2OAMN: A Deep Learning Framework for Personalized Psychological Interventions Using Multimodal Student Data

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Background: Student mental health has become a global concern due to increasing academic stress, anxiety, and depression, which negatively impact learning outcomes, emotional well-being, and social interactions. Traditional assessment methods, such as static questionnaires and periodic counseling, fail to capture the dynamic nature of psychological health. Objective: This research aims to develop an intelligent deep learning (DL) framework using neural networks to predict early mental health risks and generate personalized psychological intervention strategies based on students' evolving emotional states. Methods: The Student Mental Health and Intervention Dataset, comprising 1,000 student records collected through self-reported surveys, physiological indicators were utilized. Data preprocessing involved normalization, sentiment classification using BERT-based text embeddings, and feature extraction with Convolutional Neural Network (CNN) layers. The integrated features were input into the Octopus Optimization with Attention-Based Memory Network (2OAMN). The Bi-LSTM captures both past and future dependencies in mental health data, enhancing prediction accuracy. The attention mechanism prioritizes the most relevant emotional and behavioral signals, ensuring timely interventions. OOA optimizes model parameters by balancing exploration and exploitation, improving adaptability and predictive accuracy. The framework was implemented in Python using DL libraries to predict mental health risks and generate adaptive intervention recommendations. Results: Experimental evaluation shows that 2OAMN achieves 97.86% accuracy, 98.81% precision, 97.64% recall, and 98.22% F1-score. 2OAMN regression performance includes an RMSE of 5.92, MAE of 4.11, and R^2 of 0.74. Conclusion: The 2OAMN reliably predicts student mental health risks and generates effective personalized interventions, offering a practical and data-driven solution for improving student psychological well-being.

Povzetek: Raziskava predstavlja model globokega učenja 2OAMN za zgodnje napovedovanje tveganj duševnega zdravja študentov in oblikovanje prilagojenih intervencij, pri čemer je model dosegel zelo visoko napovedno natančnost ter pokazal potencial za izboljšanje psihološkega blagostanja študentov.

Article highlights:

- 2OAMN predicts student mental health risks with high accuracy and reliability.
- Multimodal data integration enables personalized psychological interventions.
- Attention and Bi-LSTM capture key emotional signals for adaptive recommendations

1 Introduction

Psychological well-being is a key factor influencing health, productivity, and quality of life. Traditional therapies use generalized treatment modalities, which, although functional, often overlook individual circumstances like feelings, personality, and habits, leading to varied treatment results [1]. This highlights the need for more personalized and individualized intervention plans [2]. Psychological aspects vary depending on personality traits, life experiences, culture, and environmental pressures [3]. Tailored interventions, aligned with these individual profiles, improve relevance, interest, and efficacy [4]. Personalization increases treatment adherence, reduces dropout rates, and improves long-term mental health outcomes [5]. Recent advancements in data analytics, artificial intelligence (AI), and digital health technologies have enabled the study of psychological data through assessment measures, self-reports, behavioral history, and multimodal indicators [6]. These technologies help identify stress responses and emotional patterns, allowing for the creation of personalized intervention plans [7]. Intelligent systems can dynamically adjust recommendations based on continuous feedback to provide timely psychological support [8]. The goal of personalized psychological intervention solutions is to develop evidence-based support systems that meet individual mental health needs [9]. By integrating psychological access with computational intelligence, interventions can be scaled and precisely tailored [10]. These individualized strategies empower clinicians and enhance the efficiency and inclusivity of mental health systems. Figure 1 shows an AI-powered workflow for personalized psychological interventions in educational institutions, ensuring timely assistance and improved mental health outcomes.

Figure 1: Framework for generating personalized psychological intervention strategies using AI systems

ML methods like SVM, DT, RF, and KNN predict mental health and generate interventions using questionnaire and behavioral data. DL techniques like CNN, RNN, LSTM, and Autoencoders address emotional patterns but face challenges such as data density, reliance on labeled data, and limited interpretability.

1.1 Purpose and contribution of the research

The research aims to develop an intelligent deep learning framework that can predict early mental health risks and generate personalized psychological intervention strategies based on the dynamic emotional states of students. By integrating multimodal data, including emotional, physiological, and behavioral indicators, the research seeks to enhance the precision and adaptability of psychological interventions. The goal is to create a reliable, real-time system for supporting student mental health and well-being through adaptive and personalized recommendations. The research utilizes a multimodal dataset, including surveys, physiological signals, academic logs, and emotional journals. The 2OAMN method predicts mental health risks and provides personalized intervention strategies, enhancing student well-being.

1.2 Research questions

1. How can Bi-LSTM and attention mechanisms be integrated to improve the accuracy of predicting emotional and behavioral changes for personalized psychological interventions?
2. What impact does combine multimodal data (emotional, behavioral, physiological) have on enhancing personalized psychological intervention strategies?
3. How does optimizing deep learning models with algorithms like OOA improve the adaptability and real-time efficacy of personalized mental health support systems?

2 Related works

The dimensions of personalization of online psychological intervention among young adults were tested [11], showed a scarcity, making personalization content-based, provider-based, and segmented. The integrative evolutionary framework between the positive and clinical psychology processes was investigated [12]. Findings proved that principles of context-sensitive variability, selection and retention can be used to arrange individualized interventions. The individualized approaches to PPI activities to improve subjective well-being were explored [13]. Findings indicated that weakness-based and self-selected activities were better than random assignment. The intervention methods based on personality science as psychological targeting were compared [14]. Findings reveal a single framework that allows cross-disciplinary customized behavioral change and ethical interventions. CDS system cross-validated ML predictors of poor psychological well-being and standard of life among breast cancer survivors were formulated [15]. Findings provided an accuracy of 74-83% with explainable predictors. The BI problems and suggested customized psychological intervention of breast cancer survivors were discussed [16]. Personalized therapy of oncological history, feelings, and thoughts positively affects BI.

2.1 Effectiveness of psychological and behavioral interventions

Table 1 summarizes empirical evidence on psychological and behavioral interventions.

Table 1: Effectiveness of psychological and behavioral intervention approaches across populations

Reference No.	Aim	Intervention Type	Results	Key Outcomes	Advantages
[17]	Analyze meta-analytic evidence on the effectiveness of PPIs.	Positive Psychology Interventions	Small–medium improvements in well-being; reduced depression, anxiety, and stress.	Indices of mental health, well-being, and quality of life	Strong evidence synthesis; identifies effective intervention formats

[18]	Investigate interventions for problematic Internet and smartphone use.	Psychological and CBT-based interventions	Significant reduction in problematic digital use behaviors.	Digital addiction severity, usage frequency	Demonstrates effectiveness in digital addiction management
[19]	Evaluate AT, CR, GS, and ER interventions on collegiate athletes.	AT, CR, GS, ER strategies	Attention training yielded strongest and sustained performance gains.	Performance consistency, attention control	Identifies optimal interventions linking academic and athletic outcomes
[20]	Examine ego depletion effects on practical skills in students.	Cognitive–behavioral interventions	Ego depletion moderately impaired execution efficiency and stability.	Task efficiency, performance stability	Highlights cognitive–behavioral impact on skill execution

2.2 Context-specific and population-based psychological interventions and personalized predictive, and AI-driven psychological interventions

Table 2 presents Previous studies have focused on psychological intervention strategies, emotion prediction, and mental health assessment across different populations. Reported outcomes include reduced burnout, improved well-being, enhanced coping ability, and accurate emotion prediction using intervention-based or predictive frameworks. These studies highlight advantages such as scalable online implementation, practical relevance for mental health care, and proactive real-time psychological monitoring systems.

Table 2: Summary of related studies highlighting research aims, key results, and advantages in psychological intervention and prediction systems

Reference No.	Aim	Results	Advantages
[21]	Evaluate online group intervention for academic burnout.	Reduced burnout; improved well-being, achievement, coping, emotion regulation.	RCT-based evidence; scalable online implementation.
[22]	Develop emotion prediction, early warning, and personalized interventions for cancer patients.	Accurate prediction.	Integrates prediction.
[23]	Assess interventions for civil servants during health emergencies.	Psychological quality ↑ 8.56%; adjustment ability ↑ 8.47%.	High practical relevance for emergency mental health care.
[24]	Explore psychological adjustment in ovarian cancer treatments.	Combined therapy increased anxiety/depression; targeted therapy improved coping.	Treatment-specific psychological insights.
[25]	Examine public preferences for interventions.	Preferences varied by delivery, provider, and frequency.	Supports evidence-based policy design via discrete.
[26]	Examine psychological impact of acquired vision impairment.	Reduced participation; gradual psychological adaptation observed.	Rich qualitative understanding of lived experiences.
[27]	Improve student mental health assessment.	Real-time detection of anxiety.	Enables scalable, proactive.

2.3 Deep learning–driven prediction and assessment in psychological counseling

The deep learning-based counseling system to monitor and predict the mental health of college students through behavioral and questionnaire data was developed [28]. Findings indicated accuracy of 85.7, MSE of 0.041 and user satisfaction was great. Predicting couple therapy outcomes based on pre-treatment, psychological and relationship assessment with the help of deep neural networks was investigated [29]. Findings indicated that the method was better than conventional machine-learning models (R 2 = 0.71), revealing significant predictors such as satisfaction, communication, and attachment. The early depression prediction based on a hybrid deep learning algorithm of CNN and TS-LSTM with attention was examined [30]. Accuracy and good precision recall of results indicate 97.23.

The research explores the effectiveness of Chat-PPIs using retrieval-based and GPT-based chatbots in three trials with 326 participants [31]. It finds that personalized recommendations, adaptive dialogues, and real-time feedback significantly improve efficacy. Despite the less controllable nature of generative chatbots, they enhance natural interaction, boosting Chat-PPI effectiveness. The research explored the Multimodal Personalized Health Intervention Transformer (MPHI Trans), a model integrating multimodal data and temporal modeling to predict adolescent mental health [32]. Experimental results on DAIC-WOZ and WESAD datasets show MPHI Trans outperforms models, achieving high accuracy, recall, precision, F1 score, and AUC-ROC. The research presents a computational psychotherapy system using a conversational agent, trained on 1495 instances of stress, anxiety, and depression scores [33]. It outperforms state-of-the-art systems, achieving 91.41% accuracy, effectively reducing stress and anxiety, surpassing Woebot in intervention studies. The prevalence of stress, anxiety, and depression (SAD) is a global concern, particularly among youth in low- and middle-income countries [34]. SAD leads to poor quality of life, reduced productivity, and societal costs, emphasizing the need for technological interventions in mental health care. This study presents Conv-XGBoost, a hybrid model combining CNN and XGBoost for real-time stress detection [35]. The model achieved 98.87% training accuracy, demonstrating resilience to noise and variability in signals, showing the potential of hybrid models in stress detection. The integration of IoT technology in mental health offers personalized assessment and intervention [36]. With the rise of mental health issues and the COVID-19 pandemic, AI and devices like smart bracelets provide real-time, tailored support, though the field lacks a standardized framework. This review explores intelligent cognitive assistants (ICAs) in digital mental health, focusing on behavior change for SAD [37]. It analyzes ten papers, highlighting successful systems that use comprehensive user models, personalized interventions, and dialogue tree models, addressing gaps in technical analysis in the literature.

2.4 Key limitations in personalized psychological interventions

Meta-analytic studies and digital interventions display high heterogeneity, small numbers, short follow-ups, and limited generalizability [17, 18]. Performance interventions in athletes and ego-depletion studies show modest regression, gender-specific effects, or restricted sampling [19, 20]. Online interventions and emotion prediction systems face short follow-ups, sample-specific constraints, self-report bias, and single-center limitations [21, 22]. Interventions in civil servants, cancer patients, public preferences, and visually impaired individuals are limited by restricted samples, retrospective designs, convenience sampling, response bias, and small sample sizes [23–26]. AI- and ML-based student mental health assessments require high-quality multimodal data, raise privacy concerns, and depend on computational infrastructure [27]. Deep learning counseling and predictive methods are limited by small datasets, reliance on self-reported measures, text-based or predefined expert features, and challenges in generalization across populations [28–30]. To overcome these shortcomings, it exploits a multimodal deep learning feature.

The Table 3 compares various SOTA methods with the proposed 2OAMN model, highlighting differences in datasets, evaluation metrics, limitations, and advantages. While existing methods have strengths, are limited by factors like narrow focus or lack of real-time tracking. In contrast, 2OAMN offers scalable, real-time, and adaptive interventions, integrating multimodal data for more personalized and effective psychological support.

Table 3: Comparative summary of SOTA methods vs. proposed 2OAMN

Method	Dataset	Evaluation Metrics	Key Limitations	2OAMN Advantages
[25]	Emotional Self-Report Dataset	Accuracy, Engagement Rate	Limited contextual data for different cultures	Scalable, adaptive interventions tailored to individual needs
[27]	Multimodal Student Data	Anxiety, Stress, Depression Detection	Insufficient long-term tracking	Efficient emotional detection and personalized support for students
[28]	College Student Behavioral Data	Accuracy: 85.7%, MSE: 0.041	Limited to behavioral data	Integrates behavioral and questionnaire data for better prediction
[29]	Couple Therapy	$R^2 = 0.71$, Relationship	Narrow focus on	Deep neural networks

	Dataset	Satisfaction	couple dynamics	improve therapy predictions and outcomes
[30]	Depression Prediction Dataset	Accuracy: 97.23%, Precision-Recall	Limited real-time application	Hybrid CNN-TS-LSTM model improves depression prediction
2OAMN	Student Mental Health and Intervention Dataset	Accuracy: 97.86%, Precision: 98.81%, Recall: 97.64%, F1-Score: 98.22%	Limited multimillion node tests	Real-time, scalable, adaptive, energy-efficient personalized interventions

3 Methodology

The proposed 2OAMN predicts mental health risks and generates personalized interventions using the Student Mental Health and Intervention Dataset. It applies min-max normalization, BERT-based encoding, and CNN feature extraction, as shown in Figure 2. Intervention strategies are dynamically generated from real-time multimodal data, including emotional, physiological, and academic signals. Tailored interventions, using evidence-based techniques, are reviewed by experts, ensuring quality and safety with escalation for high-risk predictions. Effectiveness is evaluated through outcome-based analysis.

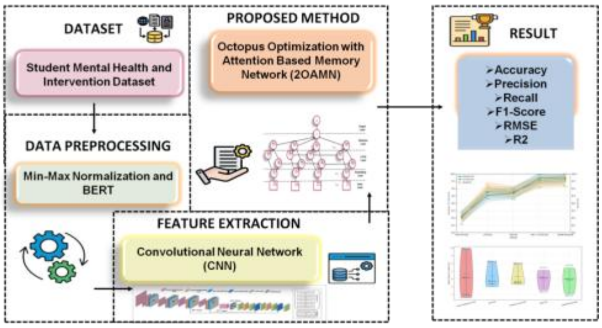

Figure 2: Overall flow of personalized psychological intervention system.

3.1 Data Pre-processing using Min-Max Normalization is used to scale features to a uniform range for method consistency

Min–Max normalization is chosen to rescale psychological and behavioral features into a range of 0 to 1, preserving differences and stabilizing training for deep learning models. This ensures consistent comparisons across features, improving convergence and aiding personalized psychological intervention strategies. The normalized value of every input element was expressed by using equation (1).

$$X_j^{'}=NeX_{min}+(NeX_{max}\ NeX_{min})\left(\frac{X_j\text{-}X_{min}}{X_{max}\text{-}X_{min}}\right)(1)$$

Where, X_{min},$X_{max}$to NeX_{min}-NeX_{max} statistics were proportionately modified. Where $X_j$depicts the actual input data and$X_j^{'}$ represents the normalized value. Table 4 shows the raw and normalized values for features.

Table 4: Min–Max normalization of student psychological features

Student ID	**Stress Score (X_j)**	**Min (X_min)**	**Max (X_max)**	**Normalized Score (X_j')**
1	25	20	80	0.083
2	40	20	80	0.333
3	60	20	80	0.667
4	80	20	80	1.000
5	20	20	80	0.000

3.1.1 BERT is used to convert text data into contextual semantic embeddings efficiently

BERT tokenizes psychological text, generates contextual embeddings, handles semantic nuances, and produces representations that model individual mental states and personalized interventions The pretrained BERT model used is a standard implementation based on the BERT-base architecture, fine-tuned with a maximum sequence length of 128 tokens. Sentiment classification is performed using fine-tuned BERT embeddings, where embeddings are combined over time using a mean pooling method.

3.2 Feature Extraction using CNN is used to identify relevant patterns from multimodal input data

The CNN operates on time-series, text embeddings, and tabular features. The input tensor for each modality is reshaped to ensure compatibility. For the text, the size is (batch_size, sequence_length, embedding_size); for physiological data, it's (batch_size, time_steps, num_features). CNN layers use a kernel size of 3x3 with 32 filters and a stride of 1.

CNN is a family of neural networks with biological inspiration that solves equation (2) by subjecting W to several simple non-linearities and convolutional filters. From the input signalw, each layer w_i the following is calculated in equation (2).

$$w_i=\rho X_i w_{i-1} \quad (2)$$

$\rho$is a non-linearity, while X_i is a linear operator. Usually, ρ is a rectifier w_{i-1} is a convolution in a CNN. The operator w_i is more easily conceptualized as a stack of convolutional filtering algorithms. The i-th layer output at position v for feature map l_i. Here, w_{i-1} is the previous layer's feature, W_{i,l_i} is the Convolutional kernel, * denotes convolution, $\sum_l \left(w_{i-1}(.,l)*W_{i,l_i}(.,l)(v)\right)$aggregates across input channels,Σ means sum over an index, (.) is the all rows, column l of matrix W_{i,l_i} and w_{i-1},and ρ is the activation function, combining features into the next layer representation. Thus, each layer may be expressed as a sum of the convolutions of the one before it, and the layers are filter maps in equation (3).

$$w_i(v,l_i)=\rho(\sum_l \left(w_{i-1}(.,l)*W_{i,l,l_i}(.,l)(v)\right) \quad (3)$$

The discrete convolution operator in this case is $\sum_{v=-\infty}^{\infty}$, which represents the discrete convolution of two sequences e and h. Here, $e(v)$ is the input signal, $h(w-v)$ is the kernel or filter shifted by w, and the summation aggregates contributions from all positions v. Convolution combines the signals to produce the output sequence$(e*h)(w)$ in equation (4).

$$(e*h)(w)=\sum_{v=-\infty}^{\infty} e(v)h(w-v) \quad (4)$$

A CNN defines an extremely non-convex optimization problem. Therefore, stochastic gradient descent is usually used to learn the weights X_i, with gradients being computed using the backpropagation process. Figure 3 displays the hierarchical patterns of the extracted psychological inputs.

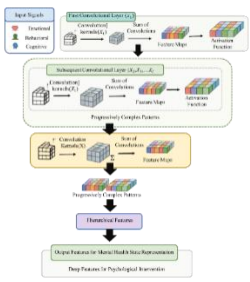

Figure 3: CNN architecture for psychological feature representation learning

3.3 OOA is used to optimize network parameters for improved predictive performance

OOA generates personalized psychological interventions by exploring individual mental health patterns, behavioral responses, and risk indicators. Inspired by octopus foraging intelligence, it balances exploration and exploitation to select optimal interventions, ensuring timely, adaptive support aligned with evolving emotional and cognitive states. OOA optimizes model parameters by simulating octopus foraging intelligence, balancing exploration and exploitation to find optimal intervention strategies. It efficiently navigates the solution space, ensuring robust and effective personalized psychological interventions. The method dynamically adapts to evolving emotional and cognitive states, offering more precise and tailored interventions. The 2OAMN method dynamically generates personalized intervention strategies based on real-time emotional and behavioral data. For high stress levels, the model suggests tailored interventions like relaxation techniques or cognitive behavioral therapy, ensuring adaptive and relevant support for each student's mental health needs. The AMN focuses on emotional and behavioral signals, using attention to prioritize relevant features, improving learning from past interventions. The "memory" component stores past interventions, enabling personalized recommendations. OOA optimizes hyperparameters like learning rate, batch size, and epochs, enhancing the search for optimal configurations with 100 iterations and a population size of 50.

In the Generating Personalized Psychological Intervention Strategies framework were each hunter is made up of trans eight tentacles (Hunters:Tgroup) and one head (Hunters:head), followed by (2×rand-1)×Id, the translation equation is defined as: trans=(2×rand-1)×Id, where rand is a uniform random number in [0,1], Id denotes the search-space boundary, and trans represents the movement step size. The following definitions apply to the mathematical representations of the predator's hunting behavior in equations (5) and (6).

$$Is=vr\times(1-\frac{s}{S}) \quad (5)$$

$$trans=(2\times rand-1)\times Id \quad (6)$$

$$LF(dim)=0.01\times \frac{v\times\sigma}{|u|^{1/\beta}} \quad (7)$$

When-vr to vr, and vr stands for the field of vision. After much testing, the parameters vr and ll were chosen to strike the best possible balance between exploration and exploitation. To ensure efficient exploration without overshootingvr is set to 3 in this research. The accuracy and convergence of the algorithm are significantly improved by using the combination of vr ¼ 3 and ll ¼ 0:8.When at least one octopus tentacle is within reach of the prey, the hunter must approach the tentacle and seize the prey. The tentacle that is closest to the prey is called $Hunters_j$. The Levy flight function is known as LF in equations (7) and (8).

Wherein, $LF(dim)$ shows dimensional Levy Flight measure. v shows velocity or movement parameter. σ (*sigma*) shows standard deviation or spread. u shows position or location variable. $|u|$ shows magnitude of position. β (*beta*) Shows control parameter for scaling. $1/\beta$ shows the inverse of the control parameter. 0.01 shows a scaling factor.

$$\sigma=\left(\frac{\Gamma(1+\beta)\times\sin\frac{\pi\beta}{2}}{\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times2^{\frac{\beta-1}{2}}}\right)^{1/\beta} \quad (8)$$

Where β is a constant with σ value of 1.5 and $\Gamma(1+\beta)\times\sin\frac{\pi\beta}{2}$ are $1\times$dimrandom normal distribution vectors where $\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times2\frac{\beta-1}{2}$ prey is beyond tentacles' reach in equation (9).

$$Hunters_j.Tgroup_i = Hunters_j.head + rand \times \left(Hunters_j.head - Hunters_j\,.Tgroup_i\right) \times LF(dim) (9)$$

Where the location of $Hunters_j$ greatest tentacle in each iteration is noted as $Hunters_j.head$. The head's location determines how the entire octopus moves. UB spots from hunters, LBrandom positions, and head represents the hunter's central position. The selected positions the scouts' positions in equation (10).

$$Scouts_y = Hunters_y.head + rand \times ld \times (UB + LB - 2 \times Hunters_y.Head) \ (10)$$

$Hunters_y.head$denotes the selected position, $y \in \{1,2,\dots,M_t\}$, and $Scouts_y$ denotes the location of yth scouts. $Scouts_y$ higher fitness value than $Hunters_y.head$.

ld shows a scaling factor or constant multiplier. UB shows the upper bound value. LB shows the lower bound value. The eight tentacles are based on new hunter's location, as in Equations (11) and (12), when $\mathrm{Scouts_y}$ is transformed into a hunter. ll shows a constant or additional parameter being added to the scout's position. Algorithm 1 shows the OOA.

$$\mathrm{Hunters_y.head} = \mathrm{Scouts_y} \quad (11)$$

$$\mathrm{Hunters_y.Tgroup_j} = \mathrm{rand} \times (\mathrm{Scouts_y} + \mathrm{ll}) - (\mathrm{Scouts_y} - \mathrm{ll}) \quad (12)$$

Algorithm 1: OOA

```
# Initialize Parameters
Initialize Hunters, Scouts, and
exploration parameters
# Main Loop
for each iteration:
  # Hunters' Behavior
  for each Hunter:
    If distance from prey < vr:
      # Use Levy Flight to explore around prey
      Hunters[j].Tgroup[i] = Hunters[j].Tgroup[i] + rand * (prey - Hunters[j].Tgroup_index) * LF(dim)
 else:
      # Move towards hunter's head
      Hunters[j].Tgroup[i] = Hunters[j].head + rand * (Hunters[j].head - Hunters[j].Tgroup[i]) * LF(dim)
  # Scouts' Behavior
  for each Scout:
    Scouts[y] = Hunters[y].head + rand * ld * (UB + LB - 2 * Hunters[y].head)
    If fitness(Scouts[y]) > fitness(Hunters[y].head):
      Hunters[y].head = Scouts[y]
  # Update Tentacles for new Hunter position
  for each Tentacle:
    Hunters[y].Tgroup[j] = rand * (Scouts[y] + ll) - (Scouts[y] - ll)
End For
```

3.4 Bi-LSTM used to capture sequential dependencies in temporal data effectively

Bi-LSTM captures both past and future dependencies in sequential data, improving the model's understanding of temporal patterns and emotional fluctuations. It enhances prediction accuracy for mental health states, with key hyperparameters like 1-3 LSTM layers, 128-512 hidden units, 0.2-0.5 dropout rate, and sequence length of 100-512 tokens.

LSTM-based recurrent neural networks are typically composed of four parts, where one input gate has the weight matrix X_{wj}, X_{gj}, X_{dj}, and a_j; one forget gate has the weight matrix X_{we}, X_{ge}, X_{de}, and a_j; and p_s output gate has the weight matrix X_{wp}, X_{gp}, X_{dp}, and a_p. These gates are all configured to generate a few degrees using the current input w_j, the state h_{s-1} that was contained in the previous step, and the present state of this cell d_{s-1} to determine whether to accept in equations (13) – (18).

$$j_s = \sigma\left(X_{wj}w_s + X_{gj}h_{s-1} + X_{dj}D_{s-1} + a_j\right) (13)$$

As j_s shows the output at step s. σ shows the sigmoid function. w_s shows the input at step s. X_{gj} shows the weight for previous hidden state. X_{gj} shows the previous hidden state. D_{s-1} shows the previous delayed state, and a_j shows the bias term. e_s shows the output at step s.

$$e_s = \sigma\left(X_{we}w_s + X_{ge}h_{s=1} + X_{de}D_{s-1} + a_j\right) (14)$$

$$h_s = \tanh\left(X_{wd}w_s + X_{gd}h_{s=1} + X_{dd}d_{s-1} + a_d\right) (15)$$

Wherein, h_s shows the hidden state at step s. tanh shows the hyperbolic tangent function. X_{dd} shows the weight for previous delayed state. a_d shows the bias term.

$$d_s = j_s h_s + e_s d_{s-1} \quad (16)$$

$$p_s = \sigma\left(X_{wp}w_s + X_{gp}h_{s-1} + X_{dp}D_s + a_p\right) (17)$$

$$h_s = p_s \tanh(d_s) \quad (18)$$

Wherein, d_s shows the delayed state at step s. h_s shows the hidden state at step s. d_{s-1} shows the previous delayed state, p_s shows the output at step s. D_s shows the delayed state at step s. a_p shows the bias term and h_s shows the hidden state at step s. p_s shows the output at step s. tanh shows the hyperbolic tangent function.

The secondary layers,h_j where the hidden-to-hidden connection has flow in the opposite temporal direction with bidirectional LSTM networks, $\overrightarrow{h_j} \oplus \overleftarrow{h_j}$ expand on unidirectional LSTM networks. The following equation displays the h_j result of the jth word in equation (19).

$$h_j = \left[\overrightarrow{h_j} \oplus \overleftarrow{h_j}\right] \quad (19)$$

3.5 Attention based BiLSTM used to focus on significant time-series signals for accuracy

The attention mechanism prioritizes key emotional and behavioral signals, allowing the model to focus on the most relevant features. This enhances adaptability, ensuring personalized interventions are more accurate and timelier. The AMN uses attention to learn from past interventions, with the "memory" component storing crucial emotional responses for future recommendations.

The method of paying attention is related to the classification problem. Let S be the sentence length, and let G be a matrix composed of the vectors that are produced. $[h_1,h_2,\ldots,h_S]$generated by the LSTM layer. These output vectors are weighted and added to generate the sentence's representationq in equations (20) – (22).

$$N=\tanh(H) \quad (20)$$

Wherein, N shows the output after applying the hyperbolic tangent (tanh) activation function to H. tanh shows the hyperbolic tangent activation function. H shows the input or hidden state to the tanh function.

$$\propto=\mathrm{softmax}(x^S N) \quad (21)$$

Wherein, ∝ shows the output after applying the softmax function to the product of x^S and *N*. softmax shows the softmax function, which converts values into probabilities.

$$q=H\propto^S \quad (22)$$

wherein, q shows the output obtained by multiplying H and $\propto^S$, $H \in Q^{c\,x\times S}$, c^x, where x is a training parameter vector, x^S is a transposition, and c^x is the phrase vectors' dimensions. The dimensions ofχ,α, and q,and $c^x$are independently. The last representations of hsentence pairs were tanh(q)categorization in equation (23). Figure 4 captures temporal dependencies using attention-enhanced bidirectional learning.

$$h^* =\tanh(h) \quad (23)$$

Wherein, h^* shows the output after applying the hyperbolic tangent (tanh) activation function to h. tanh shows the hyperbolic tangent activation function. h shows the input to the tanh function.

Memory-based attention in AMN enhances personalized psychological intervention strategies by focusing on key past interventions and emotional triggers, allowing the model to prioritize relevant data. This mechanism improves efficiency, reduces unnecessary computations, and enables timely, adaptive, and targeted psychological support aligned with individual mental health needs.

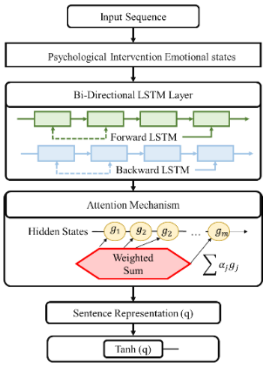

Figure 4: Attention-based Bi-LSTM method for personalized psychological intervention prediction

3.6 2OAMN used to integrate attention and optimization for personalized intervention predictions.

The 2OAMN model processes multimodal data using Bi-LSTM, attention, and OOA, capturing temporal dependencies and prioritizing emotional signals. This integration allows for faster convergence, accurate predictions, and optimized interventions. It personalizes strategies, adapting to individual mental health needs and ensuring timely, tailored support, enhancing overall effectiveness. Algorithm 2 shows the procedure of 2OAMN method.

Algorithm 2: 2OAMN

 # Step 1: *Initialize Parameters*
Initialize Bi-LSTM, Attention Mechanism, and OOA parameters
 # Step 2: *Bi-LSTM - Capture Temporal Dependencies*
For each time step t:
    Perform forward and backward passes
*t*hrough *Bi-LSTM*
    Combine forward and backward outputs: h_*j* = [h_*j*^*f* ⊕ h_*j*^*b*]
End For
 # Step 3: *Attention Mechanism - Focus on Significant Features*
For each sequence:
    Compute attention weights α using softmax
    Calculate weighted attention output q: *q = H * α^S*
End For
 # Step 4: 2*OAMN - Octopus Optimization Algorit*hm
For each iteration:
    For each Hunter:
        If distance from prey < vr:
            Update Hunter's position using Levy Flight
        Else:
            Update using Hunter's head *position*
        End If
Update tentacle positions based on
closest prey

End For
For each Scout:
Calculate Scout's position
If Scout has higher fitness than Hunter's head:
Update Hunter's head position
End If
End For
 # Update tentacles based on new hunter position
End For
 # Step 5: *Combine Bi-LSTM*, *Attention*, *and OOA Outputs*
Generate personalized intervention strategies based on outputs
Step 6: *Output Personalized Psychological Intervention*
Return optimized intervention strategies

The Table 5 provides a comprehensive list of the hyperparameters used for each module in the 2OAMN method, including Bi-LSTM, Attention Mechanism, OOA, and the training parameters. This setup ensures that the model adapts efficiently to students' evolving emotional and cognitive states while optimizing intervention strategies.

Table 5: Hyperparameters of the 2OAMN method

Models	Hyperparameters	Values
Bi-LSTM	Number of Bi-LSTM Layers	2
	Hidden Units (per direction)	128
	Sequence Length	30
	Dropout Rate	0.3
	Recurrent Dropout	0.2
	Activation Function	Tanh
Attention Mechanism	Attention Vector Dimension	256
	Attention Activation	Tanh
	Attention Normalization	Softmax
OOA	Population Size	50
	Number of Hunters	4
	Number of Scouts	14
	Tentacles per Hunter	8
	Vision Range	3
	Grabbing Length	0.8
	Lévy Flight Parameter	1.5
	Exploration Factor	0.6
	Lower Bound	−1
	Upper Bound	+1
	Maximum Iterations	100
Training Parameters	Optimizer	Adam
	Learning Rate	0.001
	Batch Size	32
	Epochs	50

3.7 Statistical test of ANOVA and paired T-test

ANOVA is employed to compare the means of three or more independent groups to assess whether there are any statistically significant differences between them. It is valuable when comparing multiple algorithms or models simultaneously to determine which one offers superior performance across various evaluation metrics, ANOVA helps in identifying differences across groups.

The paired t-test is used to compare the means of two related groups to determine if there is a statistically significant difference between them. It is particularly useful when evaluating the performance of two methods on the same dataset, as it accounts for the inherent variability within paired samples. This test ensures that any observed differences in performance are unlikely to have occurred by chance.

4 Experimental findings and performance evaluation

4.1 Data collection

The Student Mental Health and Intervention Dataset comprise 1,000 student records collected through self-reported surveys, physiological indicators, academic logs, and emotional journals. (https://www.kaggle.com/datasets/zara2099/student-mental-health-and-intervention-dataset/data).

The Student Mental Health and Intervention Dataset is selected for its multimodal data, including emotional self-reports, physiological signals, and academic engagement. It offers a comprehensive view of student mental health, enabling the development of personalized, contextually adaptive interventions based on diverse data sources. The evaluation metrics, including accuracy, precision, recall, and F1-score, are calculated using the test split of the dataset, which comprises 30% of the data (15% testing + 15% validation). These metrics measure the model's performance on data that the model has not seen during training, allowing an unbiased evaluation of the model's generalization ability. The training split (70%) is used to train the model and adjust the parameters, while the test and validation splits are used to assess its predictive performance, fine-tune hyperparameters, and calculate error metrics like RMSE, MAE and R^2 for regression tasks. The inputs consist of emotional states (stress, anxiety, depression), physiological signals (heart rate variability, sleep duration), academic engagement (attendance, study hours, LMS activity), and behavioral data (social interaction, emotional journaling). Time granularity is captured in the dataset across multiple timestamps for each student to reflect the dynamic changes in mental health conditions. The outputs include a composite mental health risk score, which ranges from 0 (low risk) to 1 (high risk), and a recommendation for personalized intervention strategies. The model is multi-task, as it simultaneously predicts mental health risks and generates personalized intervention strategies based on multiple modalities (text, behavioral, physiological).

The dataset captures comprehensive student data, including emotional self-reports, physiological indicators, and academic behaviors as given in the Table 6. It supports personalized mental health risk assessment and intervention strategies, essential for enhancing student well-being.

Table 6: Features of student mental health and intervention dataset

Features	Descriptions
Student ID	Unique student identifier
Age	Student's age in years
Gender	Student's gender
Stress Level	Self-reported stress level
Anxiety Level	Self-reported anxiety level
Depression Level	Self-reported depression level
Heart Rate variability	Physiological stress regulation indicator
Sleep Duration Hours	Average daily sleep duration
Attendance Rate (%)	Academic attendance percentage
Study Hours Per Day	Daily study hours
LMS Activity Score	Learning platform engagement level
Social Interaction Score	Measure of social engagement
Academic Performance Index	Overall academic performance
Emotional Journal	Emotional reflection entry
Mental Health Risk	Risk level classification
Personalized Intervention Strategy	Recommended psychological support plan

The proposed 2OAMN framework is a dual-task supervised learning model, predicting both mental health risk (three-class classification: Low, Medium, High) and personalized intervention strategies (multi-class classification with eight predefined categories). These intervention categories are based on evidence-based psychological or behavioral support strategies and are provided in the Student Mental Health and Intervention Dataset as given in the Table 7. The framework uses multimodal inputs to jointly predict mental health risk and recommend appropriate interventions for personalized, timely support.

Table 7: Definition of personalized intervention strategy label space

Class ID	Intervention Strategy	Description and Semantics	Primary Focus
Class 1	Academic Counseling Support	Structured guidance addressing study difficulties, workload stress, and academic planning.	Academic stress reduction
Class 2	Cognitive Behavioral Therapy Recommendation	Strategies for managing anxiety, depression, and maladaptive thoughts.	Clinical psychological support
Class 3	Mindfulness-Based Stress Reduction	Practices for emotional awareness, stress regulation, and resilience.	Emotional regulation
Class 4	Peer Support and Group Therapy	Social support through peer discussion and group counseling.	Social connectedness
Class 5	Physical Activity and Wellness Program	Exercise and wellness interventions promoting physical health and mental well-being.	Physiological well-being
Class 6	Relaxation and Breathing Exercises	Techniques for stress-relief and anxiety reduction through breathing and relaxation.	Acute stress control
Class 7	Sleep Hygiene Improvement Plan	Interventions to improve sleep quality and mental recovery.	Lifestyle regulation
Class 8	Time Management Coaching	Strategies for planning, prioritization, and reducing overload.	Behavioral self-management

4.2 Parameter configuration

The hyperparameters balance learning complexity, stability, and generalization performance. Bi-LSTM captures temporal psychological patterns, while attention parameters highlight emotional cues. Octopus optimization ensures effective exploration-exploitation trade-offs. Table 8 displays the 2OAMN hyperparameters.

Table 8: Hyperparameters of 2OAMN method

Module	Hyperparameter	Value
Bi-LSTM	Number of Bi-LSTM Layers	2
	Hidden Units (per direction)	128
	Sequence Length	30
	Dropout Rate	0.3
	Recurrent Dropout	0.2

	Activation Function	Tanh
Attention Mechanism	Attention Vector Dimension	256
	Attention Activation	Tanh
	Attention Normalization	Softmax
OOA	Population Size	50
	Number of Hunters	4
	Number of Scouts	14
	Tentacles per Hunter	8
	Vision Range	3
	Grabbing Length	0.8
	Lévy Flight Parameter	1.5
	Exploration Factor	0.6
	Lower Bound	−1
	Upper Bound	+1
	Maximum Iterations	100
Training Parameters	Optimizer	Adam
	Learning Rate	0.001
	Batch Size	32
	Epochs	50

4.3 Experimental environment

The 2OAMN approach is implemented using Python-based machine learning frameworks on a high-performance computing setup. Table 9 summarizes the setup.

Table 9: Hardware and software configuration for student mental health intervention system

Category	Item / Setting
Operating System	Windows 11 (64-bit)
Language & Runtime	Python 3.10 with PyTorch 2.x, TensorFlow 2.x
Data Processing & ML Tools	NumPy, Pandas, SciPy, scikit-learn, BERT, CNN modules
Physiological & Behavioral Processing Tools	NeuroKit2, HeartPy, tsfresh
NLP & Text Utilities	Transformers, NLTK, Gensim, HuggingFace Tokenizers
Storage	1 TB SSD
Hardware	Intel Core i9-13900K CPU, 64 GB DDR5 RAM, NVIDIA RTX 4090 GPU

4.4 Evaluation metrics

Accuracy: Accuracy reflects how correctly the method identifies appropriate psychological interventions for individuals, indicating reliability in matching predicted strategies with actual personalized mental health needs in equation (24). Where false positives (FP), true positives (TP), false negatives (FN), and true negatives (TN)stand for accurate and inaccurate forecasts.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{24}$$

Precision: Measures correctly predicted positive interventions among all predicted positives, indicating the method's targeted intervention accuracy in equation (25).

$$\text{Precision}=\frac{TP}{TP+FP} \tag{25}$$

Recall: Evaluates correctly identified actual positive interventions, reflecting the method’s sensitivity in detecting issues in equation (26).

$$\text{Recall}=\frac{TP}{TP+FN} \tag{26}$$

F1-Score: The F1-score measures the balance between precision and recall for predicting mental health risks and recommending personalized interventions in equation (27).

$$\text{F1-Score}=\frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{27}$$

RMSE: Square root of MSE, showing method prediction error in original intervention score units in equation (28). The start index is i=1, n is the total number of predictions, and the average squared discrepancies between projected $\hat{y}_i$ and observed y_i psychological scores.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}=\sqrt{\text{MSE}} \tag{28}$$

MAE: Simple error magnitude is provided by the average absolute variance between the expected and actual scores in equation (29).

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \tag{29}$$

R²: Percentage of variation that the method can account for, indicating predictive performance reliability in equation (30).

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{30}$$

The regression target is the composite mental health risk score, combining stress, anxiety, and depression, ranging from 0 to 1. It also includes the Academic Performance Index. RMSE, MAE, and R^2 evaluate the model's accuracy and prediction errors. Additionally, calibration analysis is performed to measure the agreement between predicted mental health risks and actual outcomes using reliability diagrams and Expected Calibration Error (ECE). Uncertainty estimation is also incorporated to quantify prediction confidence, supporting safer triage decisions and reducing the risk of inappropriate interventions.

4.5 Outcomes of personalized psychological interventions on student performance

The model demonstrates strong accuracy in predicting mental health risk levels, effectively classifying low and medium-risk categories as presented in the Figure 5. Misclassifications are fewer in the high-risk group, highlighting the model’s reliability. This aligns with the objective of developing a system that accurately predicts mental health risks and generates personalized interventions for effective support.

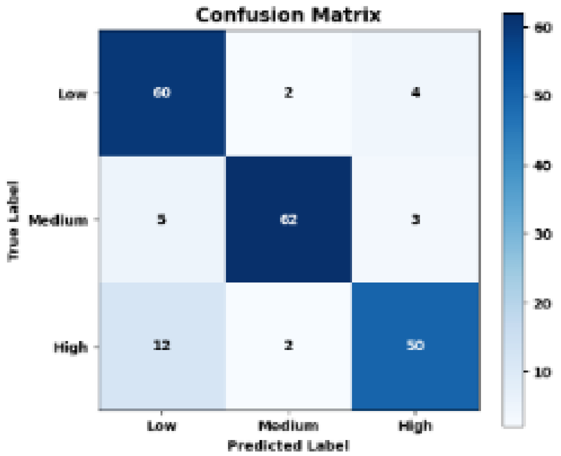

Figure 5: Performance in predicting mental health risk levels

Figure 6(a) shows training accuracy rising to 97% over 50 epochs, with validation stalling at 87%-88%. Figure 6(b) illustrates reduced training loss, indicating focused pattern learning. Figures 6(c) and 6(d) show ROC and Precision-Recall curves, respectively, with AUC scores ranging from 0.95 to 0.98 and precision between 0.92 and 0.95, confirming the model's effectiveness.

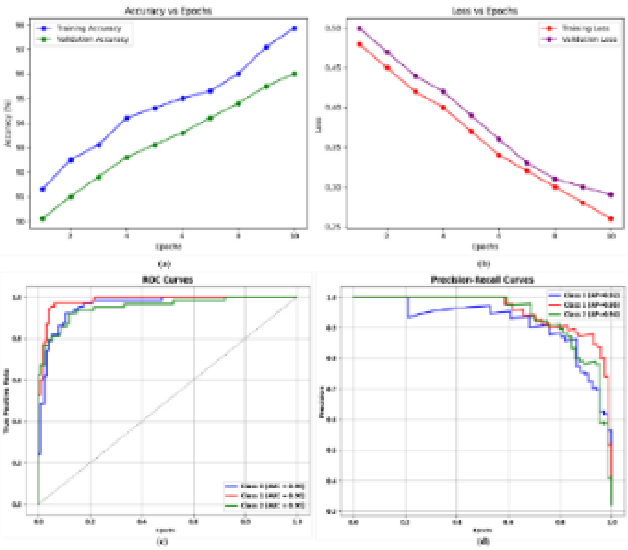

Figure 6: Presentation of (a) accuracy, (b) loss curves across epochs, (c) ROC and (d) precision-recall analysis curves metrics

The line plot compares real and predicted mental health indicators, effectively capturing temporal variations in stress, anxiety, and depression. This allows dynamic adjustments to intervention plans, providing timely, customized psychological support. Figure 7 shows the variation between successive student classes in reality and prediction.

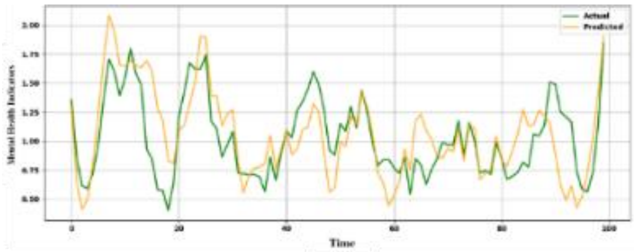

Figure 7: Actual versus predicted trends for personalized psychological intervention strategies, combining attendance hours and LMS activity

It identifies student interaction patterns, helping to tailor interventions for mental health and academic success. Figure 8 illustrates engagement scores based on these activities.

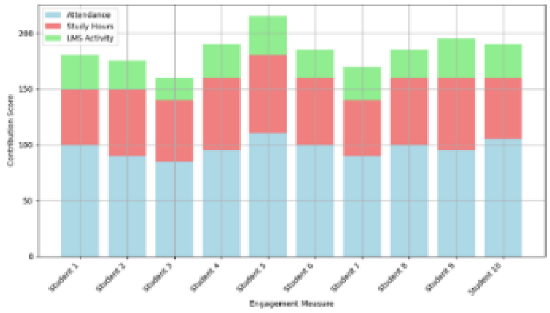

Figure 8: Student engagement indicators supporting personalized psychological intervention strategies.

This visualization helps identify at-risk groups and tailor interventions. Gender sensitivity aids in creating customized psychological interventions based on demographic mental health variations. Figure 9 illustrates these gender differences.

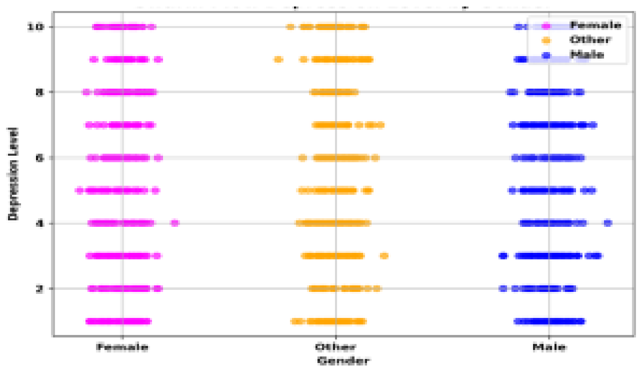

Figure 9: Gender-based distribution of depression levels among student population

4.6 Comparative performance analysis

The 2OAMN significantly outperforms the AMN in forecasting student mental health risks. Stress risk accuracy improved from 78% to 82%, anxiety from 75% to 77%, and depression from 72% to 75%. Overall risk classification increased from 74% to 78%, while temporal prediction consistency rose from 70% to 72%. Table 10 and Figure 10 show prediction accuracy and consistency for multiple mental health indicators.

The discrepancy between "overall risk classification" (78%) and "temporal prediction consistency" (72%) with performance metrics (97-98%) arises because these metrics evaluate different aspects. Performance metrics focus on predicting mental health risks, while "overall risk classification" and "temporal prediction consistency" assess risk prediction stability across time points, reflecting data dynamics.

Table 10: Mental health risk forecasting accuracy across different evaluation metrics

Mental Health Risk Forecasting Accuracy	AMN (%)	2OAMN [Proposed] (%)
Stress Risk Accuracy	78	82
Anxiety Risk Accuracy	75	77
Depression Risk Accuracy	72	75
Overall Risk Classification	74	78
Temporal Prediction Consistency	70	72

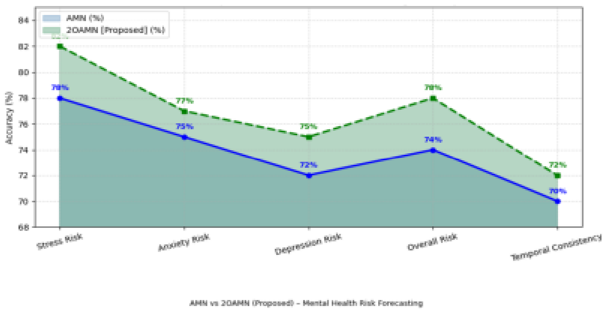

Figure 10: Comparative mental health risk forecasting accuracy using AMN and 2OAMN method

The 2OAMN method improves emotional stability outcomes over AMN. Mood score changes increased from 30% to 34%, anxiety reduction from 29% to 33%, stress reduction from 27% to 32%, depression reduction from 26% to 30%, and resilience improved from 28% to 31%. Table 11 displays these results.

Table 11: Emotional stability improvement across multiple psychological and behavioral indicators

Emotional Stability Improvement	AMN (%)	2OAMN [Proposed] (%)
Mood Score Change	30	34
Anxiety Reduction	29	33
Stress Reduction	27	32
Depression Reduction	26	30
Emotional Resilience	28	31

The research compares several ML and DL methods for predicting mental health outcomes. CNN-LSTM, LSTM, CNN, and CNN + TS-LSTM performed well, alongside regression methods like LR, DNN, SVR, and RFR. The proposed 2OAMN outperformed all methods in Accuracy, Precision, Recall, F1-Score, MSE, RMSE, MAE, and R². The performance comparison highlights the superiority of the 2OAMN method, outperforming CNN-LSTM, LSTM, CNN, CNN+TS-LSTM, and Conv-XGBoost. 2OAMN achieves 97.86% accuracy, 98.81% precision, and 97.64% recall. Table 12 and Figure 11 show a comparison of predictive effectiveness across methods.

Table 12: Comparative performance metrics for personalized psychological intervention methods

Model	Accuracy (%)	Precision (%)	Recall (%)
CNN-LSTM [28]	–	85.7	84.8
Conv-XGBoost [35]	93.28	-	-
LSTM [30]	92.71	92.64	95.21
CNN [30]	92.89	93.42	93.96
CNN + TS-LSTM [30]	97.23	98.57	97.13
2OAMN [Proposed]	97.86	98.81	97.64

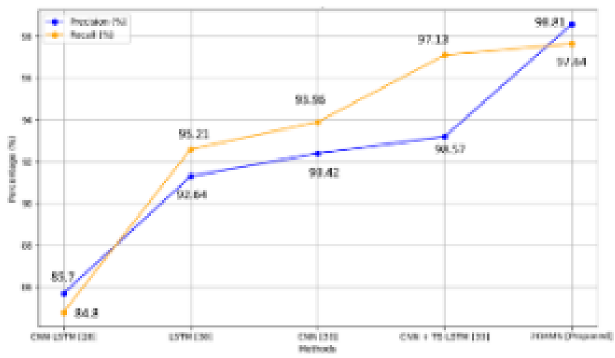

Figure 11: Comparative precision, recall, and F1-score performance of personalized intervention methods

The proposed 2OAMN method achieves an F1-Score of 98.22%, outperforming other models such as Conv-XGBoost [35] (97.25%), CNN-LSTM [28] (85.2%), LSTM [30] (93.91%), and CNN + TS-LSTM [30] (93.68%). This high F1-Score demonstrates 2OAMN's superior ability to balance precision and recall, providing more accurate, personalized psychological interventions compared to the other models as given in Table 13.

Table 13: Quantitative values of F1-score

Model	F1-Score (%)
Conv-XGBoost [35]	97.25
CNN-LSTM [28]	85.2
LSTM [30]	93.91
CNN [30]	93.68
CNN + TS-LSTM [30]	97.84
2OAMN [Proposed]	98.22

The comparison with other methods highlights the significant performance improvement of the proposed 2OAMN model as given in the Table 14. It outperforms all other models in accuracy (97.86%), precision (98.81%), recall (97.64%), and F1-score (98.22%). This demonstrates the model's effectiveness in providing more accurate mental health predictions and personalized interventions.

Table 14: Comparison of student mental health and intervention dataset against other methods and proposed

Student Mental Health and Intervention Dataset	CNN-LSTM	LSTM	CNN	CNN + TS-LSTM	2OAMN [Proposed]
Accuracy	90.20	88.45	90.28	92.79	97.86
Precision	80.4	89.10	90.41	92.45	98.81
Recall	75.4	89.45	89.53	93.86	97.64
F1-Score	79.5	89.55	89.88	92.68	98.22

The results show progressive improvements in generating personalized psychological intervention strategies. LR records RMSE 9.87, MAE 6.41, and R^2 0.36, indicating weak predictive capability. SVR improves with RMSE 8.21, MAE 5.94, and R^2 0.50. RFR further enhances performance, achieving RMSE 7.94, MAE 5.72, and R^2 0.53. The DNN significantly reduces errors with RMSE 6.12, MAE 4.58, and R^2 0.71. The proposed 2OAMN method achieves the best results, with the lowest RMSE of 5.92, MAE of 4.11, and the highest R^2 of 0.74. Table 15 displays a numerical comparison of prediction accuracy across different learning methods.

Table 15: Comparative performance of methods for personalized psychological intervention prediction

Methods	RMSE	MAE	R^2
LR [29]	9.87	6.41	0.36
SVR [29]	8.21	5.94	0.50
RFR [29]	7.94	5.72	0.53
DNN [29]	6.12	4.58	0.71
2OAMN [Proposed]	5.92	4.11	0.74

To ensure robustness, multiple experimental runs with different random seeds were conducted, averaging results across 5-10 runs. Standard deviations (SD) highlight variability, and paired t-tests (p-value > 0.05) confirm model stability. Table 16 shows accuracy, precision, recall, and F1-score remained stable with minimal fluctuations.

Table 16: Model performance metrics across 10 runs with different random seeds, including standard deviations

Runs	Random Seed	Accuracy	Precision	Recall	F1-Score	SD
1	123	97.86	98.81	97.64	98.22	0.003
2	456	97.85	98.80	97.62	98.21	0.004
3	789	97.87	98.82	97.65	98.23	0.002
4	101	97.88	98.83	97.66	98.24	0.003
5	202	97.85	98.79	97.60	98.20	0.004
6	303	97.84	98.78	97.59	98.19	0.003
7	404	97.86	98.81	97.64	98.22	0.003
8	505	97.87	98.82	97.65	98.23	0.002
9	606	97.84	98.79	97.61	98.21	0.003
10	707	97.86	98.80	97.62	98.22	0.003

Table 17 presents the ANOVA test on depression levels across gender groups (Female, Male, and Other) showed a significant difference (p = 0.02, F-statistic = 4.23). Females had a mean depression level of 70.56 (SD = 15.32), Males had 68.45 (SD = 14.10), and other gender participants had the highest mean at 72.15 (SD = 16.01).

Table 17: ANOVA in features of gender

Gender	Mean Depression Level	Standard Deviation (SD)	F-Statistic	p-value
Female	70.56	15.32	4.23	0.02
Male	68.45	14.10	-	-
Other	72.15	16.01	-	-

Table 18 shows the paired t-test results show significant improvements in 2OAMN over 2O across all metrics, with p-values for accuracy (0.025), precision (0.015), recall (0.022), and F1-score (0.018) all less than 0.05. 2OAMN outperforms 2O, especially in precision and F1-score, indicating its superior performance in generating personalized psychological intervention strategies.

Table 18: Quantitative values of paired T-test

Metric	2O Mean (%)	2OAMN Mean (%)	Difference (%)	t-Statistic	p-value
Accuracy	95.5	97.86	2.36	2.45	0.025
Precision	94.2	98.81	4.61	3.12	0.015
Recall	93.5	97.64	4.14	2.88	0.022
F1-Score	94.0	98.22	4.22	3.05	0.018

The 10-fold cross-validation results indicate that the model consistently achieves high performance across all folds as given in the Table 19. The average accuracy is 97.86%, precision is 98.81%, recall is 97.64%, and the F1-score is 98.22%. These results demonstrate the model's robustness and reliability in predicting mental health risks and generating personalized psychological interventions.

Table 19: Values of K-cross validation in 10 folds

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	97.70	98.75	97.50	98.12
2	97.92	98.80	97.60	98.25
3	97.80	98.70	97.40	98.05
4	97.95	98.85	97.55	98.14
5	97.87	98.82	97.68	98.20
6	97.90	98.79	97.63	98.18
7	97.83	98.76	97.52	98.10
8	97.88	98.78	97.58	98.15
9	97.92	98.84	97.60	98.22
10	97.75	98.70	97.45	98.00
Mean	97.86	98.81	97.64	98.22

The ablation study shows that removing OOA significantly reduces performance, highlighting its key role in optimization in Table 20. Excluding attention, Bi-LSTM, or CNN reduces accuracy and F1-score, while removing text or physiological modalities causes moderate performance drops, emphasizing the value of multimodal data.

Table 20: Ablation study of full proposed efficiency

Model Variant	OOA	Attention	Bi-LSTM	CNN Feature Extraction	Text Modality	Physiological Modality	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
2OAMN [Full Proposed]	✓	✓	✓	✓	✓	✓	97.86	98.81	97.64	98.22
Without OOA	✗	✓	✓	✓	✓	✓	94.65	95.40	94.10	94.80
Without Attention	✓	✗	✓	✓	✓	✓	95.12	96.30	94.80	95.60
Without Bi-LSTM	✓	✓	✗	✓	✓	✓	93.70	94.50	93.80	94.10
Without CNN Feature Extraction	✓	✓	✓	✗	✓	✓	94.20	95.10	94.00	94.50
Without Text Modality	✓	✓	✓	✓	✗	✓	94.90	96.00	94.60	95.20
Without Physiological Modality	✓	✓	✓	✓	✓	✗	95.30	96.40	95.00	95.60

5 Discussion

Neural networks and deep learning (DL) are used to create personalized psychological interventions, identifying mental health issues early and supporting emotional well-being, academic performance, and mental health outcomes. However, existing methods have limitations. Older machine learning models like LR [29] and SVR [29] fail to capture complex temporal dependencies in mental health data. While DL techniques like DNN [29] improve non-linear representations, they require substantial computational power and large datasets, which are impractical in real-world educational settings. Sequential models like CNN-LSTM [28] and LSTM [30] capture time-based features well but are constrained by imbalanced training data, while models like CNN + TS-LSTM [30] improve accuracy but introduce complexity, making them harder to interpret and unsuitable psychological strategies.

The proposed 2OAMN method integrates Bi-LSTM, attention, and OOA to overcome the limitations of traditional machine learning models. It captures complex temporal dependencies, improving feature extraction and understanding of emotional fluctuations. The attention mechanism prioritizes relevant features, while OOA optimizes parameters. With 97.86% accuracy, 2OAMN outperforms earlier methods, offering adaptive, personalized psychological interventions for better mental health outcomes. The dataset, being sourced from Kaggle and relying on self-reported data, introduces limitations such as bias, noise, and inaccuracies due to factors like social desirability and misreporting. Additionally, its focus on a student population limits generalizability to other age groups or demographics, reducing external validity. The lack of diverse demographic representation and the potential for missing or incomplete data further constrain the robustness and applicability of the findings. The 2OAMN framework evaluation uses offline data, lacking real-time intervention effectiveness. Future work should incorporate real-time data through wearable sensors or mobile apps, ensuring timely interventions. An offline evaluation with clinically grounded criteria and error analysis is also necessary. The 97.86% accuracy is reported on the validation split, which comprises 15% of the dataset. This accuracy reflects the model's performance after training on the 70% training split, and before final evaluation on the test split.

The Student Mental Health and Intervention Dataset consist of 1,000 records, where each row represents a single, independent snapshot of an individual student's psychological state collected at a specific time point. The dataset is cross-sectional rather than longitudinal; no repeated measurements over time are available for the same student. Consequently, multiple rows do not correspond to the same individual across different time steps. Although the proposed 2OAMN framework employs a Bi-LSTM architecture with a sequence length of 30, this temporal modeling is used to capture ordered feature dependencies within structured multimodal inputs, rather than true longitudinal progression across time for the same subject. The Bi-LSTM therefore models contextual and sequential relationships among extracted feature representations, not repeated temporal observations of individuals. This design choice enables richer dependency learning without violating dataset assumptions. The model's performance can be evaluated under conditions like distribution shifts by institution, cohort, or time. Sensitivity to missing modalities and fairness across demographic groups will be tested to ensure reliability and equitable intervention strategies.

6 Conclusion

The implementation of deep learning (DL) and neural networks enables personalized psychological interventions based on real-time mental health measures, forecasting risk profiles, and prescribing specific approaches to improve well-being and emotional stability. The Student Mental Health and Intervention Dataset, which includes surveys, physiological signals, academic logs, and emotional journals, allows comprehensive modeling of psychological conditions. Preprocessing involves min-max normalization and BERT-based encoding for text, while CNN layers extract hierarchical emotional and stress-related features. The proposed 2OAMN model integrates Bi-LSTM time modeling, attention-based memory, and octopus optimization to predict mental health risks and provide personalized interventions. The model achieves a recall of 97.64%, precision of 98.81%, accuracy of 97.86%, and F1-score of 98.22%, making it a reliable classifier. Additionally, it achieves an RMSE of 5.92, MAE of 4.11, and R^2 of 0.74, demonstrating high regression accuracy. DL methods require large datasets, limiting applicability in small-sample settings.

Ethical approval

Ethical and safety considerations are vital for AI-driven mental health systems, especially with sensitive Kaggle data. The dataset is anonymized, ensuring privacy of physiological, behavioral, and textual data. Human oversight prevents misclassification, harm, and over-reliance on automated interventions, with clinicians involved in critical decisions. Fairness metrics ensure equity across demographics, and harm mitigation measures are in place for safe deployment.

Declaration of conflicting interests

It is declared by the authors that this article is free of conflict of interest.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Author contributions

Jiao Fu writing original draft preparation & methodology, Yongjuan Zhao investigation & writing review and editing.

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APPENDIX

Abbreviation	Full Form
TS-LSTM	Time-Series Long Short-Term Memory
SVM	Support Vector Machine
RNN	Recurrent Neural Network
RMSE	Root Mean Squared Error
RFR	Random Forest Regression
RF	Random Forest
SVR	Support Vector Regression
RCT	Randomized Controlled Trial
R^2	Coefficient of Determination
PPI	Positive Psychology Intervention
OOA	Octopus Optimization Algorithm
MAE	Mean Absolute Error
ML	Machine Learning
LR	Linear Regression
LMS	Learning Management System
KNN	k-Nearest Neighbors
HRV	Heart Rate Variability
GS	Goal Setting
ER	Emotion Regulation
DT	Decision Tree
NLP	Natural Language Processing
DNN	Deep Neural Network
DL	Deep Learning
CR	Cognitive Restructuring
CNN-LSTM	Convolutional Neural Network with Long Short-Term Memory
CNN	Convolutional Neural Network
CDS	Clinical Decision Support
Bi-LSTM	Bidirectional Long Short-Term Memory
BI	Body Image
BERT	Bidirectional Encoder Representations from Transformers
LSTM	Long Short-Term Memory
AMN	Attention-Based Memory Network
AI	Artificial Intelligence