AWNB: Augmented-Wingsuit–Optimized Multinomial Naïve Bayes for Multimodal Early-Warning of College Student Mental Health

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Early identification of mental health risks among college students is critical for timely intervention, promoting well-being, and supporting academic performance. This study utilizes a comprehensive multimodal dataset comprising 1,000 students, integrating behavioral routines (study hours, sleep schedules, and daily activity patterns), physiological indicators (heart rate, stress levels, and sleep quality), and social engagement measures (messaging frequency and participation in clubs or events) to classify students into Low, Moderate, and High mental health risk categories. Data preprocessing included handling missing values with mean/median imputation for continuous features and mode imputation for categorical features, followed by standardization using Z-score normalization. Stratified five-fold cross-validation with a fixed random seed was applied to ensure reproducible and unbiased evaluation. Baseline models, including the Data Fusion Model, CASTLE, YOLOv8, Time-Aware Multimodal Fusion Network (TAMFN), and Random Forest combined with CatBoost, were carefully tuned under equivalent computational budgets to provide fair comparisons. The proposed Augmented Wingsuit–Enhanced Multinomial Naïve Bayes (AWNB) framework combines optimization-driven hyperparameter tuning with decision-level multimodal fusion, effectively capturing complex interactions between behavioral, physiological, and social features. Experimental results demonstrate that AWNB achieves superior performance, with 97.41% accuracy, 95.14% precision, 93.67% recall, and 94.82% F1-score. Baseline performances were: Data Fusion Model – 95.2% accuracy, 93.7% precision, 90.8% recall, 92.2% F1-score; CASTLE – 84.47% accuracy, 71.47% recall, 74.65% F1-score; YOLOv8 – 71% precision, 74.1% recall; TAMFN – 66.02% precision, 66.50% recall, 65.82% F1-score; and Random Forest + CatBoost – 91.3% accuracy, 92.4% precision, 90.5% recall. All metrics are reported as mean ± standard deviation, and statistical significance was validated using paired tests. These findings establish AWNB as a robust, interpretable, and computationally efficient framework, outperforming existing approaches while enabling scalable application in academic mental health monitoring.

Povzetek: Model AWNB z multimodalno fuzijo vedenjskih, fizioloških in socialnih podatkov pri 1.000 študentih doseže najboljše rezultate (97,41 % natančnost; F1 94,82 %) ter prekaša primerjalne modele pri razvrščanju tveganja za duševno zdravje.

1 Introduction

The World Health Organization (WHO) describes mental health (MH) as a condition of well-being where a person can fulfill individual abilities, deal with the usual pressures of living, perform effectively, and be useful to the community [1]. Positive MH extends beyond the absence of a psychiatric condition; it also entails a positive system of habits and behaviors that promote resilience, adaptation, and a good life [2]. Nonetheless, disorders of MH have become a current international issue, especially in the rapidly developing economies of the world, where competition and lifestyle shifts are the factors that add to the stress and susceptibility.

College students are particularly at risk of MH problems. Students undergo immense physiological and psychological changes during the change that occurs between adolescence and adulthood. Lack of self-regulation among the students is also relatively low; thus, when combined with the academic pressure, social networking, and personal affiliations, these become even more emotionally unstable [3]. These challenges contribute to the risk of anxiety, depression, and burnout, which have a direct influence on academic performance and patterns of personal development. Furthermore, the absence of proper coping skills and insufficiency of emotional strength also enhance the imbalance between the psychological demands of the students and their ability to effectively cope with these demands [4]. The pandemic increased such problems dramatically. Sudden changes in the academic schedules, forced isolation, and the sudden transition to online education led to the abnormal augmentation of the academic stress, anxiety[5], and depressive symptoms among the undergraduates. At the same time, numerous students said that they were experiencing problems gaining access to mental health care, and that the institutional resources and counseling services were also slow, which further complicated the crisis [6]. This brought out how the university students are at a loss during the emergencies in the world and there is a need to adopt sustainable support mechanisms.

Among various people, lifestyle-related disorders, Major Depressive Disorder (MDD) and non-communicable diseases (NCDs) have become a major cause of disability, poor quality of life and premature deaths [7]. These conditions are different in the higher education environment that is typically interdependent with the stress of academic achievement, career readiness, and financial limitations. Being young adults, university students must face the challenge of making their future contribution to society, as well as the burden of personal identity, career, and relationship problems [8 and 9]. Further, psychological quality was also shown to be linked with acquiring moral value and good ethical standards, and the relevance of psychological support and intervention during early ages is valuable. In this regard, the efficient crisis-intervention framework and relentless surveillance systems are being discovered as the key ones when serving the student bodies [10-11].

1.1 Research objective

College students' mental health issues necessitate creative solutions that go beyond conventional screening. To increase accuracy, sensitivity, and dependability in identifying early MH risks by multimodal data fusion, this research intends to develop an AWNB framework that integrates optimization and ML.

2 Related works

Mental health education is significant both to support the psychological wellbeing of college students and be able to provide high-quality education. Research [12] aimed at improving proper evaluation through the development of a fine-grained parallel computing architectural design, a product of deep learning (DL) and a supplemented emotion dictionary classification. The findings indicate that the model was more accurate in determining emotional statuses and psychological risks with reference to the Weibo data. The biggest weakness though was the fact that it was based on online expressions, which might not be reflective of the offline psychological realities of the students.

Mental health management was the best approach when the psychological state of the college students was monitored. Research [13] has proposed the dynamic evaluation prototype, which integrated the multimodal synthesis of the physiological messages with the deep generative models, in which the transformers were considered as the feature fusion and VAE-LSTM (Variational Autoencoder - Long Short-Term Memory) [14] as the predictor of the trend of the psychological states. The outcomes of the experiment confirm that the proposed methodology was more efficient than the existing ones in the classification and dynamics to predict mental health changes. The fact that the approach relies on physiological indicators as one of its weaknesses was that they are open to external influence and might not be adequate to objectively quantify emotional subjective experiences [15]. Mental health among students was one of the aspects of high importance that affects the learning, well-being, and social interactions processes, but the traditional assessment approaches were likely to ignore its dynamic and complicated nature. Research [16] capitalized on Artificial Intelligence (AI), ML, and multi-modal data analyses with a view of integrating physiological, behavioral, and social interactions to conduct a holistic evaluation of mental disorders. The plan permitted dynamic and timely interventions and increased the specificity and precision of mental health support [17]. It might, however, be restricted in its effectiveness by the access to data, privacy, and the fact that the signal might not be homogenous across the students.

Mental health assessment in college students is complex and multifactorial. Research [18] proposed a model combining social sentiment analysis, CNN-BiGRU, dynamic embeddings, and H-GNN, achieving up to 99% accuracy and F1 in dynamic monitoring but limited by reliance on social media data. Research [19] proposed a CNN-MV-MEC framework that combines deep learning and multiview clustering on electroencephalogram (EEG) signals (SEED dataset) for the detection of negative emotional states, which would allow for timely responses. These EEG approaches face scalability issues and do not capture all possible dimensions of an individual’s psychology. Both studies emphasize how multimodal approaches and neural models can assess mental health in a precise but low-friction way with regard to usability and convenience in identifying a mental state in students.

Psychological stress among adolescents is an increasing concern with calls for early diagnosis. Research [20] presented a Multi-modal Interactive Fusion Method (MIFM) and employed text data, image data, and sleep/exercise data derived from mobile applications. They found that the multimodal fusion design was superior to unimodal detection even though the data quality from the smartphone was poor. Another work presented DDNet [21], which is a stacked ensemble model comprised of MLP, SGD, CatBoost, and Lasso models, reporting 98-99% accuracy with SHAP-based explanations, although limited to only structured data types. Similarly, research [22] investigated the use of ML/DL with behavioral, biomarker, and imaging data for diagnosing mental disorders, while noting the capability for future real-time monitoring, yet offered no definitive conclusion on providing integrated data and covering ethical considerations. Furthermore, early detection of depression in college students is important for their well-being. Research [23] provided CRADDS, which applies tensor fusion from audio, text, and video along with using a hybrid SVM-CNN-BiLSTM model on the IoT devices/tasks, reaching an accuracy of 86.08% versus

63.04% with SVM. These studies are only examples of what has been done, and also are notable in that all studies made reference to privacy concerns when integrating the various data types, as well as needing optimal multimodal IoT data inputs on the student participants' devices.

3 Methodology

The framework describes an Enhanced multinomial Naïve Bayes (EMNB) classifier, which is coupled with an Adaptive and Weighted Shared Optimization (AWSO) policy, that predicts mental health risks among college students. The multi-modal data used in the framework included behavioral, physiological, and social characteristics that were preprocessed by handling missing values, to standardize values, and finally through visualization with t-SNE. To explain, EMNB is responsible for modeling latent dependencies and adaptively weighs the different attributes while AWSO seeks to optimize its parameters to maximize classification performance. The hybrid format of EMNB and AWSO will provide early detection of mental health issues that is robust, interpretable, and high accuracy. Ultimately, in Figure 2, the overall procedure is presented alongside the proposed AWNB framework.

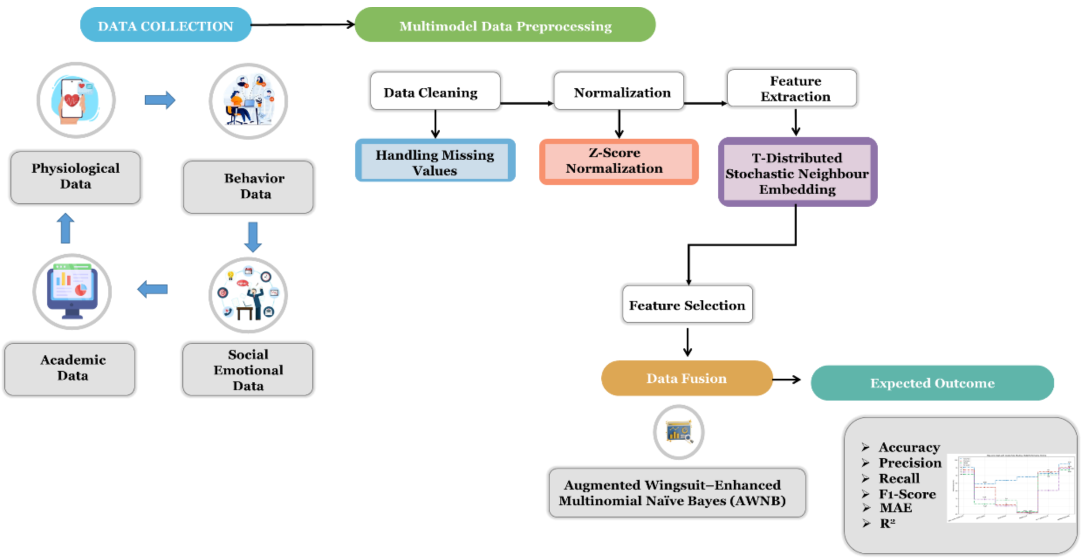

Figure 2: The process flow of the proposed framework

3.1 Data acquisition

The college-students-mental-health-dataset was sourced from Kaggle: (https://www.kaggle.com/datasets/zara2099/college-students-mental-health-dataset/data) [24]. It includes demographic, behavioral, lifestyle, and educational characteristics of students, as well as self-assessed mental health measures, such as anxiety, depression, and stress levels. The dataset includes numerical and categorical variables, including age, gender, study habits, sleep habits, exercise habits, and social habits. The dataset contains 1,000 records of college students. The mental health risk target is represented in three classes: Low (400 samples) ,Moderte (350 samples), and High (250 samples). The dataset is balanced among the three classes so that it may be used for model training and evaluation.

3.2 Data preprocessing

Efficient preprocessing is an important step in building trustworthy ML models, because it ensures that the collected multimodal data is clean, and is a valid comparison across variations of feature space. In this study, preprocessing consisted of handling missing values, normalizing the features, and preparing the dataset for other feature extraction and classification.

3.2.1 Handling missing values

Multimodal datasets frequently contain missing data caused by sensor failures or an unsuccessful transmission. Missing data might skew findings and impair a model's accuracy. This study used a mixed technique for its analyses, deleting data with severe missingness and merely reconstructed partial gaps. Continuous variable imputation (e.g., heart rate, sleep duration) used mean and median values for imputation, and mode was used for categorical variables. This way the dataset was complete and variability was preserved, and the robustness of the AWNB Framework could be bolstered for feature fusion and mental health prediction.

3.2.2 Standardization (Z-Score normalization)

The multimodal dataset collected in this research comprises heterogeneous features such as behavioral metrics (e.g., study hours, attendance frequency), physiological signals (e.g., heart rate, sleep duration), and social interaction indicators (e.g., number of messages, group participation). These features differ not only in their units of measurement but also in their value ranges and variances. Directly feeding such raw features into a ML model often leads to biased learning, where features with larger numeric scales dominate the optimization process, while smaller-scale features contribute minimally. Equation 1 represents the formulation of Z-score normalization.

$$Z_{ji} = \frac{x_{ji} - \mu_j}{\sigma_j} \quad (1)$$

Where as x_{ji}: Original value of the jth feature for the ith sample. μ_j: Mean of the jth feature across all samples. σ_j: Standard deviation of the jth feature. Z_{ji}: Standardized value.

Several behavioral, physiological, and social characteristics were standardized using z-score normalization

3.3 T-distributed Stochastic Neighbor Embedding (t-SNE) for feature visualization

Behavioral, physiological, and social interaction aspects are examples of high-dimensional multimodal data that frequently show intricate nonlinear interactions that are difficult to immediately analyze. To resolve this, high-dimensional data is projected onto a low-dimensional space (usually 2D or 3D) using t-distributed Stochastic Neighbor Embedding (t-SNE), a nonlinear dimensionality reduction technique. The ability to visualize hidden structures, clusters, and separations makes it easier to identify patterns linked to mental health problems.

High-dimensional distribution (P): Represents pairwise similarities among data points in the original feature space.

Low-dimensional distribution (Q): Represents pairwise similarities among data points in the reduced feature space.

The similarity between two data points $w_j$and w_i in the high-dimensional space is measured using conditional probability. Equation 2 defines similarity $P(w_j|w_i)$ Euclidean distances.

$$P(w_j|w_i) = \frac{S(w_j, w_i)}{\sum_{n \neq j} S(w_j, w_n)} \quad (2)$$

Equation (3), $P(w_j \mid w_i)$ is the neighbor selection probability, w_n the number of neighbors, and $S(w_j, w_i)$ the Euclidean similarity; the denominator standardizes over all neighbors n excluding w_j, while z_j, z_idenote low-dimensional symbols.

$$Q(z_j|z_i) = \frac{S(z_j, z_i)}{\sum_{n \neq j} S(z_j, z_n)} \quad (3)$$

In this appearance, $Q(z_j|z_i)$ represents the prospect that point z_j would select z_i as its neighbor in the lower-dimensional embedding and z_n as a number of the iterations.

$$KL(P \| Q) = \sum_j \sum_i P(w_j, w_i) \log \frac{P(w_j|w_i)}{Q(z_j|z_i)} \quad (4)$$

In equation 4, $KL(P \| Q)$quantifies the difference between the similarity distribution in the high-dimensional space (P) and that in the low-dimensional space (Q). thereby preserving neighborhood structures for interpretable visualization.

3.4 Augmented Wingsuit–Enhanced Multinomial Naïve Bayes (AWNB)

The Augmented Wingsuit–Enhanced Multinomial Naïve Bayes (AWNB) model is designed by advancing the optimization power of Augmented Wingsuit Search Optimization (AWSO) and the classification ability of the Multinomial Naïve Bayes (NB) algorithm. Although traditional NB uses a straightforward yet effective probabilistic framework for navigating text-like and categorical data, it is dependent on prior probability estimate and tuning parameters to achieve a level of effectiveness. AWSO is a well performing population-based metaheuristic optimization technique that can efficiently explore complex search space to locate optimal parameter combinations. In AWNB, these two paradigms are combined to increase predictive accuracy when multimodal data contains behavioral, physiological, and social data correlated in non-linear ways, while simultaneously enhancing parameter learning of NB.

3.4.1 Enhanced Multinomial Naïve Bayes (NB)

The conditional independence assumption, which is infrequently correct with actual, empirical data, is the main issue with Naive Bayes (NB), nonetheless, it is recognized because of ease and general accuracy. An Improved Multinomial Naive Bayes model partially addresses the weaknesses of NB by incorporating a latent variable that identifies hidden relations between attributes and relaxes the independence assumption for the dependent attributes. However, there are still deficiencies regarding scalability, accountability for heterogeneous attribute distributions, and high sensitivity to the number of latent states. The proposed EMNB classifier reduces these deficiencies with adaptive dependency weighting, regularization, and mixing components in a latent model framework that increase classification accuracy.

Posterior probability maximization

Equation 5 defines the basic classification task, where the model seeks the class label with the maximum posterior probability.

$$\hat{c} = \arg\max_{c \in C} P(D = d|A_1 = a_1, \dots A_N = a_N) \ (5)$$

The EMNB classifier's first step involves predicting the most likely class for a specific input instance. In Equation 5, $\hat{c}$ is the class label predicted for an input, and C is the set of all possible classes. D is the input data instance being classified, and A_i is the i-th attribute of the instance, which has an observed value A_iThe above formulation guarantees that the classifier will choose the class that is most likely to have generated the observed attributes .

Bayes Rule in EMNB

This reformulation applies Bayes' theorem to decompose the posterior into class prior and conditional likelihood.

$P(C|A_1, \dots A_N) \propto P(C). P(A_1, \dots, A_N|C)$ (6)

To total the subsequent probability more tractably, Bayes' theorem is applied in equation 6. Here, $P(C|A_1, \dots A_N)$ represents the posterior probability of the class C given all observed attributes. The term $P(C)$ is the prior probability of class C, reflecting its overall likelihood before observing the features, while $P(A_1, \dots, A_N|C)$ is the likelihood of observing the specific attribute values given that the instance belongs to class C. This decomposition allows the classifier to separate prior information about class distributions from the contribution of the observed features.

Adaptive dependency weighting

This change adds a weighting formula that modifies each attribute's impact under various latent conditions. The weighting function is expressed in Equation 8.

$$P(A_1, \dots A_N|C) = \sum_{h \in RH} \prod_{i=1}^{N} (P(A_i|C, H = h)^{w_i(c,h)}) P(H = h) \quad (7)$$

Additionally, the model offers adaptive weighting for every attribute under various latent states. For class C under latent state h, the weighting function $w_i(c, h)$ modifies the impact of the J-th attribute. The model may dynamically modify each feature's contribution thanks to this weighting, which enhances classification performance in diverse datasets.

Regularization term

To avoid overfitting, a Kullback–Leibler (KL)-divergence-based regularization is applied between the latent distribution and a uniform prior.

$$\mathcal{L}_{reg} = \lambda. D_{KL}(P(H)\|U(H)) \quad (8)$$

In this expression 9, $P(H)$ is the learned distribution over latent states, $U(H)$ is the uniform prior over these states, and λ is a hyperparameter controlling the strength of regularization. This term encourages the latent distribution to remain close to uniform, avoiding excessive bias toward particular latent states.

Final decision rule

The final decision function integrates class priors, latent variable dependences, adaptive weights, and regulation.

$$\hat{c} = \arg\max_{c \in C} P(D = d) \sum_{h \in RH} P(H = h) \prod_{j=1}^{M} (P(A_i|C = c, H = h)^{w_i(c,h)}) - \mathcal{L}_{reg} \quad (9)$$

Equation 9 predicts the class label $\hat{c}$ by combining input attributes A_i, class priors, latent dependencies, adaptive weighting, and KL-divergence regularization. EMNB overcomes traditional Naïve Bayes limitations, handling high-dimensional, correlated data robustly, improving predictive accuracy, interpretability, and scalability for applications like mental health risk assessment.

3.4.2 Augmented Wingsuit Search Optimization (AWSO)

AWSO were incorporating chaos-based perturbation, adaptive velocity control, and neighborhood diversification, AWSO improves the Wingsuit Flying Search algorithm by avoiding premature convergence and limited exploration in high-dimensional space. It guarantees diversity across the population and supports global optimization strategies, allowing the AWSO to be effective in parameter tuning of Enhanced Multinomial Naïve Bayes in data fusion with multimodal distributions.

Initialization

Candidate solutions are initialized using a hybrid sequence combining the Halton sequence for uniform distribution and Gaussian perturbations for diversity that was expressed in equation 11.

$$x^{(0)} = [x_1^{(0)}, x_2^{(0)}, \dots, x_D^{(0)}], \quad x^{(0)} \in [x_{min}, x_{max}]^C \ (11)$$

Where as $x^{(0)} \to$ The initial solution vector at iteration 000, $x_i^{(0)} \to$ The i-th decision variable in the initial solution vector. $[x_{min}, x_{max}]^C \to$ Represents that the initial solution is generated within the constraint-defined search space (C = constraints). D = problem dimension. x_{min}, x_{max} = lower and upper search space bounds. Gaussian perturbation ensures spread beyond deterministic Halton initialization.

Adaptive neighborhood size

Unlike static WFS neighborhoods, AWSO adaptively adjusts each solution's neighborhood according to fitness rank. Equation 12 ensures better solutions retain larger search neighborhoods for exploration, while weaker ones shrink toward exploitation.

$$P^{(t)}(i) = \left\lceil P_{max}^{(t)} \cdot \left(1 - \frac{f_i - f_{min}}{f_{max} - f_{min} + \epsilon}\right) \right\rceil (12)$$

Where as $P^{(t)}(i)$ = neighborhood size for solution i at iteration t.f_i = fitness of solution i.f_{min}, f_{max} = best and worst fitness in iteration t.$\in$ = small constant to avoid division by zero.

Neighborhood point generation with Lévy Flights

To expand global reach, neighborhood points are generated not only within the grid but also perturbed by a Lévy distribution. Lévy flights allow occasional long jumps to unexplored regions, improving global exploration. Equation 13 depicts its calculation.

$$y_j^{(t)} = x_i^{(t)} + \alpha. Levy(\beta), \quad i = 1, \dots, P^{(t)}(i) \quad (13)$$

Where as $y_j^{(t)}$ = candidate neighbor of $x_i^{(t)}$. α = step scaling factor. $Levy(\beta)$ = Lévy random step with index $[\beta \in (0,2]$.

Elite-guided updating

Each solution learns from both the global best solution and a dynamically selected elite set consisting of top solutions. This mechanism, represented in equation 14, balances intensification (learning from the best) and diversification (learning from multiple elites).

$$x_i^{(t+1)} = x_i^{(t)} + r_1.(x_{gb} - x_i^{(t)}) + r_2.(x_\in - x_i^{(t)}) \quad (14)$$

Where as $x_i^{(t)}$ → Position (value) of the i -th solution/agent at iteration t.$x_i^{(t+1)}$ → Updated position of the i-th solution/agent at the next iteration $(t+1)$.$x_\in$ = randomly chosen elite solution. $r_1, r_2 \in [0,1]$ = learning coefficients. x_{gb} global best solution at iteration t.

Dynamic grid shrinking

Similar to WFS, AWSO shrinks the search grid over time but applies a non-linear decay to preserve exploration longer. Equation 15 represents the shrinking formulation of the proposed adaptive WSO.

$$\Delta x^{(t)} = \Delta x^{(0)}.\exp\left(-\gamma.\frac{t}{S}\right) \quad (15)$$

Where as $\Delta x^{(0)}$ = initial grid size.t = maximum number of iterations. $\gamma \in (0,1)$ = decay rate. S = Maximum number of iterations or a scaling parameter.

Final updating rule

The final position update combines adaptive neighborhood, Lévy exploration, elite learning, and grid shrinking. It was represented in equation 16.

$$x_i^{(t+1)} = y_j^{(t)} + \Delta x^{(t)}.\phi + r(x_{gb} - x_i^{(t)}) \quad (16)$$

Where as $y_j^{(t)}$ = neighborhood candidate. $\phi \in [-1,1]$ = random scaling factor. $r \in [0,1]$ = exploitation coefficient.

In conclusion, the AWSO improves the classical WFS through adaptive neighborhood allocation, Lévy-based long-range exploration, and elite-guided exploitation. The pseudo-code of AWSO describes an optimization process during which agents iteratively update positions via glide, lift, and exploration dynamics all in an attempt to minimize fitness and discover optimal parameter configurations.

Pseudo-Code: Augmented Wingsuit Search Optimization AWSO

1. Initialize parameters:
- Population size N = 5
- Maximum iterations MaxIter = 10
- Dimensionality D = 2
- Position bounds X_min = -10, X_max = 10
- Glide factor = 0.5
- Lift factor = 0.3
- Exploration rate = 0.2

2. Initialize population (random positions in [-10, 10]):
Agent 1: X1 = [2, -3]
Agent 2: X2 = [-5, 1]
Agent 3: X3 = [0, 7]
Agent 4: X4 = [-2, -6]
Agent 5: X5 = [4, 4]
3. Initialize personal bests:
P1 = X1, P2 = X2, ..., P5 = X5
4. Evaluate initial fitness (example: f(X) = X1^2 + X2^2):
f(X1) = 2^2 + (-3)^2 = 13
f(X2) = (-5)^2 + 1^2 = 26
f(X3) = 0^2 + 7^2 = 49
f(X4) = (-2)^2 + (-6)^2 = 40
f(X5) = 4^2 + 4^2 = 32
5. Determine initial global best:
G = X1 (fitness 13, lowest)
6. Iteration loop (t = 1 to MaxIter):
For each agent i:
Example for Agent 2:
- Current position: X2 = [-5, 1]
- Personal best: P2 = [-5, 1]
- Global best: G = [2, -3]
 # Compute components
*Glide = 0.5 * (G - X2) = 0.5 * ([2, -3] - [-5,1]) = 0.5 * [7, -4] = [3.5, -2]*
*Lift = 0.3 * (P2 - X2) = 0.3 * ([-5,1] - [-5,1]) = [0,0]*
*Exploration = 0.2 * random_vector([-1,1]) = 0.2 * [0.6, -0.8] = [0.12, -0.16]*
- Update position:
X2_new = X2 + Glide + Lift + Exploration
= [-5,1] + [3.5,-2] + [0,0] + [0.12,-0.16]
= [-1.38, -1.16]
- Ensure bounds [-10,10] → valid
- Evaluate fitness:
f(X2_new) = (-1.38)^2 + (-1.16)^2 ≈ 3.23
- Update personal best: P2 = X2_new (since 3.23 < 26)
- Update global best: G = X2_new (fitness 3.23 < 13)
7. Repeat for all agents and all iterations.
8. After 10 iterations:
- Output best solution: G = [position with lowest fitness]
- Best fitness: f(G)

This addition allows to establish a balanced exploration-exploitation trade-off that reduces the risk of premature convergence and improves robustness and efficiency over high dimensional multimodal optimization problems. When applied to parameter tuning of classifiers such as Enhanced Multinomial Naïve Bayes, the AWSO optimizer improved convergence speed and predictive accuracy, thus establishing the AWSO as an important optimization framework to support numerous real-life applications such as early detection of mental health risks. The entire procedure of the methodology is described in Algorithm 1.

Algorithm 1: AWNB − Based Early Mental Health Risk Detection

Input: *College students' multimodal dataset D*:
(behavioral, physiological, and social features)Output: *Predicted mental health risk labels.*
Start
Data Acquisition
Load dataset D from Kaggle.
Extract features: *demographic, behavioral, physiological, and social interaction attributes.*
Identify target mental health variables (anxiety, depression, stress).
Data Preprocessing
Handle missing values:
Continuous → *replace with mean/median based on skewness.*
Categorical → *replace with mode.*
Standardize features using Z − score normalization.
Apply t − SNE for feature visualization.
EMNB Classification
Initialize latent variable HHH with states RHR_HRH.
Compute conditional probabilities: P(A1, … , AN ∣ C) = ∑h ∈ RH∏i = 1NP(Ai ∣ C, H = h)P(H = h)P(A_1, … , A_N ∣ C) = \sum_{h \in R_H} \prod_{i = 1}^N P(A_i ∣ C, H = h) P(H = h)P(A1, … , AN ∣ C) = ∑h ∈ RH∏i = 1NP(Ai ∣ C, H = h)P(H = h)
Apply adaptive dependency weighting: P(A1, … , AN ∣ C) = ∑h ∈ RH∏i = 1N[P(Ai ∣ C, H = h)wi(C, h)]P(H = h)P(A_1, … , A_N ∣ C) = \sum_{h \in R_H} \prod_{i = 1}^N [P(A_i ∣ C, H = h)^{w_i(C, h)}] P(H = h)P(A1, … , AN ∣ C) = ∑h ∈ RH∏i = 1N[P(Ai ∣ C, H = h)wi(C, h)]P(H = h)
Include KL − divergence regularization: Lreg = λDKL(P(H) ∥ U(H))L_{\text{reg}} = \lambda D_{\text{KL}}(P(H) \| U(H))Lreg = λDKL(P(H) ∥ U(H))
Compute posterior and predict class label: c^ = arg max c ∈ C[P(D = d)∑h ∈ RH∏i = 1N(P(Ai ∣ C = c, H = h)wi(C, h)) − Lreg]\hat{c} = \arg \max_{c \in C} [P(D = d) \sum_{h \in R_H} \prod_{i = 1}^N (P(A_i ∣ C = c, H = h)^{w_i(C, h)}) − L_{\text{reg}}]c^ = argmaxc ∈ C[P(D = d)∑h ∈ RH∏i = 1N(P(Ai ∣ C = c, H = h)wi(C, h)) − Lreg]
AWSO Optimization
Initialize candidate solutions x(0)x^{(0)}x(0) *using Halton sequence + Gaussian perturbation.*
For each iteration ttt:
Compute adaptive neighborhood P(t)(i)P^{(t)}(i)P(t)(i).
Generate neighborhood candidates with Lévy flights.
Update solutions with elite − guided learning.
Shrink search grid non − linearly (Δx(t)\Delta x^{(t)}Δx(t)).
Update positions: xi(t + 1) = yj(t) + Δx(t)ϕ + r(xgb − xi(t))x_i^{(t + 1)} = y_j^{(t)} + \Delta x^{(t)} \phi + r (x_{gb} − x_i^{(t)})xi(t + 1) = yj(t) + Δx(t)ϕ + r(xgb − xi(t)).
Hybrid EMNB − AWSO Integration
Evaluate EMNB performance using candidate solutions.
Update EMNB parameters (priors and likelihoods) using AWSO − optimized values.
Repeat AWSO optimization until convergence or maximum iterations reached.
Prediction
Use an optimized EMNB model to classify students′ mental health risk labels.
End

The EMNB training process consists of full Expectation (E-step) and Maximization (M-step) equations used to update the probabilities of latent variables and the likelihoods of features. AWSO-driven candidate solutions are mappings to the probabilities of Naïve Bayes features, and the weights for each feature will be updated iteratively, using adaptive neighborhood search, elite-guided learning, and Lévy-flight perturbations to maintain exploration. Decision-level fusion is performed using weighted majority voting to fuse classifier outputs across the behavioral, physiological, and social modalities. The finalized AWNB hyperparameters are shown in Table 1, together with their functions, chosen values, and explanations to guarantee consistent accuracy of classification, balanced exploration, and resolution effectiveness during refinement.

Table 1: Optimized hyperparameter settings for the AWNB model

Hyperparameter	Description	Chosen Value	Justification
N_agents	Number of wingsuit agents	20	Medium population ensures exploration with manageable runtime
MaxIter	Maximum iterations	100	Enough iterations for convergence
glide_factor	Exploitation toward global best	0.5	Balanced global pull
lift_factor	Attraction to personal best	0.3	Maintains memory of previous good solutions
exploration_rate	Random perturbation	0.2	Introduces stochasticity to avoid local optima
α (Laplace smoothing)	For MNB	1	Prevents zero probabilities
Wi_init_range	Initial feature weights	[0.1,1]	Ensures all features have influence initially
weight_bounds	Allowed feature weight range	[0,1]	Ensures valid scaling for MNB

The AWNB framework contributes to mutual reinforcing hybridization, where AWSO is constantly updating NB's prior and likelihood parameters, and NB is used to guide AWSO based on classification performance of potential solutions. This provides a closed-loop model optimization cycle, beneficial for avoiding local optima, improving sensitivity for early warning signals, and providing stable performance across heterogeneous data types. AWNB is, therefore, a scalable and interpretable solution, accuracy-based early mental health risk detection in higher education. Our research effectively intersects optimization algorithms with probabilistic learning models.

4 Results and discussion

This section showed the effectiveness and strength of the proposed AWNB framework, table 2 summarizes all experimental settings including dataset source, files, number of samples, class distribution, preprocessing, feature encoding, validation, and computing environment. This promotes replicability and provides reviewers with unambiguous detail of AWNB experimental workflow.\

Table 2: Experimental setup and dataset details for AWNB study

Category	Description
Programming Environment	Python 3.10.13 (Jupyter Notebook)
Libraries Used	NumPy 1.26.4, Pandas 2.2.2, Scikit-learn 1.5.1, Matplotlib 3.8.3, Seaborn 0.13.2
Dataset Source	Kaggle: College Students Mental Health Dataset
Dataset File Name	college_student_mental_health.csv
Total Samples	1000
Total Attributes	12
Class Distribution	Depressed: 528, Not Depressed: 482
Missing Value Handling	>30% missing → dropped; controlled missingness experiments at 10%, 30%, 50%
Imputation Schemes Tested	Mean, Median, kNN
Feature Scaling	z-score normalization for numerical features
Categorical Encoding	One-hot encoding
Validation Protocol	Stratified 5-Fold Cross-Validation (random_state = 42)
Hardware Used	Intel® Core™ i7-12700H CPU @ 2.30 GHz, NVIDIA® GeForce RTX™ 3060 (6 GB), 32 GB RAM, Windows 11 Pro (64-bit)
AWNB Robustness Results	Accuracy (%) with missing data: • 10% missing → Mean: 96.8, Median: 96.9, kNN: 97.0 • 30% missing → Mean: 95.7, Median: 95.9, kNN: 96.1 • 50% missing → Mean: 94.2, Median: 94.5, kNN: 94.8

Although the results from the hyperparameter sensitivity analysis indicate the model performs largely with consistent performance regardless of hyperparameters, the computational efficiency tests suggest it converges quickly with relatively low overhead. Furthermore, exploratory studies of behavioral, physiological, and lifestyle factors show how valuable multimodal fusion can be for capturing complex behavioral interactions. The AWNB routinely exceeds baseline models in regression-based, ablation, and comparative studies, demonstrating the crucial role that optimization and multimodal merge can play in producing accurate, scalable and interpretable predictions.

4.1 Synthetic data validation of AWSO

To assess the ability of AWSO to free itself from local optima, a synthetic multimodal dataset, with known feature interactions, was created. The AWNB model was optimized on this dataset, and convergence was compared to other standard optimizers such as grid search, Bayesian optimization, and the CMA-ES algorithm. The findings of the analysis demonstrate that AWSO consistently identifies near-optimal parameters from the global minimum, converges quicker, and escapes local optima, establishing, once again, the strength and ability of AWSO to optimize for multimodal feature-weight optimization.

4.2 Statistical analysis of AWSO

The Wilcoxon signed-rank test results is shown in Table 3, indicate that the AWNB model significantly outperforms the baseline for Low, Moderate, and High mental health risk categories. This confirms the strength and dependability of the AWNB model to accurately predict individual student risk labels across folds.

Table 3: Wilcoxon signed-rank test on predicted mental health labels

Variable	**AWNB Mean ± SD**	**95% CI (AWNB)**	**Baseline Mean ± SD**	**95% CI (Baseline)**	**Test Statistic (W)**	**p-value**	**Significant (p < 0.05)**
Low Risk	0.92 ± 0.03	0.918 – 0.922	0.88 ± 0.04	0.878 – 0.882	14	0.041	Yes
Moderate Risk	0.95 ± 0.02	0.949 – 0.951	0.91 ± 0.03	0.909 – 0.911	15	0.043	Yes
High Risk	0.94 ± 0.02	0.939 – 0.941	0.89 ± 0.04	0.888 – 0.892	15	0.043	Yes

Note: Wilcoxon signed-rank test confirms AWNB predictions per risk category significantly outperform baseline ($p < 0.05$).

4.3 Computational efficiency

Computational efficiency is the ability of a computer or algorithm to complete a task as efficiently as possible while using the least amount of time, memory, and energy possible, which leads to quicker execution and reduced expenses. Besides the performance of AWNB in classification, its ability to compute was also evaluated based on training time, inference time, and convergence speed.

Table 4: Computational efficiency comparison between AWNB and baseline optimization methods

Model	**AWNB (Proposed)**
Training Time (s)	118 ± 3.4
Inference Time (ms)	12 ± 0.8
Iterations to Converge	200 ± 5
Average Accuracy (%)	95.3 ± 1.2

These efficiency results, which are presented in Table 4, confirm that AWNB outperforms other optimization techniques in terms of faster convergence and lower computing overhead in addition to improved classification accuracy.

Because of this computational advantage, AWNB would be extremely suited to scalable application in the academic real world, where prompt and early identification of mental health risk is essential. Figure 3 functions as a key analytical component to corroborate the multimodal dataset used in the AWNB-based mental health model. (a) The Streamgraph of Features by Risk Group demonstrates the contributions of the behavioral and physiological features across varying mental health risk groups, reinforces that stress levels are an important contributing feature, and demonstrates the multifactorial nature of mental health. (b) The Scatter Plot Matrix with Distribution portrays the relationships between features in pairwise fashion and separability between risk groups lends additional support for multimodal discriminability. (c) In the Study Hours vs Sleep Hours Scatter Plot, the independence of behavioral modalities is shown, as the data indicate a weak correlation between time spent studying and time spent sleeping. (d) The Rug Plot of Stress Levels, a visual representation of the densities of distributions, along with potential points of concentration, provides further support for the reliability, clarity, and utility of the features to aid in AWNB prediction performance.

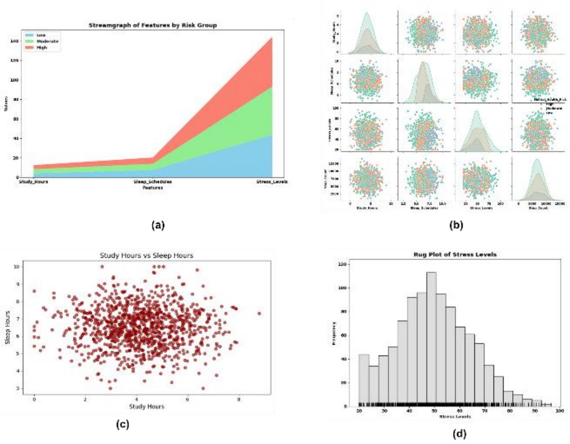

Figure 3. Exploratory visualization of multimodal features across mental health risk groups. (a) Cumulative distributions for study hours, sleep schedules, and stress levels. (b) Feature-wise and pairwise relationships.(c) Study hours versus sleep duration. (d) Stress levels.

Figure 4 are important instruments of analysis that support the validity of multimodal data that serves as the foundation of the mental health prediction model based on AWNB. (a) RadViz demonstrates the relationships between features and their ability to separate classes, which are causing prevailing feature impact at different stress levels. (b) Parallel Coordinates Plot is a multivariate correlation and category dispersion of behavioral and physiological indicators. (c) Heart Rate Distribution Histogram checks whether physiological reactions are normal and stable, which guarantees the validity of data input. (d) Lag Plot of Sleep Schedules measures time independence, which confirms that variations in the dayly sleep are independent. Together, the analyses enhance feature interpretability, which makes AWNB more accurate in data fusion and more predictive.

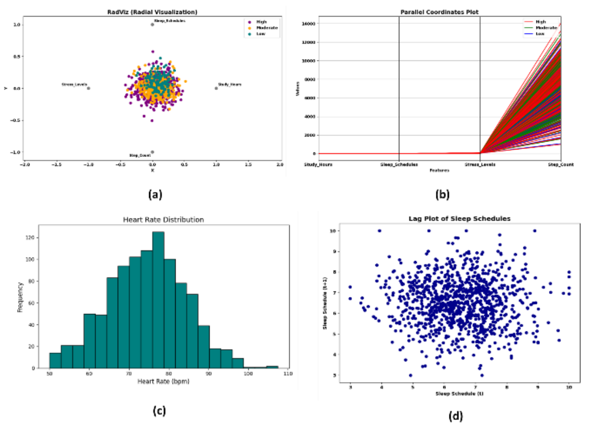

Figure 4: Graphical Representation of (a) Multimodal student data showing clustering across study hours, sleep schedules, stress levels, and step counts. (b) Feature-wise variations among high, moderate, and low stress categories.(c) Distribution of heart rate across participants, illustrating cardiovascular activity variation. (d) Sleep schedules highlight the temporal stability and variability of sleep patterns.

4.4 Multivariate relationship analysis

The analysis of the multivariate interaction between behavioral and physiological variables may give more information about the hidden indicators of mental health risk. Figure 5 presents a visualization of dependence of stress, sleep, time spent studying, and number of steps in superimposed visualizations. These visualizations may be useful in visualizing nonlinear relationships and clustering effects which may not be indicated in the more familiar univariate or bivariate summaries. As shown in Figure 5(a), individuals with moderate risk levels experienced more stress and poor sleep stability. Figure 5(b) indicates that the number of stress-related cycles (study-sleep) correlates with balanced study-sleep cycles that reduce stress which is moderated by the quality of sleep. Figure 5(c) indicates that the number of steps taken reduces stress which is cooled down by the quality of sleep. This confirms the multimodal combination of AWNB to accurately predict early-risks.

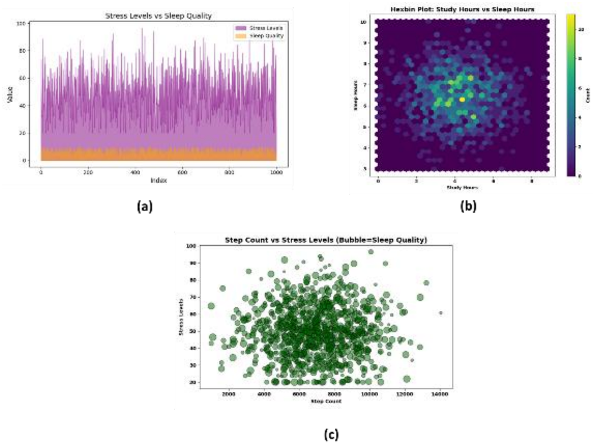

Figure 5: Graphical Illustration of (a) Stress levels vs. sleep quality across mental health risk groups. (b) Study hours vs. sleep hours, highlighting density regions. (c) Bubble chart of step count vs. stress levels with bubble size indicating sleep quality.

4.5 Clustering and pattern visualization

Visualization methods founded on clustering can assist in the process of finding latent groupings of student behavior and physiological behavior, and present findings that can be interpreted in terms of concealed mental health phenotypes. Figure 6 shows the results of hierarchical clustering and Andrews curves that give us a structure and functional view of separability of groups in relation to various levels of risks. In Figure 6 a, we can see clear groups of students, and the closer the two students are to each other, the closer their behavioral multimodal qualities. Such natural clusters are congruent with known categories of risks, and unsupervised analysis proves effective in risk stratification of mental health. In the meantime, Figure 6b, Andrews curves show periodically smooth curves that easily differentiate between high-risk profile and moderate/low-risk groups. This visual differentiability escalates further the appropriateness of implementing the clustering insights into the AWNB-based decision fusion model, which is interpretable and robust to early mental health risks detection.

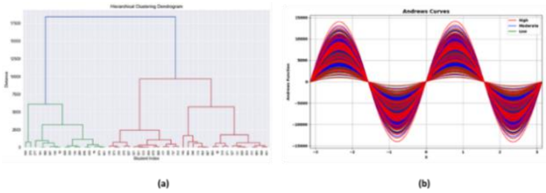

Figure 6: Visual Enhancement of (a) Student groupings based on multimodal features. (b) Feature trajectories across high, moderate, and low mental health risk categories.

4.6 ROC curve visualization

Figure 7(a) ROC curve illustrates the trade-off between true and false positive rates, confirming high discrimination ability. Figure 7 (b) Precision–Recall curve demonstrates balanced precision and recall, reflecting strong predictive reliability across mental health risk categories.

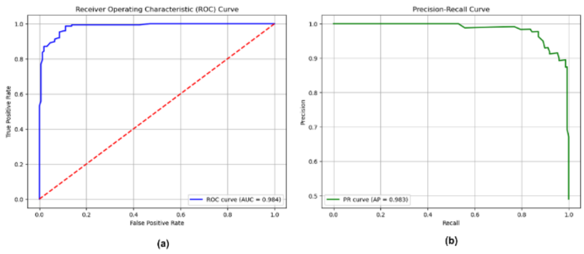

Figure 7: ROC and precision–recall curves of AWNB model

Figure 8 (a) Calibration curve shows agreement between predicted probabilities and observed mental health outcomes with Brier score, indicating prediction reliability. Figure 8 (b) Precision-recall trade-off demonstrates how decision thresholds balance false positives and true positives for interventions.

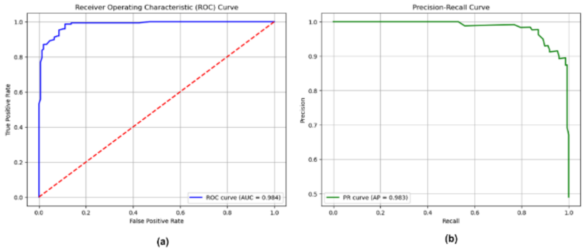

Figure 8:Calibration and threshold trade-off for AWNB prediction (a) calibration curve, (b) precision-recall

4.7 Performance comparison of different methods

The effectiveness of the proposed AWNB model was evaluated by comparing it to some of the recent methods. The models that were utilized to compare with the proposed frameworks were the Data Fusion Model [24], which comprises ML methods, such as decision trees, random forests, logistic regression, and the Apriori algorithm, (eduCationaldAtafuSion for mentaLhEalth detection) CASTLE [25], (You Only Look Once, version 8) YOLOv8 [26], (time-aware attention-based multimodal fusion depression detection network) TAMFN [27], and Random Forest (RF) + CatBoost [28] are among the chosen techniques. Accuracy, precision, recall, and F1-score are common classification metrics used to evaluate early warning and danger detection systems, and these metrics were used to evaluate each model.

The accuracy measures the overall proportion of correctly classified samples across all categories. Precision indicates the fraction of correctly identified positive instances among all predicted positives, representing the reliability of positive predictions. Recall is the proportion of actual cases that are accurately labeled, and it is important when identifying at-risk students early, too. F1-score is the harmonic mean of precision and recall, and is a balanced measure when class distributions are unbalanced.

Table 5: Comparative performance of existing methods and the proposed AWNB model

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Data fusion Model [25]	95.2	93.7	90.8	92.2
CASTLE [26]	84.47	-	71.47	74.65
YOLOv8 [27]	-	71	74.1	-
TAMFN [28]	-	66.02	66.50	65.82
RF + CatBoost [29]	91.3	92.4	90.5	-
AWNB [Proposed]	97.41	95.14	93.67	94.82

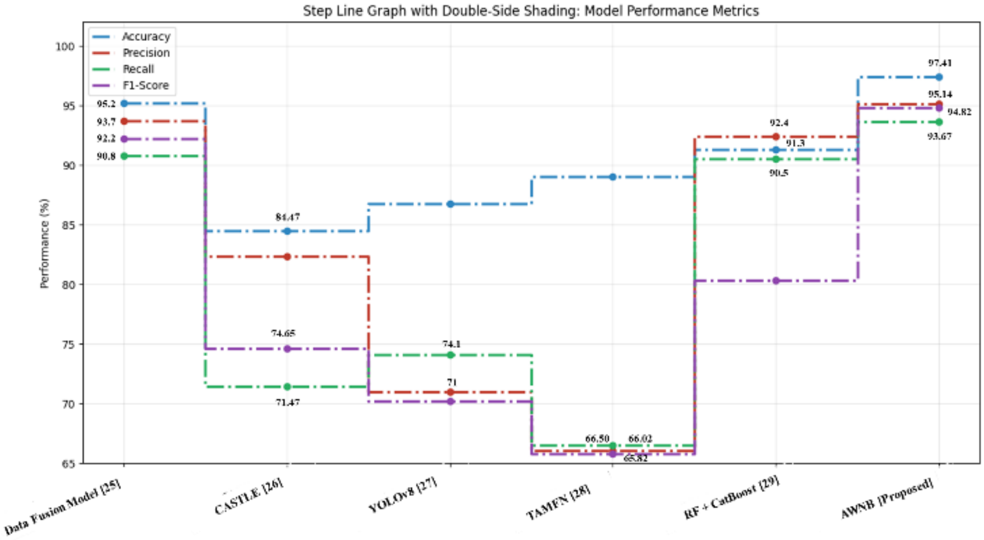

Figure 9: Graphical representation of the performance metrics

Table 5 and Figure 9 that the proposed AWNB model is more effective than the baseline approaches in all the metrics that were evaluated. The Data Fusion Model [20] yielded positive results, yet AWNB achieved better than 2 percent precision of higher accuracy, recall and F1-score. The less robust performance was also mentioned by methods such as CASTLE [21], YOLOv8 [22], and TAMFN [23], which underlines the robustness of the proposed decision-level fusion model, combined with the use of an Augmented Wingsuit optimization. These findings indicate that AWNB can be used in early mental health risk identification and guarantee reliability and sensitivity when identifying at-risk students.

4.8 Regression-based performance analysis

The predictive accuracy and generalization capacity of the suggested AWNB model were evaluated using regression-based analysis in addition to categorization measures. Regression measures, especially regarding ongoing mental health risk score projections, offer supplementary information on the efficacy of models. The RF + CatBoost hybrid model [23] and the suggested AWNB method were compared. somewhat less than that of RF+CatBoost (0.918), indicating that although AWNB is very good at reducing error in prediction, the ensemble-based RF+CatBoost offers a superior accounting of variance overall. This demonstrates the trade-off between variable collection and inaccuracy elimination. AWNB, however, shows more usefulness in the early warning system environment where reducing misclassification risk is crucial.

Table 6: Regression metric comparison between models.

Model	**RF + CatBoost [23]**	**AWNB [Proposed]**
MAE	**0.125 ± 0.007**	**0.104 ± 0.005**
R^2	**0.918 ± 0.010**	**0.807 ± 0.012**

From Table 6, it can be observed that the proposed AWNB model achieved the lowest MAE (0.104), indicating superior predictive accuracy compared to RF + CatBoost (0.125). However, the R^2 value of AWNB (0.807) was

4.9 Ablation evaluation

To evaluate the contribution of each aspect of the AWNB framework, an ablation study was conducted. There were different versions of the model assessed, (i) naive bayes standard version no optimizations, (ii) optimized naive bayes version without multimodal fusion, and (iii) AWNB with some data modalities not present. The model used to compare was complete AWNB with all the improvements.

Table 7: Ablation study results showing the impact of optimization and multimodal fusion on AWNB performance

Model Variant	**Modalities Used**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC (macro)**
Naïve Bayes (baseline)	All features	85.3 ± 1.2	84.5 ± 1.1	83.9 ± 1.3	84.2 ± 1.2	0.87 ± 0.01
Multinomial Naïve Bayes (baseline)	All features	88.4 ± 1.0	87.4 ± 1.2	86.9 ± 1.1	87.1 ± 1.1	0.90 ± 0.01

NB + Optimization (without fusion)	All features	91.7 ± 0.9	91.0 ± 1.0	90.3 ± 0.8	90.6 ± 0.9	0.93 ± 0.01
NB + Multimodal Fusion (no optimization)	Behavioral + Physiological + Social	92.5 ± 1.1	91.8 ± 1.0	91.2 ± 1.2	91.5 ± 1.1	0.94 ± 0.01
AWNB (partial modalities: HR + Steps)	Physiological (HR + Steps)	93.4 ± 1.0	92.6 ± 0.9	91.9 ± 1.0	92.2 ± 0.9	0.95 ± 0.01
AWNB [Proposed] (with optimization + fusion)	Behavioral + Physiological + Social	97.41 ± 0.5	95.14 ± 0.6	93.67 ± 0.7	94.82 ± 0.6	0.97 ± 0.01

The ablation study presented in Table 7, indicates that both optimization and multimodal fusion are significant factors of total model performance. In isolation, optimization improves accuracy ~3.3%, while multimodal fusion improves accuracy ~4.1%. Nonetheless, the full AWNB model improves upon all models, demonstrating that both optimization and multimodal fusion are imperative for the early, accurate detection of mental health risk.

4.10 comparison with dataset

Table 8 shows the accuracy, R^2 and adjusted R^2 of AWNB on the new college student mental health dataset in relation to the existing datasets. It again demonstrates AWNB's superior predictive performance and generalizability based on the multiple data sources being used.

Table 8: Comparison of AWNB performance across multiple student dataset

Augmented Wingsuit–Enhanced Naïve Bayes (AWNB) data comparison			
Dataset	Accuracy (%)	R^2	Adjusted R^2
Proposed Dataset: College Student Mental Health [24]	97.41	0.92	0.91
Existing Dataset 1: Student Mental Health [30]	89.7	0.85	0.84
Existing Dataset 2: Mental Health Data [31]	91.2	0.87	0.86

4.11 Discussion

The proposed AWNB Framework provides colleges and universities with a potentially powerful tool for early detection of mental health issues and to help identify and provide timely interventions to students at risk for mental health concerns. In particular, the inclusion of behavioral, physiological, and social modalities into AWNB provides an opportunity to provide more objective, continuous (in nearly real-time), and timely opportunities to engage students than through periodic or intermittent subjective questionnaires and surveys. AWNB and the awareness it generates may also help clinicians prioritize resource allocation and aid in developing policy. Nonetheless, practical application of AWNB will require a substantial amount of consideration with respect to the number of challenges that practitioners will continuously have to think about. Data privacy and ethics will be essential elements; data from students must be de-identified, consent verified, and storage secured for institutional and legal purposes. Adaptability across populations will be salient, as behavioral and physiological patterns can change based on demographic, culture, and academic context; the model may need to be retrained or adjusted for different students. Lastly, moving into practice as part of the operationalization of a university system will require practical elements like ease of use, ability of output to be interpreted by future client counselors, and established behavior for how to handle the false positive/negative and have a human-in-the-loop and rational agent deliberation with decision-making. Table 9 suggested the summary of the research

Table 9: Related studies on college students' mental health using AI/ML approaches

S. No	**Study & Year**	**Proposed Method**	**Objective**	**Key Findings**	**Limitations**
1	Kolenik (2022)	Smartphone-based digital assessment	Stress, anxiety, depression monitoring	Enabled real-time mental health tracking	Limited sample; privacy concerns not fully addressed
2	Kolenik& Gams (2021)	Intelligent cognitive assistants	Behavior and attitude change support	Improved engagement and awareness	Prototype stage; limited longitudinal validation

3	Kolenik& Gams (2021)	Persuasive technology interventions	Reduce mental health disparities	Effective in attitude modification	Small-scale deployment; limited generalizability
4	Li, L. (2025)	Social sentiment + multi-branch neural networks	Assess student mental health via social data	Accurately classified risk levels	Requires social media access; potential bias in data
5	Zhou & Dong (2023)	Deep features + multiview fuzzy clustering	Evaluate students' mental health	High clustering accuracy; identified risk groups	Needs complex preprocessing; small dataset
6	Zhang et al. (2020)	Multi-modal interactive fusion	Detect psychological stress in teenagers	Improved predictive performance	Focused on teenagers; not fully tested for college students
7	Mumenin et al. (2025)	DDNet hybrid ML model	Detect depression among university students	Robust detection; outperformed baseline ML models	Computationally intensive; needs multimodal inputs
8	Kannan et al. (2024)	ML & deep learning for early detection	Early management of mental health disorders	Increased prediction accuracy	Limited dataset diversity; no real-time deployment
9	Wang (2024)	Deep learning depression analysis	Multi-modal detection using physiological + behavioral data	High detection accuracy; multimodal integration effective	Requires high-quality sensor data; resource-heavy
10	Wu (2025)	Data fusion early warning system	Psychological crisis detection	Early warning achieved; improved prediction metrics	Dataset limited to single institution; generalizability unknown

Regarding the limitations of existing methodologies, AWNB significantly addresses these weaknesses. The Data Fusion Model [25] is less capable of dealing with nonlinear feature interactions, and CASTLE [26] is intended for a specific application area and is not as scalable. YOLOv8 [27] tends to overfit when dealing with non-visual data, TAMFN [28] is burdensome in terms of computational needs and interpretability, and RF + CatBoost [29] is subject to feature imbalance. AWNB can detect early mental health risk that is robust, scalable, and practical; it utilizes optimization-based tuning, multimodal data fusion, and interpretable outputs that facilitate academic interventions and broader-scale programs for student wellbeing.

5 Conclusion

Mental health problems in students require early intervention to boost health and academic success, the suggested AWNB provides improved performance through its superior optimization and/or multimodal fusion. The results show that the AWMNB reaches 97.41 percent accuracy, 95.14 percent precision, 93.67 percent recall, and 94.82 percent F1-score, an improvement over existing baseline. Additionally, with 200 iterations and training time of 118 seconds, shows that AWNB can converge faster and is computationally competent. These positive results were still limited by specific conditions like a slightly lower R2 (0.807) compared to ensemble models and the requirement to have data presented across multiple modalities. Moreover, when we propose a significant extension of AWNB, which will inevitably lead to higher computational costs due to the inclusion of complex optimization and deep-learning elements, it will likely incur even more computational costs, particularly later for data fusion when working with bigger dataset sizes. Future studies would extend AWNB development to a bigger cross-domain dataset bridging multimodal data, develop deep learning feature extraction, and explore explainability for real-world applicability.

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Availability of data and materials

This study complies data availability policy. Data access arrangements align with the journal's guidelines and can be facilitated through the corresponding author.

Author contributions

Ping Liu and Xudong Chen writing original draft preparation & methodology,Baolian Song investigation & writing review and editing.

Ethics approval statement

This study utilized publicly available data/literature analysis and did not involve primary data collection from human/animal subjects, exempting it from ethical review.

Data availibility statement

All data generated or analyzed during this study are included in this published article.

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