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MACHINE LEARNING-BASED MENTAL HEALTH RISK PREDICTION AND BEHAVIOURAL CLUSTERING AMONG MALAYSIAN UNDERGRADUATES

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ABSTRACT

Mental health issues among undergraduate students have become increasingly prevalent, affecting emotional well-being, academic performance, and overall quality of life. The growing number of students experiencing stress, anxiety, and depression highlights the need for effective predictive models to support early risk identification and personalized intervention strategies. This study investigates the performance of several machine learning approaches, including Logistic Regression (LR), Random Forest (RF), Gradient Boosting, LightGBM, Extra Trees, XGBoost, Support Vector Classifier (SVC), and a stacked ensemble model for predicting mental health risk among Malaysian undergraduate students. The study utilizes a dataset comprising demographic, academic, lifestyle, and psychological assessment attributes collected through structured self-assessment questionnaires. Model performance was evaluated using 10-fold cross-validation based on accuracy, precision, recall, and Macro F1-score metrics. Results indicate that Logistic Regression and Random Forest achieved superior predictive performance compared to other individual models and were subsequently integrated into a stacked ensemble framework to further improve classification capability. In addition, clustering analysis identified distinct behavioural characteristics among students with moderate and severe mental health risk levels. The findings highlight the potential of integrating predictive analytics and behavioural clustering in intelligent mental health support systems. This study contributes to the growing field of machine learning applications in mental health analytics and provides valuable insights for higher education institutions in supporting undergraduate well-being.

Keywords*: Mental Health, Machine Learning, Stacked Ensemble Learning, Behavioural Clustering, Undergraduate Students.*

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1. Introduction

Mental well-being plays an important role in shaping an individual's ability to manage emotions, adapt to challenges, maintain social relationships, and function effectively in daily life. The university phase is especially significant with regard to mental health among undergraduate students, as it is a period of significant academic, personal and social transition. Mental health is more than the absence of mental health disorders and is a state of well-being in which every individual can cope with stress, work and contribute to society in a positive manner (World Health Organization, 2022). Therefore, good mental health is important in helping to keep students emotionally stable, performing well academically, and functioning effectively in daily life.

Undergraduates' mental health problems are a growing concern worldwide due to the impact on emotional wellbeing, academic performance and overall quality of life. Student life in the university is filled with many kinds of stress such as academic, financial, and social adjustment stress, as well as the pressure of securing post-graduation employment. The shift from school to college can be stressful for students as they must navigate new systems of learning, new experiences of living independently, and greater autonomy in their study, among other changes, that can lead to emotional instability and psychological distress. El Morr *et al*. (2024) noted that exposure to psychological distress faced by university students is increasingly occurring because of academic and lifestyle pressures, which draws attention to the need for early mental health monitoring and action strategies. Likewise, Ramón-Arbués *et al*. (2020) indicated that depression, anxiety, and stress are highly prevalent among university students and can have a negative impact on academic achievement, social functioning and well-being.

Graduate students can face academic and other social and behavioural barriers that affect their mental health. The common factors related to stress, anxiety and depression in students are poor sleep quality, unhealthy lifestyle habits, limited social support, relationship problems, and excessive academic workload. These mental health concerns, if not addressed, can lead to a decrease or loss of motivation in school, loss of productivity, emotional fatigue, and long-term psychological effects. Eisenberg *et al*. highlighted that the lack of awareness, stigma and accessibility barriers are major obstacles that deter University students from seeking timely psychological support. Thus, there is growing interest in recent years in intelligent and accessible approaches that will help in early mental health identification.

Machine learning (ML) has become a valuable tool in healthcare analytics, capable of handling vast amounts of data, uncovering subtle behaviors, and providing predictive analytics. Logistic Regression (LR), Random Forest (RF), Gradient Boosting, LightGBM, XGBoost and Support Vector Classifier (SVC) are some of the supervised learning algorithms that have been used extensively in healthcare and psychological prediction tasks. According to Dharmarathne *et al*., (2024), machine learning methods can successfully predict mental health disorders in students based on demographic, behavioral, and lifestyle factors. Furthermore, Priya *et al*. (2020) showed that the machine learning algorithms can effectively predict stress, anxiety, and depression with promising classification performance. In addition, ensemble learning techniques can be used to improve the predictive power of these classifiers by aggregating their results to generate more accurate and reliable predictions.

In addition to supervised learning, unsupervised learning algorithms like K-Means clustering can be used to discover unknown behavioral patterns among individuals who have similar characteristics. Behavioural clustering helps to identify meaningful groups of students according to psychological and behavioural characteristics to design more individualised intervention strategies. Clustering and behavioural segmentation have been highlighted as crucial methods in mental health analytics to identify hidden behavioural patterns related to stress and emotional health, as noted by Razavi *et al*. (2023). Likewise, Shatte *et al*., (2019) noted that unsupervised learning techniques can help in the identification of hidden patterns

and characteristics in mental health data and in behavioral patterns that may only be identified with difficulty using conventional analysis techniques.

While there has been prior research on prediction of mental health using machine learning, much of the existing literature are focused mainly on classification accuracy, without taking behavioural segmentation into account for personalized support. Furthermore, limited studies have investigated the integration of multiple supervised learning models, stacked ensemble learning, and clustering analysis within the context of Malaysian undergraduate students. The absence of behavioural grouping may limit the effectiveness of intervention strategies, as students with similar risk levels may still exhibit different behavioural characteristics and support needs. Therefore, this study proposes a machine learning-based framework for mental health risk prediction and behavioural clustering among Malaysian undergraduate students.

2. Related Works

The growing incidence of mental health problems among undergraduate students has motivated researchers to consider intelligent and technology-based methods to detect and intervene mental health problems at the early stage. Machine learning techniques have garnered attention in mental health analytics in recent years, for their ability to process vast amounts of data, uncover hidden behavioral patterns, and provide predictive insights. Shatte *et al*. (2019) emphasized that the use of machine learning techniques has shown great promise in the field of mental health, especially in prediction, classification, and behavioral analysis. The development of various sources of data on behaviour, academic performance, and lifestyle have enhanced the use of predictive analytics for understanding psychological well-being in university students.

There are a number of studies that have used supervised machine learning techniques to predict mental health issues like emotional distress, stress, anxiety and depression. In 2020, Priya *et al*. (2020) predicted anxiety, depression and stress using behavioural and psychological dataset using multiple machine learning algorithms and found encouraging classification performance of different predictive models. Likewise, El Morr *et al*. (2024) created predictive machine learning models for the prediction of depression, anxiety, and stress among university students using demographic, academic, and lifestyle-related variables. By developing and testing machine learning methods, their study showed how automated mental health risk recognition and early intervention can be improved through machine learning in educational contexts. Tlachac *et al*. (2020) also investigated automated severity assessment of depression through machine learning methods, using features derived from text and speech-related data, demonstrating that the behavioural signals could play an important role in the psychological prediction performance.

The results show that various supervised learning algorithms have yielded different degrees of success in mental health prediction tasks. Logistic Regression (LR) has widely been used because of its good interpretability and performance in binary classification problems where the data comes from psychology. Another popular method is Random Forest (RF) and other tree-based methods due to their handling of nonlinear relationships and multidimensional feature interactions. Ensemble and hybrid learning strategies often outperform individual classifiers in mental health predictions by leveraging the ability to aggregate multiple predictive processes, enhancing their robustness and stability in classification. In mental health prediction, ensemble and hybrid learning strategies are often used, as they can merge multiple predictive mechanisms to provide a more robust and stable classification. In line, Jacob *et al*., (2022) revealed that the ensemble learning models outperformed the traditional single machine learning models in depression classification.

Methods like Boosting, Gradient Boosting and XGBoost have also achieved good results in healthcare and behavioural analytics. According to Chen and Guestrin (2016), XGBoost offers scalable and efficient tree boosting methods that deliver high predictive

performance with structured data. Similarly, Ke *et al*. (2017) proposed a fast training and computational efficiency gradient boosting framework named LightGBM, which is efficient for large-scale data. For these benefits, the boosting-based models are being more and more used in healthcare prediction tasks involving behavioural and psychological variables.

However, apart from conventional supervised learning techniques, Support Vector Classifier (SVC) is also investigated in healthcare prediction problems because it can draw the optimal decision boundary in high dimensional datasets. Dhama *et al*. (2020) highlighted the significance of Support Vector Machine-based model in psychological prediction problem due to their excellent generalization capability and ability to handle nonlinear feature interaction. Furthermore, Kourou *et al*. (2015) indicated that SVM models are consistently capable of achieving good classification performance in medical prediction studies, because of their ability to cope with complex distribution of data and small samples.

Apart from supervised learning, unsupervised learning techniques have increasingly been explored in mental health analytics to uncover hidden behavioural patterns and psychological characteristics. Clustering (e.g., K-Means clustering) can be used to segment people with similar behavioural profiles, facilitating a better understanding of mental health trends among segments. Clustering and behavioural segmentation methods have been gaining traction in stress and mental health monitoring systems for the detection of hidden behavioral patterns indicative of emotional distress, as noted by Razavi *et al*. (2023). Likewise, Shatte *et al*. (2019) pointed out that unsupervised learning algorithms can help identify mental health traits which are not obvious via traditional statistical analysis techniques. But, in the studied research, clustering methods were primarily used for behavioural grouping and exploratory analysis, and supervised predictive models were not used in an integrated fashion in an analytical framework, especially for undergraduate mental health analytics.

There have also been several studies that have explored factors related to mental health issues among university students. According to Ramón-Arbués *et al.*, (2020), the most important stressors for students include poor sleep quality, financial problems, academic workload, lack of social support, and unhealthy lifestyle habits. In a similar vein, Beiter *et al*. (2015) identified academic stress, financial worries, and worry about future career as significant factors in undergraduate psychological distress. The results suggest that there are several interrelated behavioral, academic, and social factors that impact mental health disorders. For this reason, machine learning methods are especially well suited, because they are able to process multidimensional datasets and discover complex feature interactions that are related to psychological well-being.

While prior research has shown the efficacy of machine learning methods in predicting mental health, there are still research gaps. Existing studies mostly regard behaviour segmentation for personalised intervention support as a secondary issue, only considering classification performance. In addition, works focused on clustering methods are frequently performed separately from predictive modelling methods. There are limited studies that have explored the use of supervised machine learning models, stacked ensembles, and clustering analysis in a single framework, especially in the context of undergraduate mental health analytics. If there are no integrated predictive and behavioural analysis, intervention strategies might not be as effective because students at the same risk level might have different behavioural characteristics, emotional patterns, and support needs.

Hence, this study aims to bridge the gap of the current studies by combining various supervised learning techniques with stacked ensemble learning and K-Means clustering in predicting mental health risk and analyzing behaviour among Malaysian undergraduate students. Several machine learning models (Logistic Regression (LR), Random Forest (RF), Gradient Boosting, LightGBM, Extra Trees, XGBoost and Support Vector Classifier (SVC)) are compared and combined into a stacked ensemble model. Furthermore, behavioural clustering is used to determine the difference in behaviours between pupils in the moderate and severe mental health risk groups. The proposed framework will use predictive modelling and

behavioural segmentation to offer more comprehensive insights into student mental health patterns and to develop intelligent and personalized intervention strategies.

3. Methodology

This study proposes a machine learning-based framework for mental health risk prediction and behavioural clustering among undergraduate students. The methodology consists of several phases as illustrated in Figure 1.

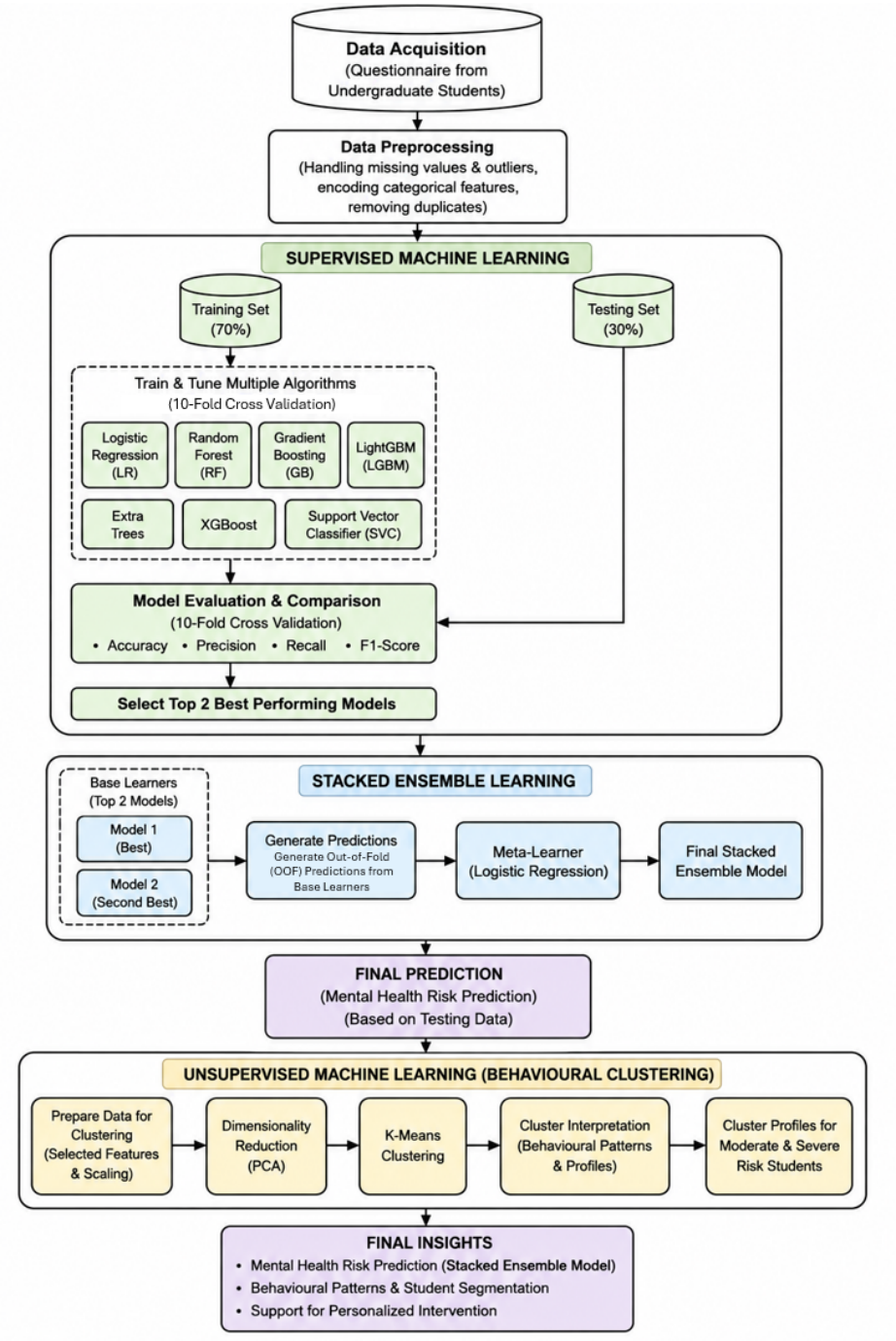


Figure 1. Workflow of the Study

3.1 Data Acquisition

The dataset utilized in this study was collected through a structured self-assessment questionnaire distributed among undergraduate students in Malaysia. The questionnaire was designed to capture academic, behavioural, lifestyle, social, and psychological-related factors associated with mental health conditions among students. The data collection process was conducted as part of the Campus Care project, a web-based mental health assessment and support platform developed by the researchers. The application was implemented and made publicly accessible through a GitHub repository to facilitate data collection and mental health assessment among undergraduate students (Foo, 2025).

The collected observations were aggregated into a single dataset to support mental health risk prediction and behavioural clustering analysis. The dataset consists of 10 predictor variables alongside a target variable representing the mental health risk category of undergraduate students. The specific description of each variable is presented in Table 1.

Table 1. Description of Study Variables

Variable	Description (Units/Values)
AcademicWorkload	Perceived academic workload experienced by the student. This variable reflects the amount of coursework, assignments, and academic tasks the student is required to manage. (Scale: 1 = Very Low Workload, 5 = Very High Workload)
CourseworkPressure	Perceived pressure related to coursework and academic performance expectations. This variable reflects the intensity of stress the student experiences from coursework deadlines and performance demands. (Scale: 1 = Very Low Pressure, 5 = Very High Pressure)
SuicidalThoughts	History or occurrence of suicidal thoughts experienced by the student. This variable is based on a self-reported screening question and serves as an indicator of acute psychological risk. (Yes/No)
SleepDuration	Average sleep duration of the student. This variable represents a lifestyle-related indicator commonly associated with psychological well-being and stress recovery. (Hours per night)
FinancialStress	Financial stress experienced by the student. This variable captures the degree of financial burden or worry related to personal expenses, tuition, or living costs. (Scale: 1 = Not at All Stressed, 5 = Very Stressed)
StudyHours	Average study hours allocated by the student. This variable reflects the student's academic time commitment and workload outside of formal class hours. (Hours per week)
PhysicalActivity	Frequency of physical activity or exercise engaged in by the student. This variable reflects a lifestyle-related factor associated with psychological well-being and stress regulation. (Scale: 1 = Never, 5 = Very Frequently)
IsolationFrequency	Frequency with which the student experiences social isolation or withdrawal from social interactions. This variable captures a behavioural indicator relevant to psychological distress and social disengagement. (Scale: 1 = Never, 5 = Very Frequently)
Age	Age of the student. This variable captures demographic variation that may relate to differences in behavioural and psychological patterns across undergraduate students. (Years)
WorkStudyBalance	Student perception towards balancing academic and personal activities. This variable reflects the student's perceived ability to manage academic responsibilities alongside personal, social, and co-curricular commitments. (Scale: 1 = Poor, 5 = Good)
MentalHealthRisk	Target variable representing the mental health risk category of the student. This variable was derived from the combined severity of depression and anxiety symptoms assessed through the PHQ and GAD instruments, and represents the classification target used for the supervised learning models. (Minimal and Mild / Moderate / Severe)

The incorporated questionnaire sections include academic-related factors, non-academic lifestyle factors, social-related factors, and psychological assessment components adapted from the Patient Health Questionnaire (PHQ) and Generalized Anxiety Disorder (GAD) assessment instruments. The PHQ questionnaire is widely utilized for assessing depression severity and psychological well-being (Kroenke *et al*., 2001), while the GAD assessment instrument is commonly applied for anxiety screening and severity evaluation (Spitzer *et al*., 2006). The target variable categorizes students into different mental health risk levels, including minimal or mild symptoms, moderate symptoms, and severe symptoms. The variables utilized in this study consist of both academic and non-academic attributes associated with undergraduate students' mental health conditions.

The data is a combination of numerical and categorical data types. AcademicWorkload, CourseworkPressure, SleepDuration, FinancialStress, StudyHours, PhysicalActivity, IsolationFrequency, Age and WorkStudyBalance are numerical variables because they are either measured by a numerical scale or continuous variables gathered by asking the respondents in the questionnaires. SleepDuration and StudyHours are in hours, Age is in years, and all other numerical variables use scale-based answers related to student perceptions and experiences. At the same time, SuicidalThoughts is the only categorical variable in the final feature set, with binary (Yes/No) responses; as a binary variable, its label encoding does not introduce any ordinality concern. The class variable MentalHealthRisk is the mental health risk category of undergraduate students, which has three classes: minimal or mild symptoms, moderate symptoms, and severe symptoms. The academic, behavioural, lifestyle and psychological related variables allow for a holistic analysis of factors affecting undergraduate students' mental health.

3.2 Data Pre-processing

The data was passed through a data pre-processing phase before its use for model training. Data pre-processing plays an important role in predictive modelling, where the performance of the model, classification accuracy, and reliability of the analytical process are directly affected (Hon *et al*., 2023). This step consists of various steps, such as dealing with missing values and outliers, removing duplicate data, encoding categorical data and splitting the data set. The main goal of the pre-processing phase is to enhance the quality, consistency and compatibility of the dataset prior to the supervised learning and clustering analysis.

The data thus obtained were first checked for missing values, duplicate entries, and inconsistencies. The data was collected from answering the structured questions so it was quantified between predetermined values and categories. To check that extremely high or low values were indicative of meaningful behavioural or psychological states, rather than data entry error, outlier inspection was performed. To ensure that there was no loss of important behavioural data that could relate to mental health issues among students, no observations were excluded during this process. Furthermore, duplicate record checking was performed to make sure that each record was a different respondent in the data. In addition, missing values were also taken into account during this process; however, no missing values were found within the collected dataset. To prepare these data sets for machine learning algorithms, the categorical variable SuicidalThoughts was converted into a numerical representation using label encoding. As SuicidalThoughts is a binary (Yes/No) variable, this encoding does not impose any unintended ordinal relationship between categories, and therefore does not present the ordinality concern that label encoding can introduce for nominal variables with more than two categories.

3.3 Supervised Machine Learning

During the supervised learning phase, multiple machine learning classifiers are developed and evaluated for mental health risk prediction among the undergraduate students. The processed dataset was split into training and testing datasets at the ratio of 70:30, i.e. 70% of the observations were used for training the model while 30% were used for testing and evaluating

the model as shown in Figure 1. In this study, various supervised learning algorithms, such as Logistic Regression (LR), Random Forest (RF), Gradient Boosting, LightGBM, Extra Trees, XGBoost and SVC are evaluated. The reason for choosing these classifiers is that they have proven to be successful in classification tasks with psychological, behavioural and healthcare related data.

Logistic Regression was used because of its interpretability and it's effectiveness in binary or multiclass classification problems, especially in healthcare prediction studies using psychological and behavioural variables (Hosmer *et al*., 2013). Random Forest and Extra Trees were added due to their ability to capture non-linear relationships between features, high dimensionality of the data and to prevent overfitting by using ensemble learning techniques (Breiman, 2001; Geurts *et al*., 2006). Meanwhile, Gradient Boosting, XGBoost and LightGBM were selected based on their boosting characteristics that sequential learning is used to minimize prediction error and generalization (Friedman, 2001; Chen & Guestrin, 2016; Ke *et al*., 2017). The Support Vector Classifier was also tested due to its ability to tackle difficult decision boundaries and large dimensionality of the data, which is applicable to classification tasks in psychological or healthcare related fields (Cortes & Vapnik, 1995).

Cross validation was performed for model training and tuning to make the model robust and avoid overfitting. In this study, 10-fold cross validation was used (divide the training data set into 10 subsets). Each time, a subset was used for validation while the others were used for training. This was repeated in an iterative manner until all subsets were used for validation. The use of cross validation can ensure that the models developed are tested in a consistent manner on different partitions of data and hence provide more consistent predictive performance. Various performance metrics such as accuracy, precision, recall, and Macro F1-score were used to assess the performance of each classifier.

Accuracy measures the overall correctness of the prediction model as presented in Equation (1).

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN} \tag{1}$$

Precision evaluates the proportion of correctly predicted positive observations as presented in Equation (2).

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall measures the capability of the model to correctly identify actual positive cases as presented in (3).

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Meanwhile, the Macro F1-score provides a balanced evaluation between precision and recall as presented in (4).

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

where TP represents the number of correctly predicted positive observations (True Positive), TN represents the number of correctly predicted negative observations (True Negative), FP represents the number of incorrectly predicted positive observations (False Positive), and FN represents the number of incorrectly predicted negative observations (False Negative).

Among these evaluation metrics, the Macro F1-score was considered particularly important due to the imbalance between mental health risk categories within the dataset. The macro-averaged Macro F1-score ensures equal consideration across all classes, including moderate and severe mental health risk groups, preventing minority classes from being

overlooked during model evaluation. After the evaluation and comparison of the models, the two classifiers with good overall performance were chosen. The selected models were then used as the base learners in the stacked ensemble learning framework to further improve the performance of mental health risk prediction.

3.4 Stacked Ensemble Learning

Following the evaluation of the supervised machine learning models, the two best-performing classifiers were selected and integrated into a stacked ensemble learning framework to further improve predictive performance. Based on the cross-validation results, Logistic Regression and Random Forest demonstrated superior classification capability compared to the other evaluated models and were therefore selected as the base learners for the stacking architecture. Stacked ensemble learning, also known as stacked generalization, is a meta-learning technique that combines predictions generated by multiple classifiers through an additional learning model known as the meta-learner (Wolpert, 1992). The primary objective of stacking is to leverage the strengths of multiple models while minimizing the weaknesses of individual classifiers, resulting in improved robustness and predictive capability. Ensemble learning approaches are widely recognized for improving classification accuracy and generalization performance in predictive analytics tasks (Sagi & Rokach, 2018).

In this study, Logistic Regression and Random Forest were utilized as the base learners. Both models were trained using the same feature set consisting of academic, behavioural, and psychological-related variables. The predictions generated by these base learners on the training dataset were subsequently used as input features for the meta-learning phase. These meta-features were obtained through the built-in cross-validation mechanism of the StackingClassifier implementation in scikit-learn, whereby out-of-fold predictions were generated using an internal five-fold cross-validation procedure that is separate from the ten-fold cross-validation used earlier for individual base-model evaluation and selection. This ensures that no base learner produced predictions on the same observations it was trained on when constructing the meta-learner's training set, thereby mitigating the risk of data leakage and overly optimistic performance estimates. Logistic Regression was employed as the meta-learner due to its simplicity, interpretability, and effectiveness in combining outputs from multiple classifiers. The stacked ensemble learning process begins by training the base learners independently using the training dataset. After generating prediction outputs, the meta-learner analyzes the prediction patterns produced by the base models and learns how to combine them to generate the final prediction. This approach enables the stacked model to capture complementary strengths from both classifiers, improving overall classification stability and reducing prediction errors. Previous studies have shown that stacking approaches are capable of outperforming standalone classifiers by integrating complementary predictive capabilities from multiple models (Ganaie *et al*., 2022).

The performance of the stacked ensemble model was subsequently evaluated using the same evaluation metrics applied during the supervised learning phase, including accuracy, precision, recall, and Macro F1-score. The stacked ensemble model demonstrated improved predictive performance compared to standalone classifiers, indicating that combining multiple classifiers can improve robustness and prediction stability in mental health classification tasks. In addition, the prediction outputs generated by the stacked ensemble model were subsequently utilized to identify undergraduate students categorized under moderate and severe mental health risk levels for further behavioural clustering analysis.

3.5 Unsupervised Machine Learning (Behavioural Clustering)

After the stacked ensemble learning procedure, the unsupervised machine learning approaches were used to find hidden behavioral patterns for undergraduate students who were classified as experiencing moderate and severe mental health risks. A key difference between supervised and unsupervised learning is that unsupervised learning does not require target labels to be provided, but rather uncovers the patterns within the data set (Shatte *et al*., 2019). The purpose

of this study was to find behavioural segmentation and the profiles of students with different psychological and lifestyle characteristics using clustering analysis. The data set with the selected behavioral and psychological related variables was preprocessed for unsupervised analysis before clustering. Numerical variables were scaled using StandardScaler so that all variables contribute equally in the clustering process (Wongoutong, 2024). Principal Component Analysis (PCA) was then used to transform the prepared data to a smaller vector space containing the most significant variance information in the data.

One of the widely used dimensionality reduction methods is PCA and it is a method used to reduce dimensions of high dimensional data without losing much information. Transformations of principal components make the visualization of the clustering more accessible and increase the efficiency of computation, by reducing the complexity of the features (Jolliffe & Cadima, 2016). In this study the PCA was used pre-clustering to increase the separation and visualization of behavioural patterns of students with varying mental health conditions. Post dimensionality reduction K-Means clustering is used to cluster students according to the similarities in behavioural and academic and psychological related attributes. K-Means is a centroid-based clustering algorithm which aims to split the observations into a set of clusters such that the distance from each data point to its cluster centroid is minimal (Lloyd, 1982). The algorithm runs over and over, allocating observations to the closest cluster center until it reaches convergence.

The clustering analysis specifically dealt with the students who were grouped under the categories of moderate and severe mental health risk level, as predicted by the outputs of the stacked ensemble model. This allows for a more detailed analysis of behaviour of those students, who are more at risk and might need psychological support or intervention. The clusters were then described in terms of predominant behaviour such as academic workload, coursework pressure, study hours, co-curricular involvement, isolation frequency, physical activity, sleep duration, financial stress, age, and recent suicidal thoughts. The clustering results offer behavioural profiles and insights into the segmentation of students to complement the supervised prediction results. The proposed framework combines predictive modelling and behavioural clustering analysis, allowing for a holistic understanding of students' mental health status as undergraduates and to develop personalised intervention and mental health support strategies. Clustering techniques have also been emphasized in previous research to aid mental health analytics and uncover latent behaviour trends and psychological patterns among student cohorts (Razavi *et al*., 2023).

4. Results

The results of the proposed machine learning framework for the prediction of mental health risk among undergraduate students are presented in this section. The distribution of the mental health risk categories is presented first to give an overview of the condition of the target variable in the data set. Then, the performance of the supervised machine learning models and the stacked ensemble model is tested using the selected performance metrics, such as accuracy, precision, recall, and Macro F1-score. An unsupervised machine learning analysis is also performed to find behavioural patterns among students that fall into moderate and severe mental health risk groups.

4.1 Output Class Distribution of Mental Health Risk Categories

Figure 2 illustrates the distribution of undergraduate students based on their mental health risk categories derived from the psychological assessment calculations. The majority of the respondents, 67.95% (212 individuals), were categorized under minimal and mild mental health risk levels. Meanwhile, 16.99% (53 individuals) were identified as experiencing moderate mental health risks, while 15.06% (47 individuals) were categorized under severe mental health risk levels. The distribution indicates that although most respondents experienced relatively

lower levels of psychological distress, a considerable proportion of undergraduate students demonstrated moderate to severe mental health risks. This finding highlights the growing concern regarding mental health conditions among undergraduate students and emphasizes the importance of early identification and intervention strategies within higher education environments.

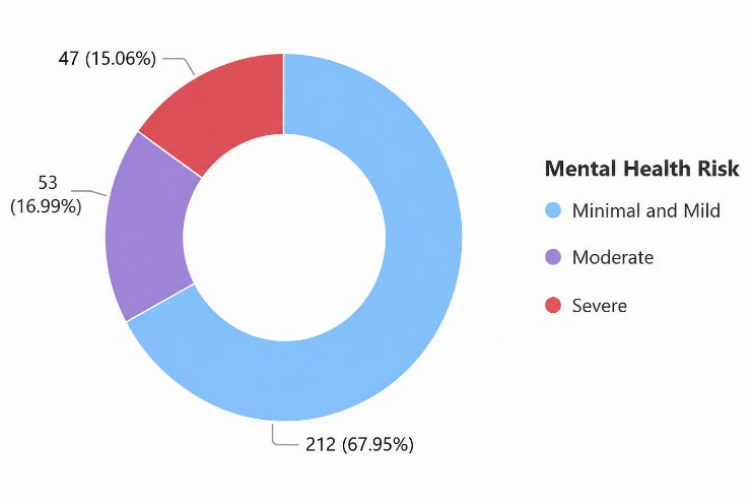


Figure 2. Mental Health Risk Categories Distribution

In addition, the class distribution demonstrates the presence of imbalance among the target classes, where the minimal or mild risk category contains substantially more observations compared to the moderate and severe risk groups. Class imbalance may influence predictive model performance by biasing the classification process towards the majority class. Therefore, evaluation metrics such as macro-averaged Macro F1-score were emphasized during model evaluation to ensure equal consideration across all mental health risk categories, particularly the minority classes representing moderate and severe psychological distress. The class imbalance present in this dataset was not directly addressed through resampling or balancing techniques, as doing so would likely alter the actual structure and distribution of the collected data. Instead, the macro-averaged Macro F1-score was adopted as it is considered a suitable evaluation measure for imbalanced classification tasks, since it computes the unweighted average of the Macro F1-score across all classes and therefore gives equal importance to minority and majority classes alike (Sokolova & Lapalme, 2009). Given that the minority classes, particularly the severe risk category (n = 47), originate from a real, live-administered questionnaire rather than a large-scale secondary or synthetic dataset, applying oversampling techniques such as SMOTE could introduce synthetic observations that do not faithfully represent the interindividual variability of genuine student responses. Techniques such as SMOTE or class-weighting may therefore be more appropriately explored in future work involving larger, multi-institutional samples, where a greater number of minority-class observations can support reliable synthetic interpolation without compromising the authenticity of the collected data.

4.2 Performance Evaluation of Supervised Machine Learning Models

This section presents the performance evaluation results of the supervised machine learning models developed for mental health risk prediction among undergraduate students. Several classification algorithms were evaluated, including Logistic Regression, Random Forest, Gradient Boosting, LightGBM, Extra Trees, XGBoost, and Support Vector Classifier. The models were assessed using accuracy, precision, recall, and Macro F1-score metrics through 10-fold cross-validation to ensure reliable and unbiased performance evaluation. Prior to model evaluation, several hyperparameters were configured and optimized to improve predictive

performance and learning stability across all classifiers. The selected parameter configurations for each supervised machine learning model are presented in Table 2.

Table 2. Optimal Parameters for Supervised Machine Learning Models

Model	Optimal Parameters
Logistic Regression	solver = 'lbfgs', max_iter = 1000
Random Forest	n_estimators = 100, max_depth = 10, random_state = 42
Gradient Boosting	n_estimators = 100, learning_rate = 0.1, max_depth = 3
LightGBM	n_estimators = 100, learning_rate = 0.1, num_leaves = 31
Extra Trees	n_estimators = 100, max_depth = 10, random_state = 42
XGBoost	n_estimators = 100, learning_rate = 0.1, max_depth = 3
Support Vector Classifier	kernel = 'rbf', C = 1.0, gamma = 'scale'

The models were trained using the optimized parameter configurations to improve classification robustness and reduce the possibility of overfitting. Ensemble-based classifiers such as Random Forest, Gradient Boosting, Extra Trees, LightGBM, and XGBoost utilized multiple estimators and controlled tree depth to improve generalization capability and predictive stability. Meanwhile, Support Vector Classifier utilized the radial basis function (RBF) kernel to better handle nonlinear decision boundaries within the dataset. The comparative performance evaluation results of all supervised machine learning models are presented in Table 3.

Table 3. Performance Evaluation Results of Supervised Machine Learning Models

Model	Accuracy	Precision	Recall	Macro F1-score
Logistic Regression	0.7251	0.5703	0.5214	0.5198
Random Forest	0.7203	0.5143	0.5159	0.4957
Gradient Boosting	0.6742	0.5281	0.4725	0.4672
LightGBM	0.6604	0.4957	0.4629	0.4528
Extra Trees	0.6883	0.4670	0.4556	0.4461
XGBoost	0.6374	0.4360	0.4273	0.4161
Support Vector Classifier	0.6697	0.2232	0.3333	0.2673

Based on the evaluation results, Logistic Regression achieved the best overall predictive performance with an accuracy of 72.51% and the highest Macro F1-score of 0.5198. The model also demonstrated balanced precision and recall values, indicating strong classification consistency across the mental health risk categories. Random Forest achieved the second highest performance with an accuracy of 72.03% and an Macro F1-score of 0.4957, demonstrating competitive predictive capability in handling behavioural and psychological-related variables. Among the ensemble boosting models, Gradient Boosting produced the strongest performance with an Macro F1-score of 0.4672, followed by LightGBM and XGBoost. Although these models demonstrated competitive classification capability, their overall performance remained slightly lower compared to Logistic Regression and Random Forest. Extra Trees also achieved relatively stable predictive performance due to its randomized ensemble learning mechanism.

Meanwhile, Support Vector Classifier recorded the lowest Macro F1-score of 0.2673 despite achieving moderate accuracy performance. This finding indicates weaker classification balance across the mental health risk categories, particularly for the minority classes involving moderate and severe mental health risks. Overall, Logistic Regression and Random Forest demonstrated superior predictive stability and balanced classification performance compared to the remaining classifiers. Therefore, both models were selected as the top-performing

classifiers and were subsequently utilized as the base learners in the stacked ensemble learning framework.

4.3 Performance Evaluation of the Stacked Ensemble Model

Following the evaluation of the supervised machine learning models, Logistic Regression and Random Forest were selected as the base learners for the stacked ensemble learning framework due to their superior predictive performance. Logistic Regression was further utilized as the meta-learner to combine the prediction outputs generated by both base classifiers. The classification performance of the proposed stacked ensemble model was evaluated using accuracy, precision, recall, and Macro F1-score metrics. Table 4 presents the comparative performance between the baseline classifiers and the stacked ensemble model.

Table 4. Performance Comparison Between Baseline Models and Stacked Ensemble Model

Model	Accuracy	Precision	Recall	Macro F1-score
Logistic Regression	0.7251	0.5703	0.5214	0.5198
Random Forest	0.7203	0.5143	0.5159	0.4957
Stacked Ensemble Model	0.7700	0.6200	0.5800	0.5700

Based on the experimental results, the stacked ensemble model achieved superior predictive performance compared to both baseline classifiers. The model recorded the highest accuracy of 77.00% alongside improvements in precision, recall, and Macro F1-score. The Macro F1-score increased from 0.5198 in Logistic Regression to 0.5700 in the stacked ensemble model, demonstrating improved classification balance across the mental health risk categories. The improvement in predictive capability indicates that the stacked ensemble framework successfully leveraged the complementary strengths of both Logistic Regression and Random Forest. Logistic Regression contributed strong generalization capability and balanced classification consistency, while Random Forest enhanced predictive robustness through its ability to capture nonlinear feature interactions and complex behavioural patterns within the dataset.

The stacked ensemble model also demonstrated improved capability in identifying students categorized under moderate and severe mental health risk groups. This finding is particularly important because accurate identification of higher-risk students supports early psychological intervention and mental health monitoring within higher education environments. The prediction outputs generated from these two higher-risk groups were subsequently utilized in the unsupervised machine learning phase to perform behavioural clustering analysis. This additional analysis enables deeper exploration of behavioural, academic, and psychological-related patterns among students experiencing elevated mental health risks.

4.4 Behavioural Clustering Analysis of Moderate and Severe Mental Health Risk Groups

Following the prediction phase using the stacked ensemble model, unsupervised machine learning analysis was conducted to identify behavioural patterns among undergraduate students categorized under moderate and severe mental health risk groups. The clustering analysis focused specifically on these two groups because they represent students with elevated psychological distress levels who may require psychological support and early intervention strategies.

Prior to clustering, the selected academic, behavioural, and psychological-related features were standardized using StandardScaler to ensure equal contribution among all variables during the clustering process. Principal Component Analysis (PCA) was subsequently applied to reduce dimensionality and simplify the dataset while preserving the most significant variance information. The PCA-transformed data were then utilized as input for K-Means clustering to partition students into distinct behavioural groups based on similarities in their

characteristics. The optimal number of clusters (K) for the K-Means algorithm was determined by evaluating the Silhouette Score across a range of candidate K values separately for the moderate and severe mental health risk groups, where K = 2 consistently produced the highest Silhouette Score and therefore the clearest and most well-separated behavioural grouping for both groups. Based on this evaluation, K-Means clustering was configured with K = 2 for both the moderate and severe mental health risk groups. The clustering analysis divided both the moderate and severe mental health risk groups into two distinct clusters. To evaluate clustering quality and separation, the Silhouette Score was utilized during the clustering process. Table 5 presents the Silhouette Score comparison before and after PCA dimensionality reduction.

Table 5. Silhouette Score Comparison Before and After PCA

Mental Health Risk Group	**Before PCA**	**After PCA**
Moderate Risk Group	0.1085	0.6631
Severe Risk Group	0.1755	0.4084

PCA significantly improved clustering quality for both mental health risk groups. The Silhouette Score increased substantially after dimensionality reduction was applied, indicating clearer cluster separation and reduced overlapping patterns within the dataset. This demonstrates that PCA successfully simplified the behavioural structure of the dataset while preserving meaningful variance information required for clustering analysis. Figure 3 illustrates the behavioural profiles for Cluster 1 within the moderate mental health risk group.

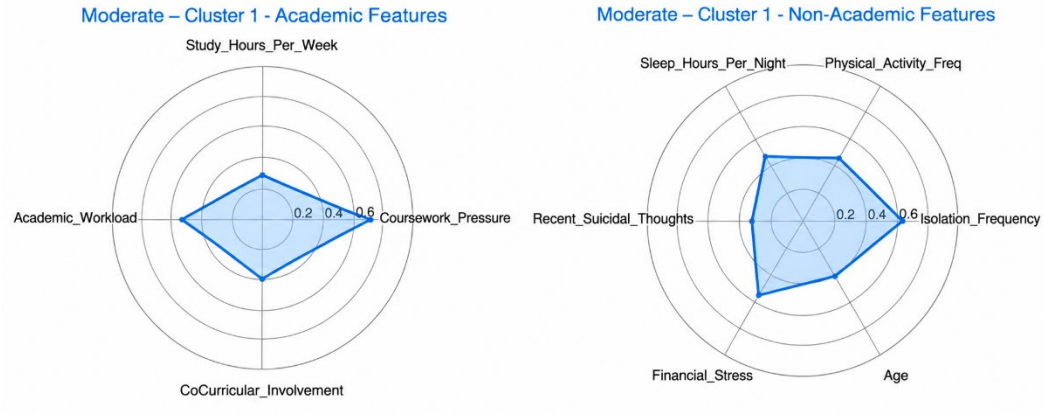


Figure 3. Academic and Non-Academic Features of Cluster 1Moderate Risk Group

Based on the academic-related features, students in this cluster demonstrated relatively higher coursework pressure and academic workload compared to study hours and co-curricular involvement. Meanwhile, the non-academic behavioural profile showed relatively higher isolation frequency and financial stress levels. These findings suggest that students within this cluster may experience moderate psychological distress primarily associated with academic burden, social isolation, and financial-related pressures.

Figure 4 presents the behavioural profiles for Cluster 2 within the moderate mental health risk group. Compared to Cluster 1, students in this cluster demonstrated relatively lower academic workload and coursework pressure. However, the non-academic features revealed higher isolation frequency and older age distribution patterns alongside lower financial stress levels. This indicates that moderate mental health risks may also be associated with behavioural and lifestyle-related factors rather than purely academic-related pressures.

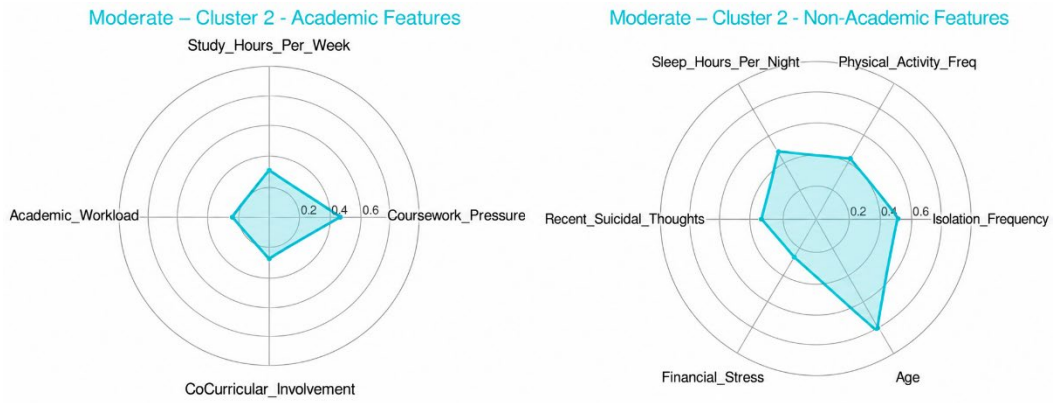


Figure 4. Academic and Non-Academic Features of Cluster 2 Moderate Risk Group

The clustering results demonstrate that students categorized under similar moderate mental health risk levels may still exhibit substantially different behavioural and psychological-related characteristics. Some students appear to experience psychological distress primarily due to academic-related pressures, while others demonstrate stronger influence from social and lifestyle-related conditions. Similarly, clustering analysis was also performed for students categorized under severe mental health risk levels. The resulting clusters revealed more pronounced behavioural and psychological-related patterns compared to the moderate risk groups. Figure 5 illustrates the academic and non-academic behavioural profiles for Severe Cluster 1.

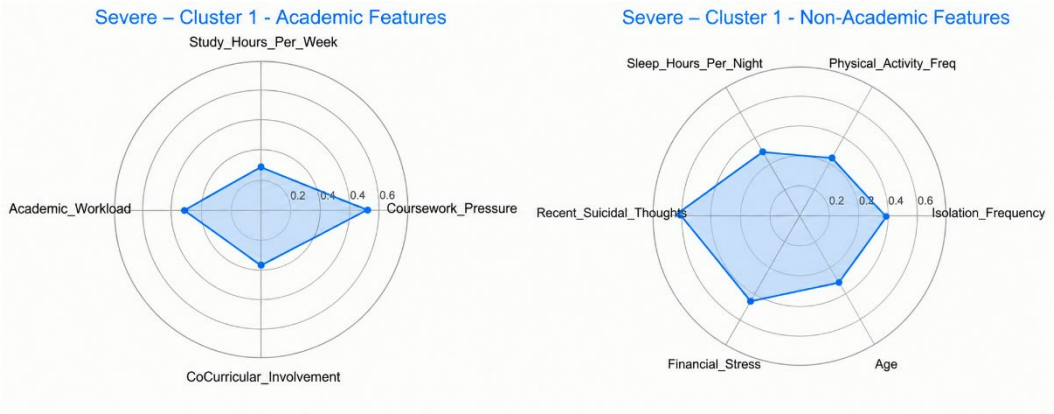


Figure 5. Academic and Non-Academic Features of Cluster 1 Severe Risk Group

The academic-related radar chart demonstrates relatively high academic workload and coursework pressure despite only moderate study hours per week. In addition, co-curricular involvement remained relatively low, suggesting that students within this cluster may experience psychological exhaustion primarily associated with academic responsibilities and limited engagement in stress-relieving extracurricular activities. The corresponding non-academic profile further indicates elevated isolation frequency, reduced physical activity, shorter sleep duration, and stronger indicators of recent suicidal thoughts. These findings suggest that students in Severe Cluster 1 experience severe mental health conditions associated with overlapping academic pressure and emotional distress factors.

Meanwhile Figure 6 presents the corresponding profiles for Severe Cluster 2. This cluster exhibited slightly different behavioural characteristics. Although academic pressure and workload remained present, the academic radar chart demonstrated comparatively lower academic-related stress than Severe Cluster 1. However, the non-academic behavioural profile revealed stronger influence from lifestyle and emotional-related factors, particularly higher

isolation frequency, poorer sleep patterns, and lower social interaction indicators. This suggests that psychological distress within Severe Cluster 2 may be more strongly influenced by behavioural and emotional instability rather than direct academic burden alone.

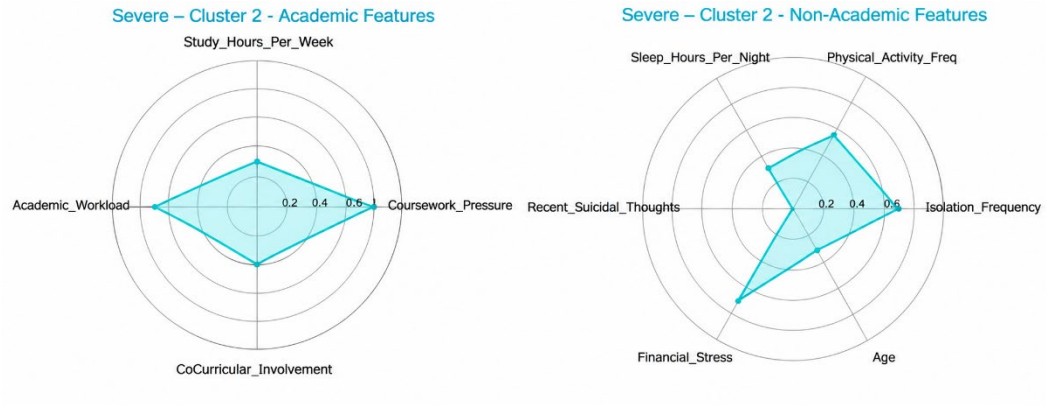


Figure 6. Academic and Non-Academic Features of Cluster 2 Severe Risk Group

The severe-risk clusters showed significantly more extreme academic and non-academic behavioural patterns, compared with the moderate-risk groups. The suicidal thought indicators tended to be lower, and the lifestyle behaviours were relatively healthier in the moderate clusters in comparison. The severe-risk clusters, meanwhile, indicated a greater focus on negative behavioural factors, including isolation frequency, academic pressure, financial stress and emotional instability. These distinctions suggest that mental well-being among undergraduate students is linked with academic stressors as well as cumulative behavioural and psychosocial stressors.

In general, the cross-clustering comparisons indicate that different behavioural profiles and contributing factors can be found for students who fall into similar mental health severity categories. The clustering analysis thus offers greater insight into the heterodoxy of mental health disorders in undergraduate students, for better targeted and personalized intervention approaches than general psychological support measures.

5. Discussion

The results of this study indicate that machine learning methods can give good prediction power for detecting the mental health risk levels of undergraduate students. According to the supervised machine learning evaluation, Logistic Regression and Random Forest provided a better predictive performance than the other classifiers, showing their effectiveness in dealing with behavioural, academic, and psychological related variables. Logistic Regression gave the best overall performance which indicated that multiple behavioural and psychological attributes in the dataset have relatively distinct classification patterns. This finding is in contrast with a few previous studies in healthcare where boosting based methods showed better predictive performance (Shatte *et al*., 2019; Priya *et al*., 2020) suggesting that the behavioural variables in this dataset are relatively linearly separable.

This good performance also further suggests the adoption of ensemble-based learning approaches for mental health analytics. Random Forest can also model nonlinear relationships and complex interactions across features, which is very suitable for behavioural and psychological data with multidimensional variables (Biau & Scornet, 2016). Ensemble learning algorithms, including Random Forest, Gradient Boosting and XGBoost are also often proven to achieve better results than traditional classifiers in healthcare context in previous studies due to their robustness and ability to minimize overfitting (Uddin *et al*., 2019).

The proposed stacked ensemble learning framework also boosted the performance of the prediction compared with the reference models. The model used in this study was a stacked ensemble of Logistic Regression and Random Forest classifiers, which effectively fused the advantages of both linear and nonlinear classifiers. The experimental findings showed an improvement in accuracy, recall, and F1 score, which meant greater classification stability and balanced prediction ability among all mental health risks. The result is consistent with that of previous studies which also showed that stacked ensemble learning could benefit the predictive power by using complementary information provided by different classifiers (Wolpert, 1992; Sagi & Rokach, 2018). These improvements are especially significant in mental health analytics, the goal of which is to identify groups of moderate and severe psychological distress as early as possible to ensure effective mental health monitoring.

Furthermore, the combination of supervised and unsupervised machine learning algorithms in the proposed framework adds more analysis value other than traditional prediction models. Supervised learning allows for the predictive classification of mental health risk level of students at the undergraduate level for observations not in the dataset, and unsupervised clustering allows for exploratory behavioural segmentation of the higher risk students identified by the model. By combining both techniques, the proposed framework can not only predict but also conduct behavioural profiling and hidden pattern discovery of students who are suffering from high psychological distress. This mixed method analysis allows for an enhanced understanding of the underlying behaviours of mental health disorders.

The behavioural clustering analysis not only predicted the presence of mental health condition, but also offered a greater understanding of the variability of mental health conditions in undergraduate students. Clustering results showed that students in the same mental health risk group can have very different characteristics related to their behaviours and psychological factors. In several clusters, there were indications of higher academic stressors; in other clusters, there were signs of behavioral styles related to social isolation, lifestyle imbalance, financial stress and emotional instability. These results suggest that mental health among undergraduates is not a solely academic burden, but rather a complex issue involving various behavioural and psychological factors. This has been observed in prior research: machine learning models have been able to detect underlying behavioral and psychological trends in health and mental health related data sets (Shatte *et al*., 2019).

The obtained Silhouette Scores, too, reflect the importance of dimensionality reduction for improving the quality of the clustering and behavioural pattern separation, with the Silhouette Scores being much better after applying PCA. PCA reduced the behavioural data while retaining the most salient variance, facilitating the ability to identify behavioural groups among the moderate and severe mental health risk students. This result is in line with other studies that have indicated PCA can help visualize clusters, minimize noise and improve separation of clusters in high dimensional data sets (Jolliffe & Cadima, 2016).

In summary, this study advances research into the application of machine learning in mental health analytics, by combining supervised prediction and unsupervised behavioural clustering in the same analytical framework. The proposed framework goes beyond the traditional work on prediction accuracy, by adding the behavioural profiling of higher-risk groups of students. Using predictive modelling and clustering analysis can help in a more complete assessment of mental health and could be used to inform the design of targeted intervention strategies, personalised counselling approaches and early mental health monitoring system in higher education institutions.

6. Conclusion and Recommendation

This study presented a machine learning approach to predict mental health risks and to cluster the behaviour of undergraduate students that combines both supervised and unsupervised

machine learning methods in one analytical approach. Experimental results proved that Logistic Regression and Random Forest showed a good predictive performance among the classifiers evaluated and when combined in a stacking ensemble learning framework, their predictive performance proves to be more efficient. Furthermore, the behavioural clustering analysis was able to cluster together different academic, behavioural, and psychological-related patterns among those students who were classified in moderate mental health risk and severe mental health risk categories, revealing the complexity and heterogeneity of mental health conditions among undergraduate students. Overall, the proposed framework serves to the evolving field of mental health analytics, where it is able to not only predictively classify a new observation, but also profile the behaviour of higher-risk students. The results of this study can help higher education institutions in formulating more targeted interventions, personalized counselling approaches and intelligent mental health support systems. In the future, larger diverse data sets, more deep learning algorithms and real-time behavioural monitoring techniques could be used to further enhance prediction performance and mental health intervention capacity.

Despite these contributions, this study is subject to certain limitations. The dataset used in this study was collected through a live, self-administered questionnaire targeting undergraduate students, resulting in a relatively modest sample size of 312 observations, with approximately 218 observations available for model training after the 70:30 train-test split. Collecting primary survey data directly from students, rather than relying on a larger secondary or publicly available dataset, involved practical constraints related to participant recruitment, time, and resource availability within the scope of this study. Given this relatively small training sample, the application of complex algorithms such as XGBoost, LightGBM, and stacked ensemble learning may increase the risk of overfitting, even though 10-fold cross-validation was employed throughout model training and evaluation to help mitigate this risk. Future studies are therefore encouraged to validate the proposed framework on larger and more diverse samples, potentially through multi-institutional data collection, to further verify the generalizability of the reported findings.

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Author Contribution

Author 1 conceptualized the study, designed the experimental framework, supervised the overall research process, and refined the manuscript structure and content. Author 2 conducted the literature review, developed the research methodology, performed the statistical and machine learning analyses, and prepared the initial manuscript draft. Author 3 managed the data pre-processing procedures, contributed to the literature review, and ensured the manuscript complied with the journal formatting and submission guidelines. Author 4 provided domain expertise, critically reviewed the manuscript for intellectual and technical quality, and assisted in finalizing the manuscript for submission. Author 5 performed the final review of the manuscript, verified the overall clarity and consistency of the study, and provided recommendations prior to submission.

Declaration of generative AI in the writing process

During the preparation of this work, the authors used ChatGPT (OpenAI) to assist with language refinement, grammatical correction, and improving the clarity of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data Availability/Supplementary Materials

The dataset used in this study is publicly available in the Campus Care GitHub repository at https://github.com/debbiefyx/Campus-Care/tree/main. The processed data and supporting materials generated during this study are available from the corresponding author upon reasonable request.

Ethics Statement

This study was reviewed and approved by the Institutional Ethics Committee of University of Wollongong Malaysia. All procedures involving human participants were conducted in accordance with the relevant institutional ethical standards. Informed consent was obtained from all participants prior to data collection, and participant anonymity and confidentiality were maintained throughout the study.

Conflict of Interest

The authors have no conflicts of interest to declare.

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