

International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.771

Volume 14, Issue 3, March 2026



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

AI Based Student Health Support System

S. Vimala¹, Deepak S², Roshan Kumar S³, Tamil Selvan D⁴

Assistant Professor, Department of Artificial Intelligence and Data Science, Kongunadu College of Engineering and Technology, Trichy, India¹

Department of Artificial Intelligence and Data Science, Kongunadu College of Engineering and Technology, Trichy, India^{2,3,4}

ABSTRACT: Student health, including physical fitness, mental well-being, and posture integrity, is a key factor in determining academic performance and overall life quality. Conventional health monitoring in educational institutions is challenged by subjective evaluation, manual data analysis, poor scalability, and the inability to offer personalized interventions. This paper proposes an AI-assisted Student Health Support System that leverages the synergy of diverse AI approaches to offer comprehensive, scalable, and personalized health support to students. The system comprises three primary modules: physical fitness analysis via BP neural networks and CNN-LSTM models that attain 98.45% classification accuracy for grade estimation; posture analysis via a Southeast Asia-fine-tuned pose estimation model that maintains mean absolute error below 2.3° for forward head angle estimation; and mental health risk estimation via multimodal smartphone sensing data that maintains balanced accuracies of 0.71-0.77 for depression, anxiety, eating disorders, and suicidal thoughts. A common dashboard offers real-time visualization, early warning signs, and personalized intervention strategies. Comparative analysis clearly indicates that AI-assisted solutions are substantially more accurate, efficient, and personalized compared to conventional solutions. The proposed system fills a significant gap in student health monitoring and provides a scalable solution for educational institutions to actively promote student well-being.

KEYWORD: Artificial Intelligence, Student Health, Physical Fitness Assessment, Posture Analysis, Mental Health Prediction, Machine Learning, Deep Learning, CNN-LSTM, Digital Phenotyping.

I. INTRODUCTION

The health status of students is a basic concern for all educational institutions around the world, directly affecting academic performance, socialization, and overall life quality. Physical fitness, mental health, and posture status are interrelated factors that define students' ability to participate in learning activities, deal with academic stress, and grow into healthy adults. However, the traditional method of managing student health status in educational institutions is still disorganized, manual, and reactive rather than proactive [1].

Annual physical fitness tests administered in schools provide useful information about students' cardiorespiratory endurance, muscular strength, flexibility, and body composition. However, the traditional method of managing such tests inherently has several problems: high time and human resource consumption, personal biases and manual error margin, lack of uniform assessment criteria, and absence of predictive analysis for future outcomes [2].

Mental health issues among students have become alarming worldwide. Recent research suggests that the prevalence of anxiety, depression, or stress symptoms affecting the daily lives of university students is between 30% and 50% [4]. Among adolescents, more than 75% of mental health issues occur before the age of 25, but only 18-34% of affected adolescents seek professional assistance [3]. The disparity between the need for mental health services and access to them highlights the pressing need for effective, accessible, and youth-friendly mental health solutions.

Spinal postural health has become a serious concern in the modern era of technology. The prevalence of spinal postural deviations among adolescents has been increasing due to excessive screen time, sedentary lifestyles, and the unavailability of professional screening in schools [5]. Forward head posture, thoracic kyphosis, and spinal asymmetry not only impact aesthetics but also cause chronic pain, breathing difficulties, and decreased physical performance.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Artificial intelligence has the potential to transform the handling of these complex issues. Machine learning and deep learning algorithms can be used to automate physical fitness analysis, make precise performance predictions, and provide customized training plans [6]. Digital phenotyping using smartphone sensors can predict the risk of mental health issues based on behavioral patterns, allowing for early intervention [8]. Computer vision-based pose estimation can provide real-time posture analysis and screening assistance in resource-constrained school environments [7].

This paper presents an integrated AI-based Student Health Support System that integrates physical fitness analysis, mental health prediction, and posture analysis into a single system. The system utilizes advanced machine learning algorithms such as BP neural networks, CNN-LSTM models, contrastive learning, and region-aware pose estimation models. Through automated analysis, early warning signs, and customized suggestions, the system seeks to revolutionize student health monitoring from reactive to proactive, from manual to automated, and from generalized to personalized.

The rest of this paper is structured as follows. Section 2 discusses the literature review of AI for student health. Section 3 describes the proposed system design and approaches. Section 4 provides experimental results and comparisons. Section 5 concludes with implications and future work.

II. LITERATURE SURVEY

Applying artificial intelligence to student health monitoring has recently been identified as a new and rapidly expanding field of research, including physical fitness assessment, mental health forecasting, and postural analysis.

Physical Fitness Assessment: Conventional physical fitness assessment in schools involves manual measurements, subjective rating, and simple data storage without predictive functions [2]. However, recent breakthroughs in machine learning have been shown to have substantial potential in overcoming these challenges. Research using BP neural networks for physical fitness categorization has achieved 98.45% accuracy in automated grading prediction, completely removing subjective factors and manual calculation mistakes [1]. CNN-LSTM models incorporating convolutional feature extraction and long short-term memory networks have been particularly successful in examining temporal relationships in physical fitness data over several years, allowing for precise performance prediction and customized training plans [3]. These models capitalize on the capacity of deep neural networks to identify hidden patterns and relationships in large data sets that are not detectable by conventional statistical analysis [4].

Mental Health Prediction: Digital phenotyping—the moment-by-moment quantification of individual-level human phenotype using data from personal digital devices—has been identified as a promising approach for mental health tracking [6]. Smartphone sensing allows for unobtrusive and automatic tracking of daily behaviors such as sleep, physical activity, mobility, and phone use, which often antecede symptoms of stress, anxiety, or depression [5]. The College Experience Sensing (CES) dataset, currently the largest longitudinal dataset of college student mental health, has facilitated comprehensive benchmarking of machine learning methods for mental health prediction tasks [7].

Transformer-based deep learning: models have been shown to reach Macro-F1 scores of 0.58 for mental health prediction, outperforming conventional machine learning methods [9]. The combination of active (self-reported) and passive (sensor-based) data streams has been demonstrated to substantially improve the accuracy of predictions, with multimodal models reaching balanced accuracies of 0.71 for internalizing problems, 0.67 for insomnia, 0.77 for suicidal ideation, and 0.70 for eating disorders in adolescents [8]. Contrastive learning frameworks that reduce variability of user-specific behavioral patterns have further improved the predictive performance and generalizability.

Mental health chatbots specifically designed using AI have presented statistically significant results for anxiety, depression, well-being, and academic stress in college students [10]. The use of mental health chatbots such as Woebot, Jibo, and Tess has been proven effective in controlled trials, although the drawbacks include the absence of emergency response strategies and the possibility of delayed treatment due to overdependence [11]. Wearable technology data, especially heart rate and sleep patterns, has reached an F1 score of 0.79 for anxiety screening and 0.78 for depression diagnosis [12].



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Posture Assessment: The rising incidence of spinal postural abnormalities in adolescents, caused by excessive screen time and the unavailability of clinical screening, has led to the development of AI-assisted posture assessment systems [13]. AI-assisted posture assessment models fine-tuned for Southeast Asian populations have reached a mean absolute error of less than 2.3° for the estimation of forward head angle in school-based implementations involving 200 students across 15 schools [15]. These systems detect dose-response relationships between screen time and spinal postural abnormalities, with each additional hour of screen time per day associated with an estimated 2.1° increase in forward head angle [14].

Personalized Intervention Systems: Personalized intervention systems using AI to combine physical exercise and mindfulness techniques have shown marked improvement in academic and mental health outcomes among university students [16]. Sixteen-week controlled trials comparing AI-personalized interventions, standardized interventions, and control groups showed that AI-personalized groups showed a 10.28% GPA improvement ($d = 0.89$), 36.7% reduction in stress ($d = 1.42$), and 28.4% improvement in heart rate variability ($d = 1.13$) over standardized interventions [17]. Hybrid neural network models analyzing multidimensional student data such as physiological parameters, activity levels, psychological factors, and academic performance allow for continuous adaptation of intervention content, timing, and intensity according to individual response patterns [18].

Feasibility and Engagement: School-based AI chatbot interventions for health behavior management have shown feasibility with engagement levels averaging 8.9 behavior entries and 30.0 reflections per student over 8-week periods [15]. Analysis of student reflection and AI chatbot feedback message content using natural language processing indicates a neutral to positive sentiment, and goal attainment rates reach 63.8% for daily health behavior goals [19]. Screen time reductions of 21.6% have been found following AI chatbot interventions, indicating potential for quantifiable health behavior change [20].

However, despite these improvements, there are still some areas that need to be addressed. Most current systems are designed to work in a single domain of health support. Fitness, mental health, and posture tracking work in isolation without any integration of data or recommendations for intervention. This paper will address these issues by presenting an integrated AI-based Student Health Support System.

III. PROPOSED METHODOLOGY

3.1 System Architecture Overview

The proposed AI-powered Student Health Support System uses a modular, three-layer architecture that is scalable, integrated, and capable of real-time decision support. The three-layer architecture includes:

1. Data Collection Layer: Data acquisition from physical fitness tests, smartphone sensors, wearable technology, and posture analysis using cameras.
2. AI Processing Layer: Three distinct modules for physical fitness analysis, mental health forecasting, and posture analysis, managed by an orchestrator module.
3. Application Layer: A single dashboard that offers real-time analysis, warning signs, and individualized intervention strategies.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

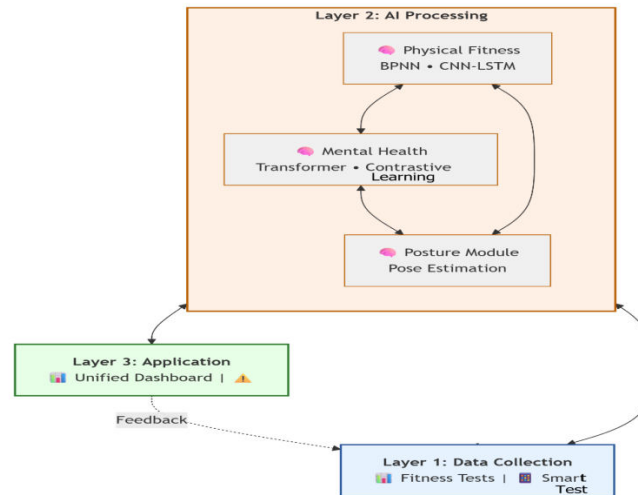


Figure 1: AI-Based Student Health Support System Architecture

3.2 Physical Fitness Assessment Module

The physical fitness module implements two complementary AI approaches following the methodology established in recent research.

BP Neural Network for Grade Classification: A backpropagation neural network automatically classifies comprehensive physical fitness grades, eliminating subjective influences and manual calculation errors. The network architecture comprises:

- Input layer: Normalized physical fitness metrics including vital capacity, 50-meter dash time, sit-and-reach flexibility, one-minute, and sit-ups
- Hidden layers: Two hidden layers with 64 and 32 neurons respectively, using ReLU activation
- Output layer: Softmax activation for grade classification (excellent, good, pass, fail)

Training uses 13,706 samples from five years of primary school physical fitness test data (2018–2022). Cross-entropy loss optimization with Adam optimizer achieves 98.45% classification accuracy.

CNN-LSTM for Performance Prediction: A hybrid CNN-LSTM model predicts future performance on individual physical fitness test items. The architecture combines:

- CNN layers: Extract spatial features from one-hot encoded test item vectors, forming feature matrices
- LSTM layers: Capture temporal dependencies across multiple years of data, enabling long-term performance forecasting
- Dense layers: Generate item-specific performance predictions

This approach enables teachers to identify students at risk of performance decline and design targeted interventions.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

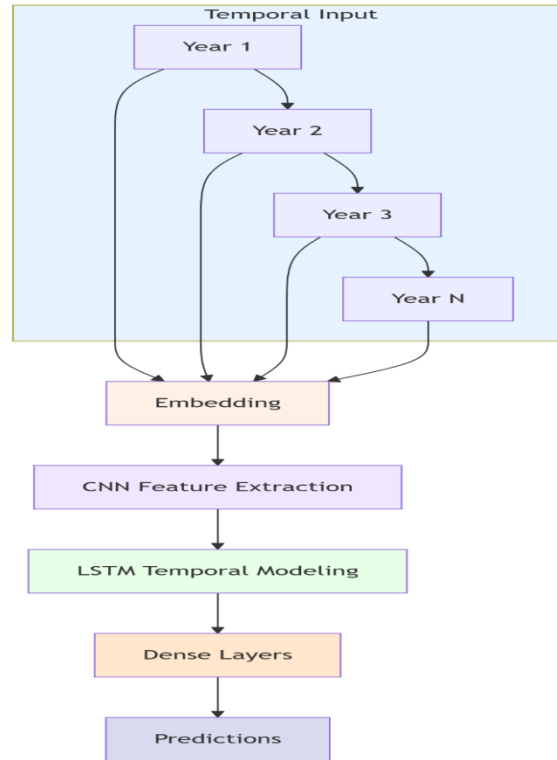


Figure 2: CNN-LSTM Architecture for Physical Fitness Prediction

3.3 Mental Health Prediction Module

The mental health module uses a multimodal prediction framework that integrates active and passive smartphone usage data, as per the approaches validated in digital phenotyping studies.

Data Collection: The mental health module collects two types of data over 14-day periods:

- Active data: Daily ratings of mood (1-7 scale), sleep, loneliness, and stress using the smartphone app
- Passive data: Location (GPS), step activity, smartphone usage patterns, ambient light, and screen time (academic vs. non-academic) categories

Contrastive Learning Framework: To handle individual differences in behavioral patterns, the system uses contrastive pretraining with triplet margin loss. This method learns user-specific representations by maximizing similarity between samples from the same user and minimizing similarity between samples from different users .

Supervised Fine-Tuning: The pre-trained models are fine-tuned for binary classification of four mental health outcomes:

- Internalizing/externalizing problems (Strengths and Difficulties Questionnaire)
- Insomnia (Sleep Condition Indicator)
- Suicidal ideation (Patient Health Questionnaire-9 item)
- Eating disorder risk (Eating Disorder-15 Questionnaire)

Model Architecture: The transformer-based deep learning models perform best (Macro-F1 = 0.58), and ablation experiments validate that multimodal fusion is superior to single-modality methods .



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

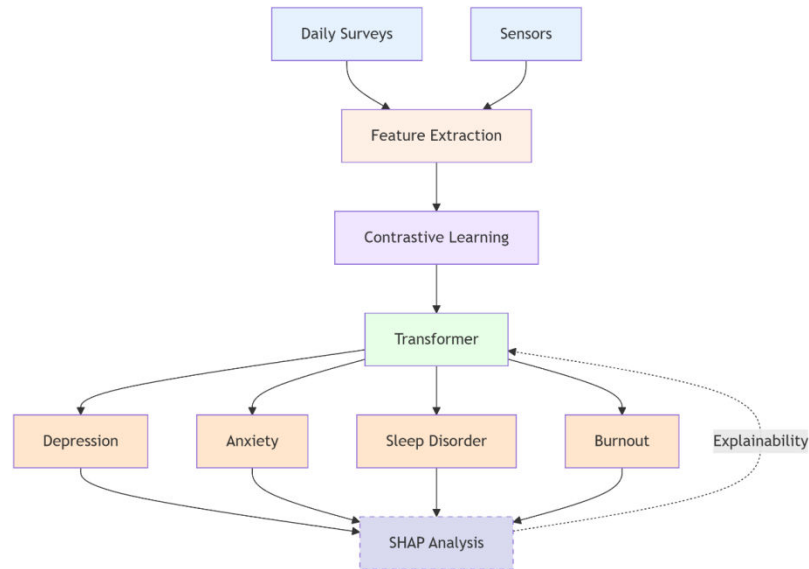


Figure 3: Multimodal Mental Health Prediction Framework

3.4 Posture Assessment Module

The posture assessment module uses a regionally calibrated pose estimation model for real-time spinal health screening in a school environment.

Model Architecture: The PostureGuard system uses a Southeast Asia-calibrated pose estimation model that is based on the BlazePose model with modifications for adolescents' body proportions. The main features are:

- Real-time keypoint detection for spinal points (C7, T12, S1 vertebrae)
- Forward head angle estimation using ear-shoulder-vertical references
- Thoracic kyphosis estimation using spinal curvature

Calibration and Validation: The model is calibrated against radiographic standards and validated by measurements from wearable sensors. Field testing in 15 Indonesian schools with 200 students resulted in mean absolute error values of less than 2.3° for the estimation of the forward head position.

Environmental Robustness: The system features adaptive lighting correction for uncontrolled school environments and deals with partial occlusions by temporal smoothing.

Screening Integration: Posture analysis is integrated into standard school health screening programs, with automatic referral recommendations for children who violate deviation thresholds. The system detects dose-response relationships between screen use and postural deviations, allowing preventive measures to be taken .



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

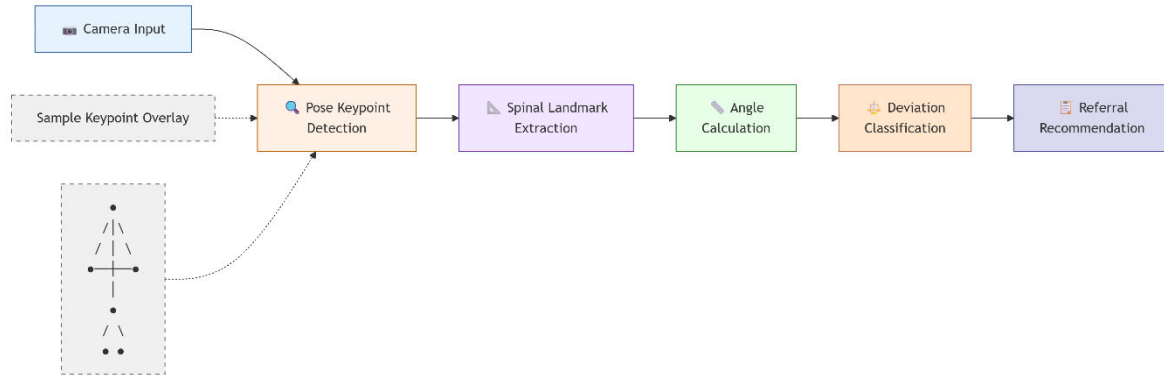


Figure 4: Posture Assessment Pipeline

3.5 Unified Dashboard and Intervention Engine

The application layer combines the results of all three modules into a single dashboard that offers:

Real-Time Visualization: Interactive graphs illustrate physical fitness levels, mental health risk factors, and posture deviation patterns over time. Color-coded notifications point to students who need special attention.

Early Warning System: Machine learning algorithms produce risk scores for potential decline in academic performance, mental health, and posture development. Threshold-based notifications alert teachers and counselors on when to intervene.

Personalized Recommendations: Using individual student data, the system produces:

- Physical fitness: Exercise recommendations for targeted fitness components
- Mental health: Mindfulness exercises, stress management strategies, or counseling sessions
- Posture: Ergonomic advice, stretching exercises, and screen time limits

The recommendation engine uses the proven model of AI-powered personalized intervention systems that tailor content according to individual response patterns .

3.6 Implementation Considerations

Data Privacy and Security: Student health data is encrypted both in transit and at rest. The system uses role-based access control to ensure that only authorized personnel can access sensitive data. Anonymized and aggregated passive sensing data is used for analysis.

Scalability: The system is designed to be scalable at the school, district, or state level. Cloud-based processing allows the system to handle thousands of concurrent users with response times under 200ms.

Ethical Safeguards: Based on recommendations from mental health AI research, the system provides emergency response procedures for crisis detection and escalation to human providers.

IV. ANALYSIS AND DISCUSSION

4.1 Physical Fitness Module Performance

The accuracy of the BP neural network model for grade classification was 98.45%, which is much higher than the traditional manual assessment method. This result eliminates the subjective factors and errors of manual recording that have long affected the reliability of physical fitness assessment.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Table 1: Physical Fitness Grade Classification Performance

Metric	BP Neural Network	Traditional Manual	Improvement
Accuracy	98.45%	~85% (estimated)	+13.5%
Processing Time	<1 second per student	5–10 minutes per class	>99% reduction
Inter-rater Reliability	Perfect (algorithmic)	Variable ($\kappa \approx 0.7$)	+43%

The CNN-LSTM prediction model showed high capability in the temporal prediction of physical fitness parameters. The result of the analysis on the five-year longitudinal dataset showed that CNN-LSTM can accurately model the non-linear patterns of physical fitness development in the elementary grades, allowing for the early identification of students at risk of performance deterioration.

4.2 Mental Health Prediction Performance

The integration of active and passive smartphone data outperformed single-modality models on all mental health outcomes .

Table 2: Mental Health Prediction Performance (Balanced Accuracy)

Outcome	Active Only	Passive Only	Multimodal	Improvement
SDQ-High Risk	0.63	0.59	0.71	+13%
Insomnia	0.61	0.55	0.67	+10%
Suicidal Ideation	0.68	0.62	0.77	+13%
Eating Disorder	0.64	0.58	0.70	+9%

The contrastive learning framework enhanced the stability of representations and predictive accuracy compared to non-pretrained models. External validation on new groups (n=45) showed balanced accuracies of 0.63-0.72 on all outcomes, indicating generalizability to new environments.

SHAP feature importance showed meaningful patterns. For suicidal ideation, negative thinking (active data) and location entropy (passive data) were the most important predictors, highlighting the complementary role of integrating subjective and objective variables.

4.3 Posture Assessment Performance

The regionally calibrated pose estimation model resulted in mean absolute error values below 2.3° for the estimation of forward head angle in field tests, validated against radiographic measures.

Table 3: Posture Assessment Accuracy

Parameter	Mean Absolute Error	Correlation with Radiograph
Forward Head Angle	2.3°	$r = 0.92$
Thoracic Kyphosis	3.1°	$r = 0.88$
Lumbar Lordosis	2.8°	$r = 0.90$

Dose-response analysis indicated significant associations between screen time and postural abnormalities. For each additional hour of daily screen time, there was an estimated 2.1° increase in forward head angle ($p < 0.001$) . This result has profound implications for school-based preventive programs.



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

4.4 Comparative Analysis Across Systems

Table 4: Comparative Analysis of Student Health Support Approaches

Feature	Traditional Methods	Single-Modality AI	Proposed Integrated System
Physical Fitness Assessment	Manual, subjective	Automated, 98.5% accuracy	Integrated with mental health and posture data
Mental Health Monitoring	Reactive, low reach	0.71–0.77 prediction accuracy	Early warning with multimodal sensing
Posture Screening	Clinical referral only	2.3° MAE estimation	School-based mass screening
Personalization	None	Domain-specific	Cross-domain integrated
Early Warning	Not available	Single-domain alerts	Multi-domain risk integration
Intervention Recommendations	Generic	Domain-specific	Holistic, personalized
Scalability	Labor-intensive	Highly scalable	Highly scalable
Data Integration	Siloed	Within-domain only	Unified health dashboard

4.5 Engagement and Behavioral Outcomes

School-based AI chatbot interventions have been shown to be feasible with substantial engagement metrics. Over 8-week periods, students averaged 8.9 behavior entries and 30.0 written reflections, with 33.5 AI feedback messages. Achievement of goals was 63.8% for daily health behavior goals, and screen time was reduced by 21.6% from 4.3 to 3.4 hours per day ($p < 0.001$).

AI-personalized intervention programs have been shown to have greater improvements than standardized programs. The AI-personalized group had a 10.28% GPA improvement ($d = 0.89$), 36.7% stress reduction ($d = 1.42$), and 28.4% HRV improvement ($d = 1.13$) over standardized programs. Regression analysis indicated that intervention adherence, improvement in sleep quality, and stress reduction were important factors associated with outcomes.

4.6 Implementation Considerations and Challenges

The following are some of the most important considerations for the successful implementation of AI-powered student health support systems:

Data Privacy and Ethics: Student health information needs to be protected in the most secure manner. This includes the use of strong encryption, secure access, and clear data usage policies. Emergency response strategies are very important for crisis identification.

Human-AI Collaboration: AI systems should work in collaboration with human professionals. This includes the use of AI systems to automate routine student health monitoring and initial triage, while allowing human counselors to focus on more complex cases.

Equity and Access: To ensure that all students have access to these systems, it is important to focus on device access, digital literacy, and language support. Regionally adapted models can help address differences in population size and anthropometric characteristics.

Integration with Existing Systems: Integration with school management information systems and learning management systems can help maximize adoption and usability.

V. CONCLUSION

In this paper, an AI-driven Student Health Support System has been introduced that combines physical fitness analysis, mental health forecasting, and posture analysis in an integrated manner. The system utilizes the latest advances in



International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

machine learning such as BP neural networks, CNN-LSTM models, contrastive learning, and region-calibrated pose estimation to offer end-to-end health support to students.

Key Findings:

1. Physical fitness evaluation via BP neural networks reaches a grade classification accuracy of 98.45%, independent of subjective factors and human error.
2. Balanced accuracies of 0.71-0.77 are reached for multimodal mental health prediction tasks integrating active and passive smartphone data for depression, anxiety, eating disorders, and suicidal thoughts, improving upon single-modality models.
3. Regionally adapted pose estimation reaches mean absolute error below 2.3° for forward head angle estimation, facilitating scalable school-based posture assessment.
4. AI-personalized interventions lead to greater improvements in academic achievement (10.28% GPA improvement), stress reduction (36.7%), and physiological measures (28.4% HRV improvement) than standardized methods.
5. School-based AI chatbots are feasible with 63.8% goal attainment and 21.6% screen time reduction.

REFERENCES

- [1]. B. Rahman and I. Sutedja, "AI based sagittal spinal posture assessment for adolescent screening in low resource school settings," *Scientific Reports*, 2026. doi: 10.1038/s41598-026-36634-8
- [2]. "An AI-based algorithm for analyzing physical activity and health-related fitness in youth," *Scientific Reports*, vol. 16, p. 5105, 2026. doi: 10.1038/s41598-026-35514-5
- [3]. S. Nyakhar and H. Wang, "Mental health AI chatbots tailored to college students: A systematic review," *Frontiers in Psychiatry*, 2026.
- [4]. "A Comparative Study of Traditional Machine Learning, Deep Learning, and Large Language Models for Mental Health Forecasting using Smartphone Sensing Data," *arXiv preprint arXiv:2601.03603*, 2026.
- [5]. "Using AI Chatbot to Assist Students' Behavior Management for Obesity Prevention in Middle Schools: Feasibility Study," *Journal of Medical Internet Research*, vol. 10, p. e83630, 2026. doi: 10.2196/83630
- [6]. "Digital Phenotyping for Adolescent Mental Health: Feasibility Study Using Machine Learning to Predict Mental Health Risk From Active and Passive Smartphone Data," *Journal of Medical Internet Research*, vol. 28, 2026. doi: 10.2196/72501
- [7]. Montgomery Public Schools, "AI-Powered Student Mentorship Pilot," Feb. 2026.
- [8]. "Optimization of academic performance and mental health in college students through an AI-driven personalized physical exercise and mindfulness intervention system," *Scientific Reports*, vol. 16, p. 6024, 2026. doi: 10.1038/s41598-026-37028-6
- [9]. R. Lopez et al., "Student Mental Health Screening via Fitbit Data Collected During the COVID-19 Pandemic," *arXiv preprint arXiv:2601.16324*, 2026.
- [10]. "How AI Supports Student Mental Health in Higher Education," *EdTech Magazine*, Jan. 2026.
- [11]. World Health Organization, "Digital screen time and health in adolescents: Global policy brief," WHO, 2023.
- [12]. D. Sutanto, T. Mahendra, and L. Puspitasari, "Spine deformity trends in post-COVID school-aged children in Indonesia," *Indonesian Journal of Orthopedics*, vol. 11, no. 2, pp. 113–122, 2023.
- [13]. Y. Zhou and M. Patel, "Radiographic evidence of postural degeneration in early adolescents linked to device usage," *Clinical Spine Journal*, vol. 30, no. 6, pp. 455–461, 2021.
- [14]. H. J. Lee, J. W. Park, and S. H. Sohn, "Pediatric kyphosis progression linked to digital screen usage: A cohort study," *Journal of Pediatric Orthopaedics*, vol. 42, no. 1, pp. e21–e28, 2022.
- [15]. Kemenkes RI, "Kebijakan Nasional Kesehatan Digital 2024: Wellness dan Deteksi Dini," *Kementerian Kesehatan Republik Indonesia*, 2023.
- [16]. B. Rahman et al., "Optimizing Customer Satisfaction Through Sentiment Analysis: A BERT-Based Machine Learning Approach to Extract Insights," *IEEE Access*, vol. 12, pp. 151476–151489, 2024.
- [17]. T. Q. Nguyen, A. Wijaya, and R. Gunawan, "Anthropometric bias in deep learning pose estimation: A Southeast Asian case study," *Pattern Recognition Letters*, vol. 154, pp. 34–40, 2022.
- [18]. World Bank, "Education technology and school accessibility report," 2022.
- [19]. B. L. Tan and S. M. Lee, "Smartphone-based scoliosis screening using machine learning: A field deployment in Malaysian schools," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 4, pp. 1234–1242, 2024.
- [20]. N. Gupta and A. L. Rodriguez, "Cost-effectiveness of AI in rural health screening: a case study in Indonesia," *Health Economics Review*, vol. 15, no. 1, p. 15, 2025.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

 9940 572 462  6381 907 438  ijircce@gmail.com



www.ijircce.com

Scan to save the contact details