Development Of A Personalized Framework For Mental Health Education Integrating Neural Networks And Big Data Analysis

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Received: Apr. 04, 2026; Accepted: May 27, 2026

Mental Health (MH) disorders are becoming increasingly prevalent across diverse populations, yet conventional MH education often lacks personalisation, reducing its effectiveness. However, current frameworks do not effectively integrate heterogeneous data sources nor adaptively respond to individual user needs and progress. This research aims to develop a personalised MH education framework termed Neural Attention and NSGA-II Powered Educational Network (NeuroNSGA-EdNet) that integrates neural network modelling and big data analysis to deliver adaptive, user-specific content. The primary objective is to improve MH literacy, promote early awareness, and enhance user engagement through data-driven personalisation. The NeuroNSGA-EdNet framework incorporates heterogeneous data sources, including social media activity, wearable sensor data, academic records, and self-reported psychological assessments. Data pre-processing techniques such as Z-score normalisation, tokenisation, and missing value imputation ensure consistency and quality. An attention-based Convolutional Long Short-Term Memory (ConvLSTM) network models temporal and contextual patterns in the data. Personalised content recommendations are generated using a Non-dominated Sorting Genetic Algorithm (NSGA-II), optimising multiple objectives based on individual psychological profiles. A feedback and adaptive learning loop continuously update recommendations based on user interactions and learning outcomes. The experimental validation conducted using a systematic train-validation-test split approach on a heterogeneous dataset revealed an accuracy of 98.4%, 86.1% precision, 89.4% recall, and 91.6% F1. Users reported higher satisfaction with personalised learning paths compared to static modules. NeuroNSGA-EdNet integrates AI and big data for personalised MH education, combining deep learning, genetic optimisation, and adaptive feedback to enhance MH literacy and support early intervention.

Keywords: Personalised Framework, Mental Health, Education, Big Data, Neural Attention, and NSGA-II Powered Educational Network (NeuroNSGA-EdNet), Psychological Assessments.

http://dx.doi.org/10.6180/jase.202612_35.035

1. Introduction

Mental health (MH) has emerged as a critical global issue affecting individuals across ages, regions, and backgrounds [1]. The growing burden of digital information and social isolation highlights the limitations of rigid education frameworks that cannot adapt to changing personal and digital contexts, leading to inadequate psychological support and emphasising the need for early diagnosis and personalised treatment through AI-based adaptive approaches. Conventional MH educational models are described as inflexible and use a standardised approach, failing to cater to the individual psychological, emotional, and behavioral characteristics of learners.

Fig. 1 illustrates how personalised learning in the context of mental health education is done through the use

Fig. 1. Key Components of Personalised MH Education Frame.

of personal information and AI. The process is constantly improved through feedback mechanisms to provide personalised services.

Although ML and DL methods like SVMs, Random Forests, CNNs, and RNNs support MH analysis, they often lack personalisation and interpretability. However, current methodologies like FEPS-MH, SA-BFRNN, and ESN cannot deal with the heterogeneity of multimodal data and behavioural change dynamics, hence limiting their efficiency in providing consistent personalization. To address these gaps, this study proposes NeuroNSGA-EdNet, integrating neural attention, NSGA-II, and big data for adaptive MH education. ANN has been widely applied in power load analysis [2] and electricity usage trends [3], while [4] highlighted AI's role in sustainable infrastructure and decision-making. Unlike existing mental health education frameworks that rely on predictive analytics or fixed interventions, NeuroNSGA-EdNet introduces a holistic approach by integrating attention-based ConvLSTM with NSGA-II for multi-objective optimisation of personalised content delivery.

The main contributions of this work are as follows:

- Proposed framework NeuroNSGA-EdNet incorporating attention-based ConvLSTM and NSGA-II algorithms for personalised mental health education.
- Multi-objective optimisation of precision, personalisation, and efficiency.
- Feedback system for dynamic updates of individualised learning content.
- Strategies for incorporating multiple types of data for training the models.

2. Related works

Recent studies highlight neural networks, fuzzy logic, and big data in MH education. Ji [5] proposed FEPS-MH for improved prediction and intervention, while Sundaram et al. [6] developed an ensemble MH care system. Jia [7] applied LSTM-RNN with IoT for MH support. Tian and Yi [8] further confirmed AI-driven MH systems for prediction, intervention, and risk monitoring. Several studies highlight ANN and ML applications: Najim et al. [2] for power load analysis, BaniMustafa and Al-Omari [3] for electricity consumption, and (Alnsour et al., 2024) for sustainable infrastructure and decision-making. Norouzi and Machado [9] proposed a machine learning model for predicting depression, anxiety, and stress for early mental health assessment. Vallu et al. [10] proposed an AI-driven digital twin framework for real-time stress detection, while NeuroNSGA-EdNet applies AI-based learning and adaptive optimisation for personalised mental health education.

Several studies have examined the use of transformer and graph neural networks for predicting mental states. These methods, however, tend to face issues of personalisation, fail to optimise multiple objectives effectively, and lack support for continuous adaptive learning using different data sources. Most of the current methods are also concerned more with static predictions rather than dynamic and personalised mental health education as shown in Table 1.

2.1. Research Gaps

FEPS-MH improves accuracy but struggles with high-dimensional data and real-time adaptability [5]. Ensemble ML models lack interpretability [6], and RNN-LSTM approaches rely on high-quality IoT data, limiting low-resource use [7]. NeuroNSGA-EdNet addresses these issues using neural attention and NSGA-II for adaptive personalised MH education.

3. Methodology

Personalised MH Education data were preprocessed (Z-score, tokenization, imputation), and NeuroNSGA-EdNet (ConvLSTM + NSGA-II) enables adaptive mental health education. The dataset is divided into training (70%), validation (15%), and testing (15%) sets for unbiased evaluation and model generalisation. Fig. 2 shows the overall flow of the methodologies.

Workflow demonstrates the creation of a tailored mental well-being dataset using processing operations such as normalisation and data imputation. After that, an AI-driven classification model is used along with accuracy, precision, recall, and F1-Score measures for assessing model performance.

Table 1. Summary of Related Works on Personalised MH Education.

Reference Name	Method	Result	Advantages
Gan and Jin [11]	Support Vector Machine (SVM) with Depression Knowledge Graph and Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU) model	Improved predictive accuracy for depressive behaviour	Superior prediction performance; theoretical basis for enhancing MH interventions
Xing [12]	Radial Basis Function (RBF), Analytic Hierarchy Process (AHP), and Improved Backpropagation (BP) Neural Network	Enhanced prediction accuracy and model stability for MH and civic learning outcomes	Stable across large data volumes; integrates multifactor evaluation
Zhao and Tang [13]	Deep Computational Model using Manually Annotated Microblog Datasets and Big Data Analytics	Identified key social, economic, and cultural factors affecting MH	Broad contextual analysis; uses realworld data for better insight
Wang [14]	ARFIMA Model with statistical time-series analysis	Identified the relationship between college students' MH fluctuations and civics program outcomes	Captures long-term trends and temporal fluctuations; useful for educational policy and MH monitoring

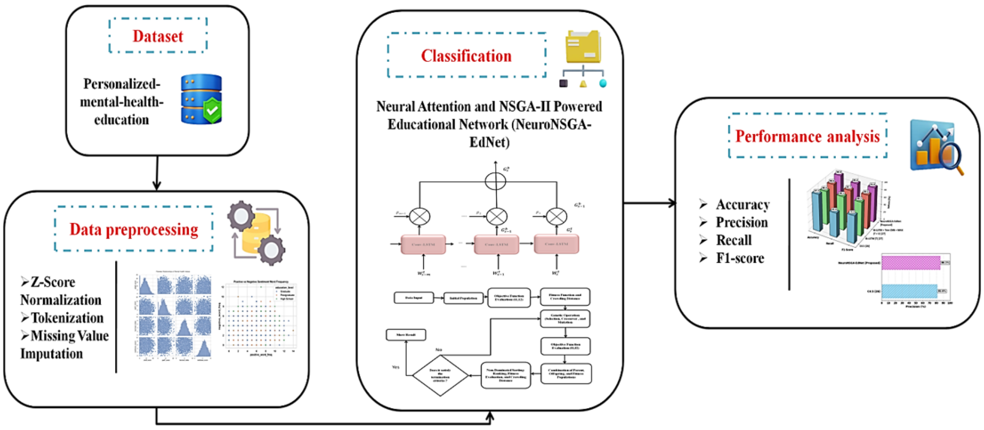

Fig. 2. Overall Flow of MH Education.

3.1. Data Collection

The Personalized Mental Health Education Dataset on Kaggle includes multimodal profiles such as surveys, emotional assessments, behavioural interactions, and academic performance, supporting AI-based personalized recommendation and adaptive learning. It enables analysis of mental wellness, behavior patterns, academic links, and emotional regulation for MH education. The dataset used in this study is publicly available on Kaggle and is accessible for research purposes. All data are anonymised to preserve privacy and comply with ethical standards for responsible use of mental health data. This data is based on labelled data, obtained from scores of psychological tests and responses given by themselves. The labels assist in framing this challenge as a supervised learning algorithm and personalising it to make recommendations. The dataset exhibits a balanced class distribution across mental health categories, ensuring unbiased model training. The sample size of 10,000 is sufficient to capture diverse behavioural and psychological variations for robust deep learning performance. The dataset contains several variables, including surveys, behaviours, emotions, and education data, among others, indicating a varied set of features. Some minor sparseness caused by the unavailability of data is managed through imputation. The dataset is considered a multimodal framework by combining different sources of information, such as behavioural data, emotional measures, and psychological self-reports, to facilitate mental health assessment.

Source: https://www.kaggle.com/datasets/ziya07/personalized-mental-health-education-dataset/data.

3.2. Data Pre-processing

Data preprocessing, including missing value imputation, improves accuracy, reliability, and data quality for effective model training and personalized MH education.

3.2.1. *Z-Score Normalisation*

Z-score normalisation standardises all features to zero mean and unit variance, ensuring consistent scaling across datasets and improving model performance. It is defined as:

$$d' = \frac{d - \mu}{\sigma} \tag{1}$$

Eq. (1) defines Z-score normalization where $d' = (d - \mu)/\sigma$ and feature means and standard deviations from training data are retained for consistency.

3.2.2. *Tokenization*

Tokenisation is applied to textual MH data to convert unstructured text into meaningful units, preserving semantic relationships and enabling efficient NLP processing. The Z-score normalization technique should be adopted instead of the min-max normalisation method because it is robust against outliers and can handle heterogeneous data. Tokenization helps preserve semantic structures effectively, while missing values are handled by imputation.

3.3. NeuroNSGA-EdNet

NeuroNSGA-EdNet integrates neural attention mechanisms with NSGA-II to deliver adaptive, personalised MH education. The feedback process is built into the proposed system such that it constantly checks user progress and adapts learning material to learners' behaviour and performance levels. This framework integrates both neural networks and big data to discover valuable insights from diverse mental well-being datasets. The framework provides customised and adaptive content according to the behaviour and psychology of individual users. Neural attention extracts salient behavioural and cognitive features, while NSGA-II optimises content relevance, engagement, and learning progression. Leveraging big data analytics, the framework enables real-time personalisation, scalable interventions, and sustained learner engagement.

The fusion of ConvLSTM, attention, and NSGA-II is utilised for pattern recognition and feature extraction while optimising various objectives like precision, customisation, and performance within the context of mental health education.

3.3.1. *Neural Attention*

The neural attention model employs a ConvLSTM architecture to capture spatial-temporal patterns in users' behavioural, emotional, and physiological MH data, enabling adaptive and personalised content delivery. Compared to Transformer architectures, ConvLSTM with attention is more appropriate for this problem because it can easily learn the local spatial-temporal structure present in psychology-related data without involving much computational power. In contrast, Transformers need substantial amounts of data and computational power, while the proposed model offers a better interpretation of individualised psychological education. Attention helps the ConvLSTM focus on important time steps, improving the interpretability of psychological signals. As shown in Fig. 3, ConvLSTM integrates convolutional and LSTM layers to model spatial correlations and temporal dependencies in MH data.

$$W_s^t = \sigma\left(X_t * W_s^t + a_t\right) \tag{2}$$

Eq. (2) defines σ, a convolution filter X_t, and bias a_t for processing spatial-temporal MH data. The resulting features H_s^t are fed into stacked LSTM layers to capture temporal evolution.

$$j_s = \sigma\left(X_{hj} j_s^t + X_{gj} j_{s-1}^t + X_{dj} \odot D_{s-1} + a_j\right) \tag{3}$$

Eq. (3) defines the update gate j_s controls how much new information is added at time step s, using weight matrices, current/previous inputs, previous cell state, and bias with sigmoid activation and element-wise operations.

$$e_s = \sigma\left(X_{he} J_s^t + X_{ge} J_{s-1}^t + X_{de} \odot D_{s-1} + a_e\right) \tag{4}$$

Eq. (4) defines the forget gate e_s regulates how much past information is retained using weight matrices, inputs, previous cell state, and bias with sigmoid gating. The cell state D_s combines forget and update gates with the candidate state using weight matrices and $\tanh(\cdot)$ for non-linearity as shown in Eq. (5).

$$D_s = e_s \odot D_{s-1} + j_s \odot \tanh\left(X_{hd} J_s^t + X_{gd} J_{s-1}^t + a_d\right) \tag{5}$$

$$G_s^t = p_s \odot \tanh\left(D_s\right) \tag{6}$$

Eq. (6) defines the output G_s^t is generated from the cell state D_s scaled by p_s and passed through $\tanh(\cdot)$. The final spatial-temporal representation is G_ε^t.

A mixed approach using the CNN algorithm to extract features and LSTM to identify patterns within sequences. The attention process is used to draw out the most critical data.

Attention Mechanism

As illustrated in Fig. 4, an attention mechanism weights ConvLSTM outputs to emphasise the most relevant time steps. The attended output is:

$$G_s^b = \sum_{l=1}^{m+1} \beta_l H_{s-(l-1)}^t \tag{7}$$

with attention weights:

$$\beta_l = \frac{\exp\left(t_l\right)}{\sum_{l=1}^{m+1} \exp\left(t_l\right)} \tag{8}$$

$$t_s = U_t^S \tanh\left(X_{gt} H_s^t + X_{kt} G_k^t\right) \tag{9}$$

Eqs. (7) and (8) define G_s^t as the Conv-LSTM hidden output with learnable parameters. Eq. (9) compute attention β from inputs and past time steps, where β controls information flow to highlight key MH signals for adaptive personalised education. The attention module increases transparency in the model by scoring each temporal input based on its relevance to the output decision. High attention weights reflect a stronger influence of behavior and emotions, making the decision-making process comprehensible.

3.3.2. *NSGA-II*

NSGA-II optimises conflicting objectives by selecting neural configurations balancing accuracy, personalisation, and learning effectiveness. NSGA-II is used as a multi-objective optimisation algorithm for selecting the best neural network parameters for personalised content recommendations while maintaining accuracy, model complexity, and loss. It uses elitism, dominance ranking, and crowding distance to ensure optimality and diversity through Pareto-based selection.

$$c_j^1 = \frac{\left|e_1^{(j+1)} - e_1^{(j-1)}\right|}{e_1^{\max} - e_1^{\min}} \tag{10}$$

$$c_j^2 = \frac{\left|e_2^{(j+1)} - e_2^{(j-1)}\right|}{e_2^{\max} - e_2^{\min}} \tag{11}$$

Eqs. (10) and (11) defines the crowding distance c_j^2 for the second objective, calculated using neighbouring solutions $e_2^{(j+1)}$ and $e_2^{(j-1)}$, normalised by $e_2^{\max} - e_2^{\min}$.

$$c = c_j^1 + c_j^2 \tag{12}$$

Algorithm 1. NeuroNSGA-EdNet.

BEGIN
Input: Dataset (10,000 samples, 25 features); neural network with attention; NSGA-II parameters (N = 50, G = 100).
Preprocess: Normalise data; split into train (70%), validation (15%), test (15%).
Initialise: Generate 50 random neural models. Define objectives:
minimize loss (f1), maximize accuracy (f2), minimize parameters (f3).
For each generation (1–100):
a. Train each model (10 epochs) and evaluate on validation data.
b. Apply NSGA-II: non-dominated sorting, crowding distance, tournament selection.
c. Apply crossover (Pc = 0.9) and mutation (Pm = 0.1) to generate offspring.
d. Select top 50 models based on rank and diversity.
Select: Final Pareto-optimal models.
Evaluate: Test selected models on test data.
Output: Optimal models, attention heatmaps, and NSGA-II Pareto front.
END

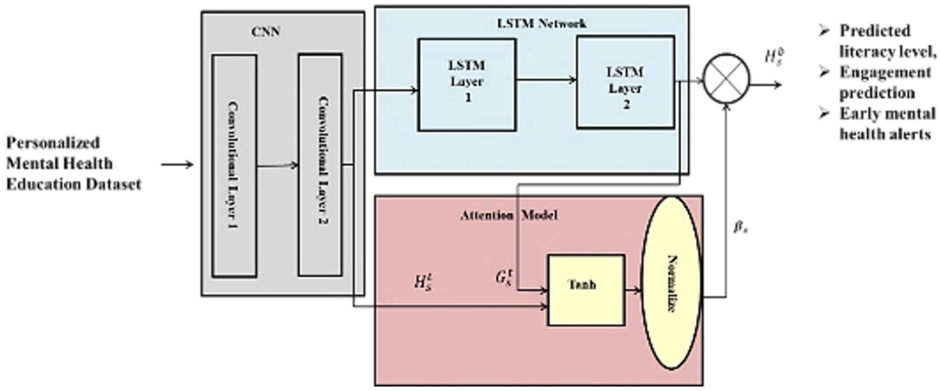

Fig. 3. Conv-LSTM module with an attention mechanism.

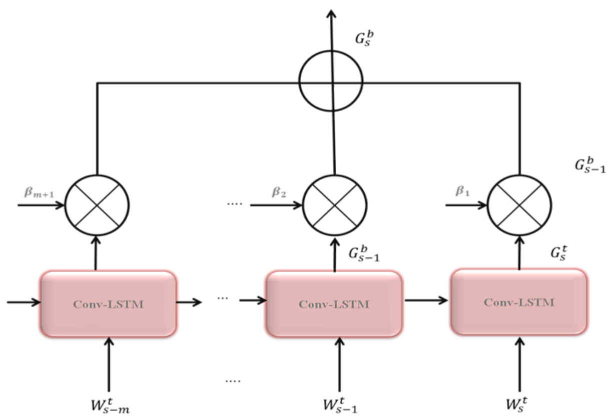

Fig. 4. The attention mechanism with Conv-LSTM networks.

Eq. (12) gives the total crowding distance c as the sum of c_j^1 and c_j^2, used to preserve diversity in NSGA-II. Higher crowding distance indicates greater solution diversity and higher selection priority. NSGA-II generates a Pareto-optimal set of neural models through iterative optimization in Fig. 5. The Pareto frontier can be employed to plot trade-offs among accuracy, model complexity, and loss, thus providing the ability to pick non-dominated solutions with balanced performances. Hyperparameter settings are provided in Table 2.

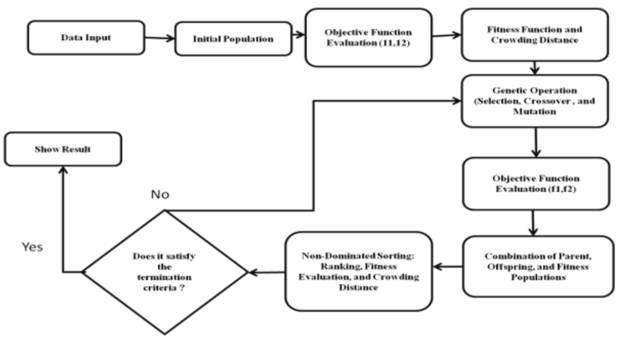

Fig. 5. NSGA-II algorithm flowchart.

4. Results and discussion

The experiment was implemented in Python and evaluated using Accuracy, Precision, Recall, and F1-score with comparisons to C4.5,

Table 2. Hyperparameters of NeuroNSGA-EdNet.

Category	Hyperparameter	Value / Range
Neural Network	Input Dimension	25
	Hidden Layer Sizes	[64, 32]
	Output Layer	1 (Binary classification)
	Activation Function	ReLU (hidden layers), Sigmoid (output)
	Dropout Rate	0.3
	Batch Size	64
	Learning Rate	0.001
	Optimizer	Adam
	Epochs per Individual	10
	Attention Heads	4 (search range: 2-8)
	Loss Function	Binary Cross-Entropy
NSGA-II	Population Size (N)	50
	Generations (G)	100
	Crossover Probability (Pc)	0.9
	Mutation Probability (Pm)	0.1
	Selection Method	Binary Tournament
	Crossover Type	Two-point crossover
	Mutation Strategy	Random Gaussian / layer structure-based
	Elitism	Yes
Objective Functions	f1: Accuracy	Target > 85%
	f2: Model Complexity	Target < 500,000 parameters
	f3: Loss	Target < 0.3

BiLSTM, and BiLSTM + Trim CNN + Max Pooling. Results show a weak correlation between study hours and outcomes, highlighting the need for personalised MH education using neural networks and big data analytics in Fig. 6.

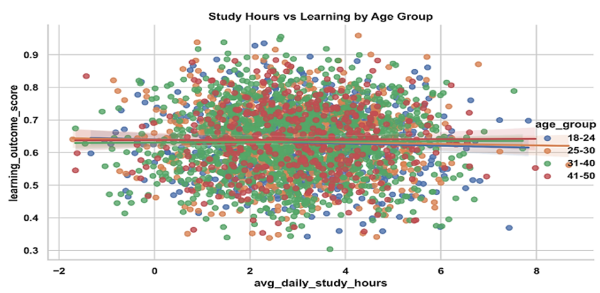

Fig. 6. Study Time Influence Across Age in Personalised Framework.

4.1. Performance Metric

The experiments were conducted in Python by making use of standard deep learning libraries available on a GPU-enabled machine. The random seeds were fixed to guarantee consistency of results. The training configuration and hyperparameters, including the Adam optimizer, learning rate (0.001), batch size (64), and 10 training epochs per individual, are detailed in Table 2 to ensure experimental transparency and reproducibility. Model performance is evaluated using Accuracy, Precision, Recall, and F1-score for a comprehensive assessment of classification effectiveness. The dataset includes samples representing both students and professionals to maintain a diverse and realistic evaluation. The dataset is divided into training (70%), validation (15%), and testing (15%) sets to establish unbiased evaluation and model generalisation.

The proposed NeuroNSGA-EdNet achieves 98.4% accuracy, 86.1% precision, 89.4% recall, and 91.6% F1-score, demonstrating strong and consistent performance. The proposed model is compared with both traditional (C4.5) and deep learning (BiLSTM-based) approaches to demonstrate its effectiveness. The selected baseline models include traditional, deep learning, transformer-based, and recent advanced approaches for better comparative evaluation in mental health prediction tasks. Accuracy measures correctness, precision reflects reliability, recall shows detection ability, and F1-score balances both; C4.5, Bi-LSTM (T), and Bi-LSTM + Trim CNN + MAX achieve 97.3%, 88.4%, and 90.6% accuracy, while NeuroNSGA-EdNet attains best performance at 98.4%, as shown in Table 3.

The proposed framework of NeuroNSGA-EdNet applies splitting into training, validation, and testing phases with model selection based on validation. Regularisation approaches and selective training improve generalisation performance. The reliability of the model performance was validated through repeated experiments for robustness and consistency of results. The attention weights make for an interpretable solution, showing which behavioural and emotional indicators are used to make predictions, thereby making the model not only accurate but also interpretable.

4.2. Discussion

A neural network and big data framework improve MH education, while NeuroNSGA-EdNet uses neural attention and NSGA-II for adaptive personalized MH education. The NeuroNSGA-EdNet model can facilitate the detection of mental health risks early on as well as provide personalised education interventions in educational settings, which can enhance learner engagement and mental well-being. Users reported higher satisfaction with personalised learning paths compared to static educational modules, highlighting the effectiveness of adaptive learning in improving engagement and educational outcomes. However, the effectiveness of the model relies on the availability of quality-labelled data and may

Table 3. Comparative Evaluation of MH Education Models Using Performance Metric.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
C4.5 [8]	97.3%	81.6%	63.8%	72.2%
Bi-LSTM (T) [15]	88.4%	-	88.1%	88.2%
Bi-LSTM + Trim CNN + MAX (T+V) [15]	90.6%	-	87.7%	89.1%
Transformer-based MH Model (SOTA baseline) [13]	97.8%	85.0%	88.9%	91.0%
NeuroNSGA-EdNet	98.4%	86.1%	89.4%	91.6%

be hindered by several factors during its practical implementation.

5. Conclusion

A personalized MH education framework combining neural networks and big data analysis has been proposed to deliver adaptive learning experiences, enhance mental health literacy, and support individualised content recommendations. Preprocessed MH Education data (Z-score, tokenization, missing values) enabled NeuroNSGA-EdNet (ConvLSTM + attention + NSGA-II) to achieve 98.4% accuracy, with limits in privacy, transparency, and data quality.

Acknowledgment

The author expresses sincere gratitude to Zhengzhou University of Aeronautics for academic and institutional support, and thanks colleagues and peers for their valuable insights.

Declaration

Code Availability

Not applicable

Data Availability

Not applicable

Funding

Not applicable

Conflict of interest

Not applicable

Authors Contribution

Cheng Xing designed the framework, analyzed and validated results, wrote the article, collected data, provided software support, reviewed the work, and managed the process.

Ethical Approval

This article does not contain any studies involving human participants or animals performed by any of the authors.

Consent to Participate

Not applicable

Consent to Publication

All authors have provided consent for publication of this manuscript.

Competing Interests

The authors declare no competing interests

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