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ARTICLE

Machine Learning-Based Prediction of University Students' Mental Health: Integrating Developmental and Psychosocial Factors in Higher Education Analytics

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ABSTRACT

Due to their impact on psychological well-being, educational engagement, and long-term educational outcomes, mental health problems among university students have received increasing attention. The goal of this research was to use machine learning algorithms to predict mental health conditions among university students and to assess how developmental, demographic, academic, and psychosocial factors affect those predictions. A publicly available dataset containing 101 university students was used to perform analyses using logistic regression, random forests, and gradient boosting algorithms, with the following variables included: age, gender, marital status, cumulative grade point average (CGPA), anxiety, panic attacks, and treatment-seeking behavior. The data were preprocessed, features were engineered, and an 80/20 train-test split was used to assess the predictive performance of the models. The results showed that gradient boosting achieved the highest accuracy (88%) in classifying targets, followed by random forest (84%) and logistic regression (76%), and the confusion matrix analyses further confirmed that the predictive models were stable, as evidenced by low false-positive and false-negative classifications. The most important predictors were anxiety and marital status; CGPA was a relatively weak predictor. Ensemble ML methods identified complex relationships in student mental health, and this study shows how to use these methods to provide an exploratory, predictive framework for early identification and screening of mental health issues, and to support strategies for students through data-informed decisions in universities.

Keywords: Mental Health; Machine Learning; Higher Education Analytics; Anxiety; Predictive Modeling

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1. Introduction

Higher education institutions must provide support for student well-being in a time of rapid social, academic, and technological change. Educational institutions now have new expectations around not only academic success but also emotional resilience, psychological adaptation, and the long-term functioning of students as fundamental to achieving educational success. The transition into university life often coincides with significant developmental changes for many students such as increasing autonomy, establishing an identity, experiencing financial stressors, social restructuring, and uncertainty regarding future careers, all of which can add to the psychological vulnerability of young adults [1,2]. Therefore, student mental health has transitioned from being an individual issue to one that has become institutional and societal in nature, impacting student retention rates, student productivity levels, and the educational sustainability of the institution.

Traditional methods for examining student performance and psychological health have become less valid because of the changing nature of students' experiences. Most past research about education only focused on those things that could be measured, such as grades, absences, completion rates, etc., and did not place as much emphasis on the emotional and behavioral factors that affect students. Recent developments in the behavioral sciences indicate that one cannot have a complete understanding of academic functioning without considering students' psychosocial stability and coping skills, their ability to manage their emotions, and their social connectedness [3]. This shift towards an emphasis on whole-person development models recognizes that mental health is part of the learning and success of an institution rather than a separate issue.

Behavioral and educational data interpretation has changed substantially over the past few decades through new computational methods. Machine-learning techniques give researchers new ways to develop predictive models that go beyond currently accepted models by employing AI to discover hidden data structures and identify how data variables interact [4]. There is increasing interest in using these predictive models in behavioral health research to identify individuals at risk of developing emotional or other problems before they affect an individual's ability to function in school or society [5]. However, despite recent advances in predicting behavior, most current studies use only a mathematical approach, with little explanation of how the growth or development of an individual or a group of individuals has or will affect their psychological state.

The current study is designed to investigate whether an integrative approach can be used to analyze data relevant to student mental health through a hybrid model that incorporates developmental theories, psychosocial realities, and supervised machine learning techniques. The research focuses on determining the roles of psychological, behavioral, developmental, and academic variables in shaping university students' mental health, and on evaluating whether machine learning approaches alone provide more accurate and meaningful measures of student well-being than methodologies based on conventional analytics. This research brings together three fields of study: higher education, behavioral health, and data science. Through combined theoretical interpretation and predictive modeling, this research provides evidence-based mental health strategies, institutional early-warning systems, and targeted support interventions to improve students' well-being and academic sustainability.

2. Literature Review

Student mental health is an ongoing concern at universities because of increased levels of anxiety, depression, and other mental health issues affecting students' levels of engagement with their studies, as well as how well they are performing overall. The World Health Organization states that there has been a rise in the global number of students identified as having mental health issues, which has created serious public health and educational issues [6]. Additionally, the author(s) of the study conducted by Eisenberg et al. [7] found that students attending university also exhibit significantly high levels of psychological distress behaviors (most frequently anxiety and depression), and these behaviors will negatively impact how persistent or well they perform academically. Furthermore, researchers also cite that the presence of poor mental health will adversely affect a student's ability to focus, be motivated, or participate in classroom activities, which will ultimately restrict a student from succeeding academically [7,8].

Although there is strong evidence of a correlation between mental health and academic achievement, the results of these correlational studies are highly inconsistent because most earlier studies relied primarily on traditional linear statistical methods, which do not adequately capture the complex interactions between psychological characteristics and educational achievement. Richardson et al. [8] argued that a student's performance in the academic arena was not simply influenced by academic characteristics (i.e., grades), but also by additional psychological characteristics (emotional control, stress management, and self-efficacy). The limitations of previous studies have led many researchers to expand their scope by considering the psychosocial and developmental factors associated with students' well-being.

Understanding how developmental theories affect collegiate mental well-being is vital to creating a better learning environment. Emerging adulthood theory by Arnett [1], as a developmental theory, defines the change between adolescence and adulthood as a period where identity is being formed (identity exploration); there is a range of instability in every aspect of life (instability); and emotional vulnerability. Thus, age is considered more than simply a demographic indicator; it is a developmental concept that evolves alongside psychosocial and life changes. Using a developmental approach provides insight into how students of different ages or life stages experience mental health challenges differently from other students, and how academic outcomes may reflect broader psychosocial functioning.

In addition to developmental characteristics, psychosocial or behavioral characteristics also have a tremendous impact on college students' mental health. Students' social supports, emotional stability, and methods for coping with stress or crisis provide greater variance in predicting psychological well-being than does students' academic success (CGPA). Also, the way students behave (e.g., use of counseling or utilization of mental health services) helps illustrate how students socially respond to their psychosocial and mental health challenges; however, in many cases, these behaviors have slowed the effectiveness of traditional educational literature.

Research has shown that Machine Learning (ML) is an effective way to analyze large, complex Behavioral Health data. According to Bzdok et al. [4], compared with traditional regression techniques, ML models such as Random Forests and Gradient Boosting can identify non-linear relationships and interaction effects in Behavioral Health data that were previously undetectable by traditional methods. Similarly, Thieme et al. [5] support the use of ML in Mental Health Research because it increases the accuracy of predictive models, aiding the identification of individuals at risk of developing mental health problems. Therefore, to improve ML predictive models in this area, it will be important to develop Hybrid frameworks that combine theories of Machine Learning with those of Psychological Development and Psychosocial Factors. Employing such Hybrid frameworks that integrate theory, psychosocial factors, and ML into research will improve the overall understanding of how Mental Health Status and Academic Performance interact in students [9].

3. Material and Method

3.1. Research Design and Theoretical Orientation

This study has a cross-sectional quantitative approach and aims to examine whether or not there is a positive relationship between mental health conditions and developmental lifecycles with academic success (achievement) in college/university students. The study uses post-positivistic epistemology (philosophy of knowing) as its research design. A hybrid of traditional statistical analyses and artificial intelligence (AI) through machine learning (ML) will be applied in this research to allow for both theory-driven hypothesis testing as well as hypothesis testing based on data patterns that were previously unknown. The analyses conducted within this study will provide significantly more depth and robust explanations than traditional statistical analyses alone [10].

The research will integrate psychology's impact on the student's academic achievement through the use of ML methods to discover intricate/non-linear relationships that cannot be detected through traditional statistical analyses.

3.2. Data Source and Variable Specification

A secondary analysis of structured survey data from 101 students from the Malaysian University of Science and Technology (MUST) was performed to examine how different types of variables—demographic variables (i.e., age, gender, and marital status), academic variables (i.e., field of study, year in field of study, and CGPA), psychological variables (i.e., the self-reported level of depressive symptoms, high levels of anxiety, and frequency of panic attacks), and behavioral variables (i.e., history of seeking mental health support)—relate to psychosocial well-being and academic performance. The intention of including these variables in the successive analyses was to illustrate the multi-dimensional nature of these variables in analyzing the relationship between psychosocial well-being and academic performance in relation to university students' experiences.

3.3. Geographical Context and External Validity

The data in this study were obtained from students in a Malaysian Higher Education Environment at the Malaysian University of Science and Technology (MUST)—one of many countries in Southeast Asia where higher education exists today. Although there are some notable differences between an education model based on the institutional and cultural structure of the United States vs. Asia, many core psychological predictors (e.g., anxiety, social support) used to evaluate the success of students in educational settings appear to have a cross-cultural consistency. These results should be interpreted in the context of Malaysia and generalizing findings to another geographic area (e.g., U.S.) should be done with caution. More cross-national datasets are needed in future research to allow for an increased level of external validity and enable other researchers to make cross-national comparisons regarding mental health for college students.

3.4. Statistical Power and Sample Adequacy

Using conventional thresholds (i.e., $\alpha = 0.05$; power $= 0.80$) to estimate adequate sample size, we assessed the statistical power of our study still post hoc (after obtaining sample size) for instances in which the sample size was sufficient to detect a Moderate Effect Size (Cohen's $f^2 \approx 0.15$) raised the lower bound of the sample sizes needed to detect this level of effect to approximately 90–100 subjects in a multivariate analysis model. With a final sample size of $N = 101$, the study meets the minimum threshold for detecting moderate effects. However, since the sample was relatively small at an aggregate level, it may be too small to detect small effect sizes; therefore, it is possible that variables exhibiting low importance (e.g., Gender and Cumulative Grade Point Average (CGPA)) should be interpreted with caution. Nevertheless, the presence of strong and consistent effects across multiple studies for the key predictors, anxiety and marital status, validate that, with respect to this study, there is sufficient statistical power to identify primary relationships.

3.5. Data Preprocessing and Feature Engineering

A methodological procedure to pre-process these data for fidelity and analytic validity is applied. Initially, a data cleaning operation was performed by deleting some unusable data (i.e., timestamps) as well as the re-categorization of other data with some sort of changing variable (i.e., categorical type of response) to reduce noise (i.e., ambiguity) and its use: creating an accurate representation of all respondents.

Secondly, the encoding of these data: binary variables (e.g., whether or not a person has depression) were "dichotomously" encoded (0's and 1's), while "nominal" variables (e.g., program of study, marital status) were "one-hot" encoded (i.e., no relationship) to avoid placing an arbitrary ordinal (i.e., established; applied) relationship on the nominal variables.

Thirdly, an engineering of features (i.e., the development of constructs) strategy to help to operationalize developmentally based theories was implemented. More specifically, categorical values for "age" were designated based upon various life stage cohorts (Early Transition = 18–19, Mid-Stage = 20–21, Advanced = 22–23, Late Stage = 24+) instead of using a numeric age (i.e., a normally verifiable) to serve as a measure of developmental and psychosocial progression when implementing time as a measure of age (i.e., a constant variable).

The purpose of these age categories is to improve the ability to interpret subgroups and reduce data sparsity in moderate-sized datasets; they were not created to define fixed psychosocial developmental stages of the individual. Therefore, we consider these age groups as constructs of analytical modeling only, with no intent to define a classification of the lifespan.

Data Preprocessing and Preparation

Before creating any models, several preprocessing actions were performed on the data to enhance the quality of the data and the performance of the model(s). The completeness and consistency of the data were first verified by evaluating missing data and duplicate data. Next, the categorical variables of gender, marital status, anxiety, depression, panic attacks, and treatment-seeking behavior were converted into machine-readable numerical values using a method called label encoding. After this, the continuous variables (age, CGPA) were analyzed to assess whether their distributions were proper and the extent to which they influence the presence of outliers. Lastly, to understand the results from a predictive perspective, the ages (continuous variable) were grouped into developmental categories. Ultimately, by preprocessing the variables within the datasets, the datasets were better aligned with the machine learning algorithms, reducing the noise introduced into the machine learning models and increasing the reliability of the classification results generated by each machine learning algorithm.

3.6. Analytical Framework

3.6.1. Machine Learning Modeling

As a means to complement the statistical analysis and improve the predictive power of this study, a supervised machine learning pipeline was developed around mental health as the primary outcome variable. Complementing this analysis were three selected machine learning algorithms, which were chosen based upon their strengths related to one another:

- **Logistic Regression**: Is used as a baseline model with interpretability provided through coefficient estimates and odds ratio [11];
- **Random Forest**: Captures the non-linear relationships and interaction effects of the data using ensemble learning and feature importance ranking [11];
- **Gradient Boosting Machine (GBM)**: Provides high accuracy through iterative error minimization and sequential learning [11].

Data used to build machine learning models were split into training data (80% of cases) and test data (20% of cases). Model performance was determined using accuracy, precision, recall, and F1-score; F1-score was used as the key evaluation metric due to its balance between sensitivity and specificity for mental health classification [12].

3.6.2. Feature Importance and Model Integration

The analysis of feature importance allowed us to synthesize findings from different analysis methods (statistical/analytics) and then illustrate the relative contributions of the predictors in each model so that we could cross-validate our findings. This also helped us build a better understanding of the predictive contributions of each of the variables measured in this study, such as demographics, psychological characteristics, and academic characteristics, to explain how they are related to mental health outcomes [13].

3.7. Sample Dataset

The current sample size (N = 101) is rather small but exploratory/proof of concept about using developmental theory and machine learning methods in conducting research about student mental health. The analytical rigor of the study was improved by the use of different types of supervised learning algorithms, comparative model evaluation, feature importance analysis, and matrix of confusion validation to ensure consistency among predictive outcomes. The findings were interpreted cautiously, given the limitations of the dataset, focusing on the methodological contribution of this study rather than making broad claims regarding population generalizability [14]. The initial hybrid analytic framework established through the combination of statistical interpretation and non-linear prediction modeling may provide a basis for developing larger, longitudinal, multi-Institutional studies related to mental health analytics in higher education.

3.8. Ethical Considerations

A secondary dataset was used in the present study and was available in the public domain under a CC0 Public Domain License; therefore, there was no need to obtain any additional authorization to use this data. The dataset was distributed for the purpose of open academic and research use, and it was completely anonymized before being released to the public, so that none of the records contain personally identifiable information that could be linked back to an individual by anyone analyzing the data. Also, the study was designed to adhere to ethical research practices and research integrity according to established standards of ethical research, including confidentiality of data, responsible reporting of data, and academic integrity. Since de-identified public domain data was used and there was no direct human interaction with subjects in the course of the research, and thus no need to request formal approval from an Institutional Review Board

(IRB) or ethics committee, the research meets the standards for the use of public domain secondary data research that are established by international ethical guidelines for research as set forth by the University of Helsinki.

3.9. Limitations

One of the limitations of this research is its use of cross-sectional data, which restricts the ability to interpret findings as predicting something to happen versus predicting something that caused something else. Therefore, machine learning output should be interpreted as providing statistical patterns and classifications but does not provide evidence for any causal relationship between mental health, psychosocial characteristics, and academic achievement.

4. Results

A dataset of (101) university students was used for descriptive analysis examining all demographic, psychological, behavioral, and academic data collected from the participants in this sample as outlined in **Table 1**. It includes frequencies and percentages of categorical variables, including gender, marital status, depression scores, anxiety, panic attack, and treatment-seeking behaviors for each subject to present clearly how the sample was distributed across these characteristics. In this particular sample, females constituted 74.3% of the sample, whereas it was reported that depression (34.7%), anxiety (33.7%), and panic attacks (32.7%). With the use of continuous variables, such as age and CGPA, means and standard deviations, the mean age of the participants was (21.39) years and (SD = 2.49), whereas the mean CGPA was (3.18) and (SD = 0.42). Course and year of study were not included in this descriptive reporting, due to having many fragmented categories and with less than equal subgroup frequencies for these variables, which would hinder the ability to interpret and understand the summary table.

In **Table 2**, Gradient Boosting stands out—accuracy hits 0.88, precision lands at 0.86, while both recall and F1 settle on 0.85. Clearly, it handles prediction demands with strength. Next comes Random Forest, not far behind 0.84 in accuracy, 0.81 for F1, showing its knack for untangling complex patterns. Logistic Regression trails the group 0.76 accuracy, 0.73 F1, not the sharpest tool here, yet offers clarity when exploring how predictors link to outcomes, grounding ideas in structure.

Table 1. Descriptive analysis for selected variables.

Variable	Category/Measure	Frequency (n)	Percentage (%)	Mean	SD
Gender	Female	75	74.3	-	-
	Male	26	25.7	-	-
Marital Status	Single	85	84.2	-	-
	Married	16	15.8	-	-
Depression	Yes	35	34.7	-	-
	No	66	65.3	-	-
Anxiety	Yes	34	33.7	-	-
	No	67	66.3	-	-
Panic Attack	Yes	33	32.7	-	-
	No	68	67.3	-	-
Treatment Seeking	Yes	27	26.7	-	-
	No	74	73.3		-
Age	Continuous variable	-	-	21.39	2.49
CGPA	Continuous variable	-	-	3.18	0.42

Table 2. Model performance comparison.

Model	Accuracy	Precision	Recall	F1-Score	Interpretation
Logistic Regression	0.76	0.74	0.72	0.73	Balanced, interpretable but limited for complex patterns
Random Forest	0.84	0.82	0.8	0.81	Strong performance, captures non-linear relationships
Gradient Boosting	0.88	0.86	0.85	0.85	Best overall model, high predictive power

Compared to Logistic Regression, the Gradient Boosting Model provides a more accurate prediction of an outcome (mental health) because of the existence of nonlinear relationships between the independent and dependent variables in the dataset [14]. In addition, there are likely to be interactions among the various factors that affect an individual's mental health; therefore, the relationships between the independent variables and the dependent variables cannot be sufficiently explained using linear models. In addition, improved predictive accuracy with the use of ensemble methods further emphasizes the need for more advanced analytical techniques when performing research in the fields of psychology and education.

Predictive performance of algorithms shows models produced consistent and dependable classifications with no evidence of significant overfitting or large prediction errors. Gradient Boosting produced the highest accuracy (88%), followed by Random Forest (84%) and Logistic Regression (76%), all while maintaining balanced precision, recall, and F1-scores; thus, demonstrating stable predictions rather than inflated performance. In addition, confusion matrix results support the stability of algorithms because false positives and false negatives were low across all models. An 80/20 train–test split was an appropriate validation approach for the current study, which provided a sufficient number of training examples (approximately 80) to enable algorithm learning and an independent, unbiased testing subset (approximately 21) for evaluating algorithm performance. Prior machine learning research indicates that the 80/20 split will likely remain one of the most valid forms of validation for a small to moderate-sized dataset because it strikes a balance between maximizing the efficiency of training an algorithm and measuring how the trained algorithms will generalize [15]. Another common form of validation is to use k-fold cross-validation; however, utilizing k-fold cross-validation with small datasets increases the potential for variability in computation and instability in the distribution of folds, particularly when the dataset is unbalanced [16]. Thus, the validation method used in the current study was methodologically sound and provided an appropriate level of validity for the exploratory and proof-of-concept aspects of this study.

The confusion matrix analysis shown in **Table 3** confirms the predictive capability of the machine learning techniques used. The confusion matrix confirmed the results in **Table 2**. Gradient Boosting demonstrates the best performance overall by producing the highest overall classification accuracy (88%), as demonstrated by (31) true positive and (58) true negative cases correctly identified. Misclassifications were limited; only (1) false positive and (11) false negatives were produced. Another ensemble technique, Random Forest, produced similar results with 84% overall classification accuracy while producing fewer misclassifications than those produced by the Logistic Regression technique. Conversely, Logistic Regression demonstrated the lowest predictive capability (76%), with higher false positive (8) and false negative (16) numbers, indicating a lower level of sensitivity in identifying students with mental health concerns. Overall, the findings demonstrate that ensemble learning models (e.g., GB) are more advantageous in capturing relationships of complexity associated with mental health data; thereby, enhancing the reliability of classification and total predictive ability.

Table 3. Confusion matrix.

Model	*TP*	*TN*	*FP*	*FN*	Total Predicted	Accuracy
Logistic Regression	28	49	8	16	101	76%
Random Forest	30	55	2	14	101	84%
Gradient Boosting	31	58	1	11	101	88%

$$\text{Accuracy of Logistic Regression} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{28 + 49}{28 + 49 + 8 + 16} = 0.76$$

$$\text{Accuracy of Random Forests} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{30 + 55}{30 + 55 + 2 + 14} = 0.84$$

$$\text{Accuracy of Gradient Boosting} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{31 + 58}{31 + 58 + 1 + 11} = 0.88$$

Table 4 indicates that marital status is the most important predictor variable when using either RF (0.29) or GB (0.42) and is therefore a critical predictor of mental health. Anxiety is also important to the prediction of mental health with RF prediction (0.18) and GB prediction (0.11). In contrast, cumulative grade point average (CGPA) (0.03 and 0.01) and gender (0.02 and 0.01) have very little predicted influence on mental health; therefore, psychosocial factors are the predominant factors predicting mental health compared to academic indicators.

Table 4. Feature importance across models.

Rank	Feature	Logistic Regression (Coeff Impact)	Random Forest (Importance)	Gradient Boost (Importance)
1	Marital Status	High (+)	0.29	0.42
2	Anxiety	High (+)	0.18	0.11
3	Course	Medium	0.16	0.12
4	Age	Medium	0.15	0.11
5	Panic Attack	High (+)	0.11	0.03
6	Treatment Seeking	Medium	0.07	0.05
7	Year of Study	Medium	0.04	0.01
8	CGPA	Medium (−)	0.03	0.01
9	Gender	Low	0.02	0.01

Marital status appeared to be the most important predictor of mental health across all models, indicating that marital status may serve as an indicator of the relational stability present in an individual's social support system. In addition, high levels of anxiety were also found to play a significant role in predicting mental health outcomes. Conversely, academic indicators like CGPA had a much smaller impact on the prediction of mental health compared to all other predictors, suggesting that academic performance may be a byproduct rather than a cause of poor mental health [15].

Values of feature importance presented in **Table 4** are meant to be an interpretive measure of the relative contributions of models to each feature rather than a standardized estimate of causal effects of features on the target variable. The percentages reported for the impact of each feature reflect approximately the change in predictive contributions produced by the features when comparing the performance of the different models and thus should not be treated as a mathematically equivalent value across the different algorithms. Because Logistic Regression Coefficients, Impurity-based feature importance for Random Forests, and Gain feature metrics of Gradient Boosting Models quantify different statistical properties and use different units of measurement, the presence of multicollinearity among the other academic-related variables will likely impact the variable importance rankings across the three different classes of models, especially between models using Tree-based ensemble methods. Accordingly, the feature importance analysis should be considered exploratory and should not be used for definitive comparative inferences among model specifications [13].

Based on the integration of model performance, feature importance, and theoretical implications into a unified framework, **Table 5** provides a higher-order synthesis of the analytical results. In contrast to previously isolated statistical outcomes shown in individual tables, this table provides insight into the structural patterns associated with mental health prediction, as well as those that may extend beyond the study context.

Table 5. Integrated predictive insight and theoretical implications.

Analytical Dimension	Key Insight	Evidence across Models	Theoretical Interpretation	Practical Implication
Predictive Structure	There are non-linear relationships that drive mental health	GB (0.88) > RF (0.84) > LR (0.76)	Supported complexity theory in psychological processes	Use ML-based screening tools instead of linear risk scoring
Psychosocial Dominance	Emotional and social variables outweigh academic indicators	Anxiety (0.11), Marital Status (0.42) vs. CGPA (0.01)	Aligns with biopsychosocial model	Prioritize counseling and social support systems
Developmental Dynamics	Age impacts mental health through life-stage transitions	Moderate importance (0.11–0.15)	Supports life-course theory (emerging adulthood)	Design age-specific intervention programs
Behavioral Responsiveness	Treatment-seeking improves predictive accuracy	Moderate importance (0.05–0.07)	Reflects active coping and adaptive behavior	Promote help-seeking awareness campaigns
Academic Reframing	Academic performance is a weak predictor but likely an outcome	CGPA has low importance across all models	Challenges traditional academic-centric assumptions	Shift focus from grades to well-being monitoring

Table 5. *Cont.*

Analytical Dimension	Key Insight	Evidence across Models	Theoretical Interpretation	Practical Implication
Model Complementarity	Statistical and ML models provide complementary insights	LR (interpretability) + ML (accuracy)	Supports hybrid analytical frameworks	Combine explainability with predictive systems in practice
Risk Identification Efficiency	High recall ensures effective detection of at-risk students	Recall = 0.85 across models	Supports early intervention theory	Implement predictive early-warning systems in universities

Collectively, the results of this study indicate that mental health outcome variables primarily result from complex, non-linear interactions among psychosocial and developmental variables, with minimal effect from traditional academic measures. This reinforces the notion that understanding student well-being will not be accomplished solely with linear or academic models.

The primary findings from **Table 5** further support this conclusion; psychosocial constructs such as marital status and anxiety consistently dominate predictive performance across models, indicating the significance of emotional and relational stability in determining mental health outcomes. Depending on how age is addressed developmentally, the moderate effect of age on predictive performance indicates that transitions through different life stages are likely to have a considerable impact on psychological vulnerability. In addition, by introducing behavioral variables such as treatment-seeking, the analysis becomes multidimensional in nature, reinforcing the point that student responses to mental health challenges are active rather than passive events.

The machine learning models employed various age-stage categories as predicted variables and structured developmentally proxy rather than measured directly psychologically. Categorical transformation of continuous age variables is commonly used in predictive modeling to capture non-linear variation and transitional differences among subpopulations, particularly in smaller datasets. Therefore, the developed age groups should be viewed as representing a general position of development in the context of the university and were designed to increase interpretability, not to represent precise measures of psychosocial identity development or life-course accomplishment.

The convergence of traditional statistical approaches with machine learning is an important example of complementary strengths in both methodologies [17]. Machine learning has effectively increased prediction accuracy by identifying complex relationships within data, whereas statistical modeling has developed to provide interpretability and a theoretical base for its use. The use of both methodologies has allowed for improved analytical rigor, as well as the ability to link between data-driven findings and psychological theory. All of this leads to a comprehensive framework that provides an enhanced methodological and theoretical understanding of the mental health of students, as well as providing useful information for institutional interventions and policymaking.

5. Discussion

Results from this study strengthen existing evidence of a multidimensional psychosocial model of student mental health that cannot be fully explained using traditional linear approaches. Ensemble machine learning techniques, such as gradient boosting or random forests, have demonstrated their ability to identify complex, non-linear relationships among various demographic, behavioral, and psychological factors. The results of this study add to the previous literature, showing that mental health-related outcomes are multidimensional and require analytic methods that can effectively evaluate interaction effects and hidden structures in the data [4,17]. The strong influence of anxiety and marital status on predicting university students' mental health outcomes is consistent with existing psychological research showing that emotional regulation, social support, and stability of relationships are the primary predictors of vulnerability to developing mental health issues within the student population [7,8]. Furthermore, the relatively low predictive ability of CGPA provides further support for emerging literature suggesting that academic achievement is an indirect result of psychological distress rather than a direct cause of mental health challenges [8]. This investigation contributes to both [1] knowledge base and the emerging adulthood theoretical framework by defining age as a set of developmental stages rather than merely counting up from zero on a time continuum; in addition, it emphasizes how transitional psychosocial experiences impact mental health during the university years.

By developing a hybrid framework that integrates statistical logic with feature importance analysis using machine learning, the study contributes to ongoing discussions about the nexus of statistical reasoning and predictive analytics in social science research[18]. Unlike predictive models that prioritize prediction accuracy over interpretability, this study combines interpretable statistical reasoning with machine learning feature importance analysis to improve both explanatory and predictive validity. This combined framework is also a direct response to recent calls for cross-disciplinary analytic approaches in mental health and education research[19–22]. The consistency of accuracy measures, F1-scores, and confusion matrix outputs indicates that the models did generalize adequately; therefore, we can rule out extreme overfitting despite the moderate sample sizes. Furthermore, balanced classification results indicate that the algorithms showed stable sensitivity and specificity across mental health categories. These results are particularly significant because previous educational studies with small datasets have shown low predictive accuracy and poor external validity when they lack sound theoretical foundations or proper validation practices[23–25]. Therefore, this study supports the notion that a carefully crafted exploratory machine learning framework can produce theoretically consistent and meaningful insights, even with moderately sized datasets, as long as justification for the validation process, feature engineering, and theoretical integration is provided.

6. Conclusions

This research showed that different types of algorithms can be used to determine whether someone at a university has a mental health problem based on personal information, such as age, where they grew up, how well they do in school, or how many people they regularly hang out with. It also showed that these methods usually predict mental health well when ensemble learning is used; if that did not work well, then logistic regression could be used. The study identified four important indicators for predicting mental health problems: anxiety, whether a person has had an anxiety attack, whether a person is married, and whether a person seeks help. While CGPA does not seem to be a very good predictor of mental health problems, there are likely other psychological and/or social variables that correlate with the way in which people who have mental health problems classify themselves as having met mental health conditions compared to pure academics alone.

The research also contributes to research methods by combining interpretable (understandable) analytical techniques to predict a student's mental health (student mental health) using predictions from statistics and machine learning models for use as an exploratory framework for predicting students' mental health. The consistency of the accuracy metrics, confusion tables, and model validations was confirmed by the validation of the statistical models, demonstrating that no significant overfitting or fluctuation occurred in the classification (accuracy) performance. While the cross-sectional and moderate sample sizes were limiting factors in this research, the results demonstrate the potential for machine learning models to perform analytical analyses of college students' mental health. Future research should use much larger longitudinal databases from multiple institutions and/or locations (e.g., different university/campus populations) so that results can be generalized to varied student populations.

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Institutional Review Board Statement

This study used fully de-identified, public domain data available under a CC0 Public Domain License. In accordance with the Declaration of Helsinki, no direct interaction with human participants occurred, and the dataset contained no personally identifiable information. Therefore, formal approval from an Institutional Review Board or ethics committee was not required. All analyses were conducted following ethical research practices, including data confidentiality, responsible reporting, and academic integrity.

Informed Consent Statement

Informed consent was obtained from all individual participants included in the study.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author (H.S.: saad@ucmo.edu) on reasonable request.

Conflicts of Interest

The author declares that he has no competing interests.

AI Use Statement

No generative AI tools were used for content generation or data analysis. AI was employed solely for language editing and proofreading support.

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