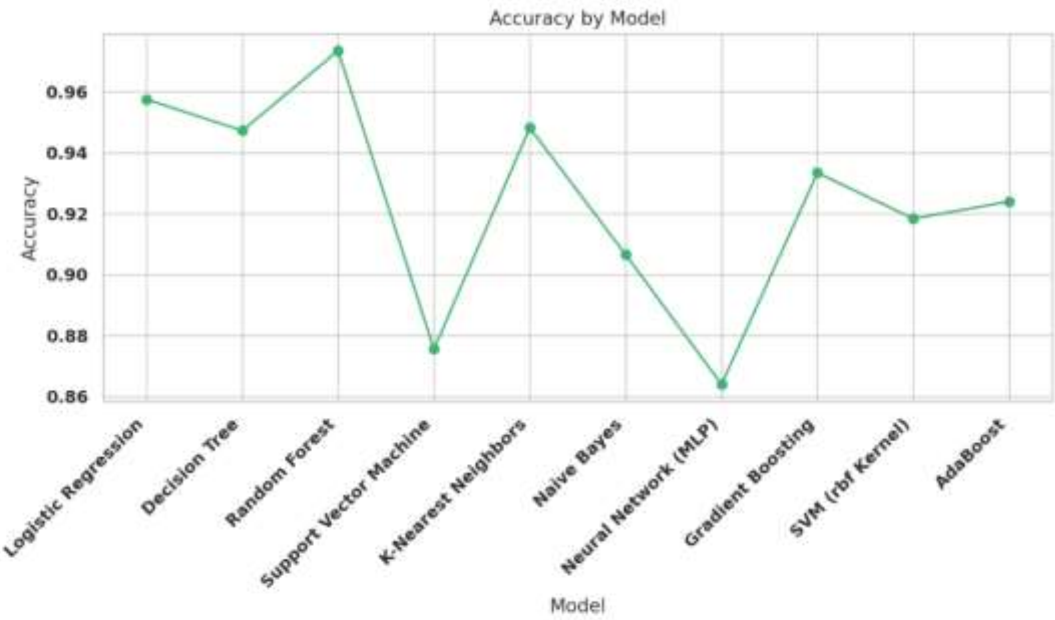

Figure 3: Accuracy by Model

A visual depiction of the model performance indicators depicted in Figure 4, such as accuracy, sensitivity (TRP), specificity (TNP), P-value PPV, P-value NPV, and F-score, is provided by the matplotlib library in Python. In line with pair plot mapping for the data, this figure presents the association pairs of different evaluation metrics. Each branch further unveils the relationships between these two numbers and others, wrapping them up as an integral set, demonstrating how they contribute to the whole system. Researchers will be able to see such relationships. They therefore can understand what tradeoffs they have to compromise when modeling with different metrics and which models are efficient at precision, recall and overall accuracy.

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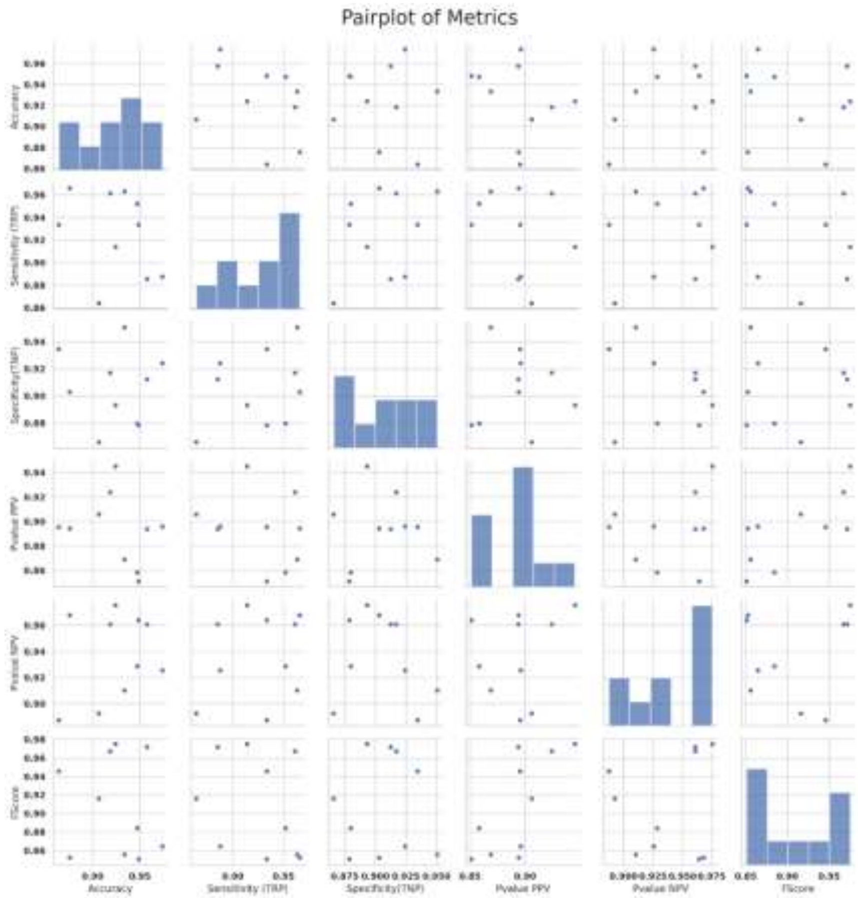

Figure 4: Pairplot of Metrics

These findings reaffirm the need to tackle mental health problems, facilitate healthy courses of study, and create a safe social learning space to ease the way to success. This study that applies cutting-edge feature selection and classification methods offers in-depth knowledge about the complex interrelations between mental health, the way we study, and our performance. The learned understanding can guide towards making focused programs and sending support plans. Eventually, one would expect an improvement in health and achievements in studies.

5. Conclusion

The goal of this study was to discern the psychosocial determinants of students' lives in the context of programming courses, where the bSFS Algorithm Guided with WOA was observed to bear the lowest average number of errors and the smallest average size of selected classes and where Random Forest produced the highest accuracy, sensitivity, and specificity. Those findings, in turn, shed light on the role-playing of social factors, including note-taking habits, depression status, and the length and quality of sleep-in academic performance. These findings highlight the importance of mental health and study habits that must be considered when developing intervention strategies. The main applied benefits of these insights involve developing inclusive educational initiatives and focused mental health interventions, such as counseling services and stress-curbing programs. To widen the scope of our research, it is also crucial to identify other factors worthy of investigation, enlarge the data sizes, and update the data set over time to assess how these factors may change the trend. On the contrary, the current research also recognizes its weaknesses: size and area of focus. Therefore, these two should be used to achieve better results. Overall, the study underlines the role of psychosocial factors in enriching students' lives and significantly impacting their academic and personal achievements. Therefore, placing great emphasis on the psychosocial factors that enhance students' wellness and success will cause significant achievement.

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