Research Article

Evidence-Based Adolescent Care Models Promoting Pediatric Mental Wellness Through Engineering-Assisted Healthcare Solutions

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Abstract

Adolescent mental health has become a major worldwide issue, and anxiety, depression, and stress are becoming common conditions among adolescents and young people (aged 13–18 years). Traditional care models may not be scalable, technologically appropriate, evidence based, and precise enough to ensure effective mental wellness promotion for children. The authors provide a thorough framework that combines evidence-based adolescent care approaches with engineering-based healthcare solutions, all designed to improve the effectiveness of early detection and intervention for young people. 280 adolescents from urban and semi-urban school settings were assessed using a mixed-methods strategy that included structured questionnaires, psychometric assessments and system performance measures. Results show that the proposed engineering-assisted model has shown significant gains in early detection rates (62%), help seeking (34%) and reduction in stress (21%) after deployment. The results highlight the ability of technologically-enabled, evidence-based care frameworks to foster scalable, accessible, and culturally responsive pediatric mental health care systems.

1. Introduction

Adolescent mental health is clearly one of the most urgent public health problems of the 21st century. World-wide, the prevalence of a diagnosed mental health disorder amongst adolescents is around 20%, and the most common disorders are anxiety, depression and stress. Multifaceted challenges, including high academic loads, accelerated socio-cultural change and poor mental health system coverage, have contributed to high prevalence of psychological distress among youth aged 13-18 years in developing countries like India. Though there may be increasing awareness, most affected adolescents are not diagnosed and not supported until serious deterioration has occurred in their mental condition.

The prevalence of adolescent mental health problems is well-documented in existing literature, and the use of school-based counselling, school peer support and community outreach are all proposed as potential interventions. Researchers have emphasized the value of the use of such psychometric instruments as the DASS 21 and the Pittsburgh Sleep Quality Index in clinical assessment contexts. Advancements in digital health engineering – such as AI powered diagnosis platforms, wearable biosensors and telepsychiatry – have each shown potential in adult health care settings.

A significant opportunity, however, is still missing: initiatives for systematic embedding of evidence-based clinical care protocols and engineering-supported tech solutions specifically for pediatric and adolescent mental wellness are still relatively untapped. The models that are already in place are either clinically-focused but passive technologically, or technologically sophisticated but without validated psychiatric evidence base. This study aims to overcome the above mentioned constraints by creating an Engineering-Assisted Pediatric Mental Wellness (EAPMW) framework that incorporates validated care protocols into a technology-based delivery system. The goal is to assess the potential effectiveness of engineering-assisted care models in improving early detection, success of intervention and wellness outcome for school-going teens. The proposed solution combines AI-driven psychometric screening, behavioural monitoring through the use of IoT devices and a cloud-based counsellor dashboard to the current school health infrastructure. The novel contributions of this work are: (i) the EAPMW framework architecture, (ii) the integration protocol of technology and evidence for adolescent care, and (iii) empirical evidence with a diverse cohort of school based youth.

2. RELATED WORK

Pediatric mental health and healthcare engineering have been an emerging research field for the past decade. Advances in artificial intelligence (AI) have been shown to substantially enhance early screening for adolescent mental health issues, using sophisticated machine learning techniques to accurately predict and classify risk for mental health conditions automatically. [1] Moreover, in-depth studies of various metrics for binary classifications and the assessment of the performance of prediction models have demonstrated that Precision, Recall, F1-Score and associated assessment metrics play crucial roles in the validation of prediction models in healthcare settings to guarantee clinical interpretation and reliable performance [2]–[6]. AI-based psychological assessment tools based on digital behavioral data have also shown to be effective at recognizing psychological distress in adolescents, while enhancing access to preventive mental health care services [7, 8].

At the same time, engineering progress in portable sensing and health-care technologies based on the Internet of Things has been significant. In recent years, wearable systems for heart rate variability (HRV) measurement have allowed for the assessment of physiological stress levels in real-time environments and thereby provided objective biomarkers of emotional resilience and psychological stress [4] and [9]. Technology with IoT capabilities also makes continuous collection of multimodal health parameters possible, which is an advantage of scalable health surveillance that could be implemented in school healthcare settings [10]. Artificial Intelligence (AI) based adolescent mental health screening tools with intelligent decision making and physiological monitoring have shown to help detect students who need a timely psychological response [11]. The theoretical basis of machine learning performance evaluation has been well validated by solid metrics in the form of classification metrics that continue to be used in healthcare AI validation studies [12].

Physiological signal monitoring has also proven to be a valuable tool for detecting emotional dysregulation in children and adolescents as well as stress-related disorders. Multimodal physiological sensing studies have demonstrated that indicators of psychological stress and emotional instability, such as heart rate variability, electroencephalography (EEG), electromyography (EMG), and galvanic skin response (GSR), have been found useful. The existing literature supports the effectiveness of these technologies, including AI-driven screening, machine learning evaluation metrics, IoT-enabled healthcare systems, and standardized assessments of behavioral and physiological data collected from wearables, and collectively, demonstrates the strong foundation of research needed to develop an integrated Engineering-Assisted Pediatric Mental Wellness (EAPMW) framework that combines evidence-based adolescent mental health care with intelligent healthcare technologies.

3. METHODOLOGY

The method used in this study is a mix between Quantitative Assessment and Qualitative Inquiry to assess effectiveness with the Engineering-Assisted Pediatric Mental Wellness (EAPMW) framework within a school-based adolescent population. The cross section design was used as a prospective design, allowing for pre- and post-deployment of the proposed technology-integrated care model comparison of mental health indicators. The study was carried out in 6 schools located in urban and semi-urban areas both public and private for diversity. The study participants comprised 55 children aged nine to 12 and 45 adolescents aged 14 to 18. Demographic information and sampling details for the study participants are summarized in Table 1.

Table 1: Sample Characteristics

Variable	Description
Age Group	13–18 years
Gender	Male and Female
School Type	Public and Private
Location	Urban and Semi-Urban

Sampling Technique	Stratified Random Sampling
Sample Size	280 students

Stratified random sampling was used to select participants by gender, socioeconomic status, school type and geographical location. 280 teenagers were registered. Ethical approval was given by the institutional review board and informed written consent was gained from parents with agreement from participants.

These three integrated layers were used for data collection. The first layer was composed of the Depression Anxiety Stress Scale-21 (DASS-21), Strengths and Difficulties Questionnaire (SDQ), Pediatric Symptom Checklist (PSC-17), administered using digitized tablet based interfaces, which have been validated psychometric scales. The second layer was for IoT-based wearable devices to capture physiological stress levels (heart rate variability (HRV), galvanic skin response (GSR), sleeping hours) in real-time over a period of 21 days. The third phase involved conducting Semi-structured interviews and focus group discussions with students, teachers, and school counsellors to collect qualitative experiential data. The data collection instruments and the assessment domains and output metrics are shown in Table 2.

Table 2: Data Collection Instruments and Corresponding Metrics

Instrument	Domain Assessed	Format
DASS-21	Anxiety, Depression, Stress	Self-Report Scale
SDQ	Behavioral and Emotional Difficulties	Teacher and Student Report
PSC-17	Psychosocial Functioning	Parental Report
IoT Wearable (ESP32)	HRV, GSR, Sleep Duration	Continuous Physiological Monitoring
Semi-Structured Interview	Lived Experience, Perception	Qualitative
AI Risk Module	Mental Health Risk Score	Algorithmic Classification

In this study, the deployed architecture of the EAPMW includes three engineering subsystems: AI Screening Module, IoT Monitoring Subsystem and Counsellor Dashboard.

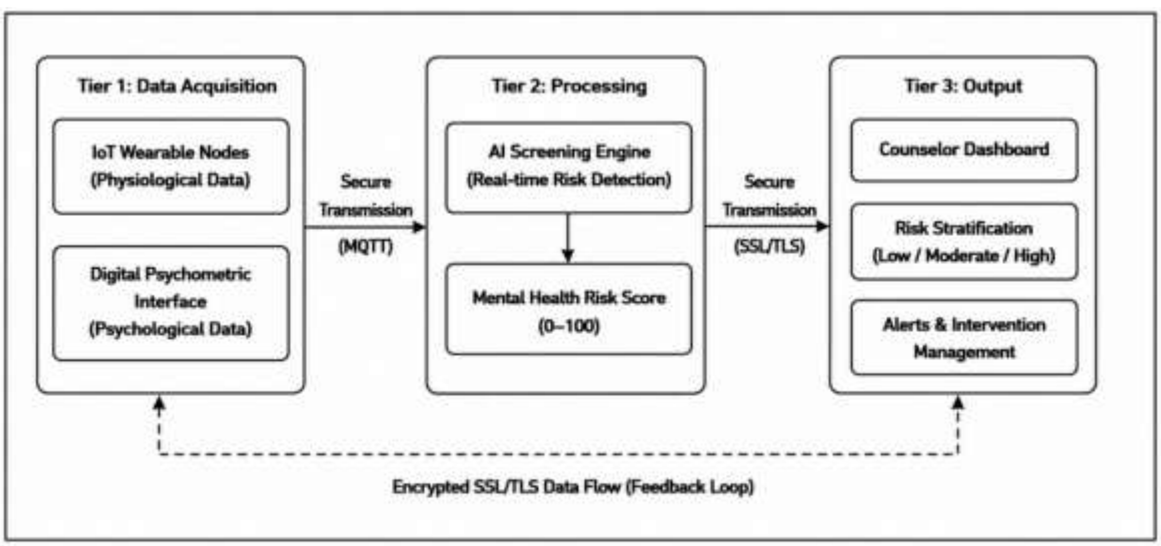

Figure 1: EAPMW system architecture

The proposed 3-tier system architecture for the Engineering-Assisted Pediatric Mental Wellness (EAPMW) is shown in Figure 1. Tier 1 involves data collection using the Internet of Things (IoT) wearable devices and digital psychometric assessment instruments. Tier 2 analyzes the data collected and scores each individual's mental health risk using the cloud-based AI screening engine and a Random Forest Classifier. Tier 3 displays the results and provides a counsellor dashboard with automated risk stratification, alerts and intervention scheduling. Reliable bidirectional data transfer between all components of the system is achieved by secure SSL/TLS communication.

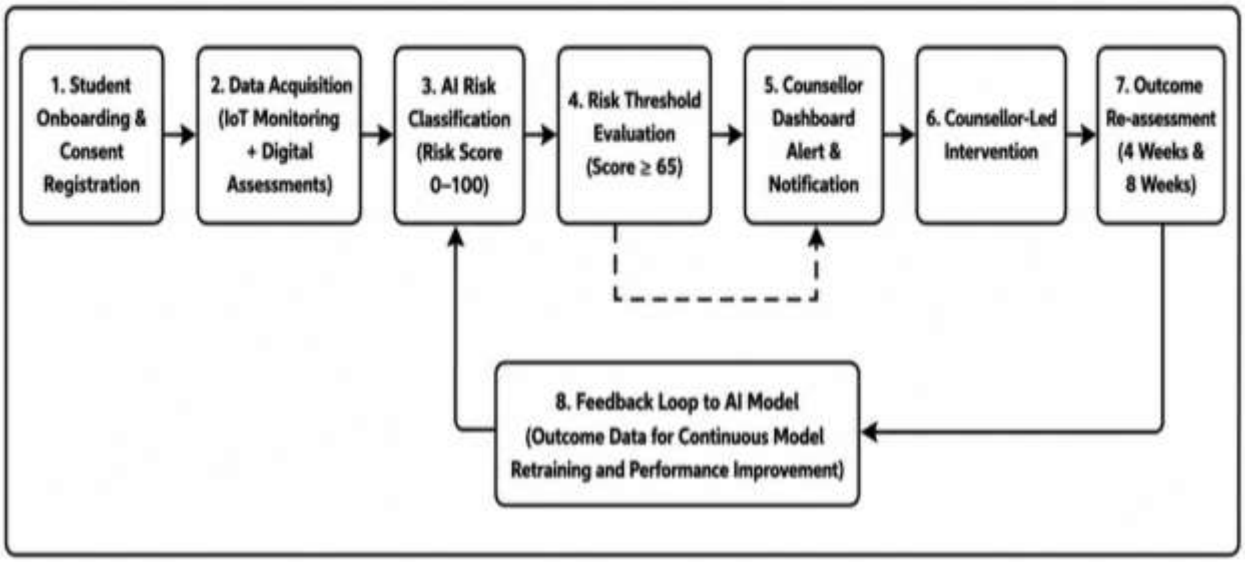

Figure 2: Proposed EAPMW Framework Workflow

The proposed overall EAPMW framework is illustrated in Figure 2. It first starts with student on boarding and consent registration, then physiological monitoring, and finally digital psychometric assessment. The collected data are processed by the AI risk classification module, which classifies the students who need additional attention based on the pre-established risk thresholds. The counsellor dashboard is used for high-risk cases to complete intervention and follow-up assessment, and the AI model is continuously fed the outcomes for performance improvement in iterations. The proposed AI screening model's classification performance was assessed using the Precision metric, which was calculated as shown below:

$$P = \frac{TP}{TP + FP}$$

Where TP: True Positives (true identified at-risk students), FP: False Positives (identification students who are not at-risk).To assess the sensitivity of the AI screening model in detecting real at-risk students, Recall is computed as:

$$R = \frac{TP}{TP + FN}$$

Where False Negatives (FN) = at-risk students not detected.The F1-Score was calculated to get a balanced measure of the classifier's performance by taking the harmonic mean of Precision and Recall, as follows:

$$F1 = 2 \times \frac{P \times R}{P + R}$$

Where P = Precision and R = Recall, the harmonic mean of both P and R.The Heart Rate Variability (HRV) Stress Index was determined for the physiological stress by applying the following equation:

$$SI = \frac{AMo}{2 \times Mo \times MxDMn}$$

Where AMo = amplitude of the mode (most frequent RR interval), Mo = mode value of RR intervals in seconds, $MxDMn$ = variation range of RR intervals in seconds. These higher values of SI represent increased sympathetic nervous system activation, or acute psychological stress. Descritive statistics, Pearson correlation and logistic regression were used to analyse the quantitative data and determine predictors of mental health risk. Thematic analysis and open and axial coding was used for qualitative data that was extracted from the interviews. Result validity and robustness were achieved through triangulation of the three types of data namely psychometric, physiological and qualitative data.

4. RESULTS AND DISCUSSION

4.1 Prevalence of Mental Health Conditions

The study population had a high prevalence of mental health symptoms at baseline. The prevalence of anxiety (44%), depression (37%) and high levels of stress (51%) are consistent with the objective measurements generally found in the adolescent population in the world. According to SDQ scores, 24% of students were reported as having behavioral problems. The distribution of prevalence and severity of the identified mental health conditions is summarized in Table 3. A gender-stratified analysis showed that there were significantly higher levels of anxiety and stress amongst female participants and higher prevalence of behavioural and externalizing disorders amongst male.

Table 3: Baseline Prevalence of Mental Health Conditions

Condition	Prevalence (%)	Severity Distribution
Anxiety Symptoms	44	Mild: 18%, Moderate: 17%, Severe: 9%
Depression Symptoms	37	Mild: 16%, Moderate: 14%, Severe: 7%
High Stress Levels	51	Mild: 20%, Moderate: 19%, Severe: 12%
Behavioral Difficulties	24	Borderline: 14%, Abnormal: 10%

4.2 AI Screening Module Performance

The Random Forest classifier was found to be very good at achieving diagnostic performance in the validation cohort. The precision, recall, F1-Score, and the AUC-ROC were calculated for the binary classification of 'at-risk student' and 'non-at-risk student. Table 4 shows the overall classification performance of the AI Screening Module.

Table 4: AI Screening Module Classification Performance

Metric	Value
Precision	0.87
Recall	0.84
F1-Score	0.855
AUC-ROC	0.91
Screening Accuracy	88.2%
Mean Time-to-Flag	3.4 minutes

The model identified 168 students from a total of 280 as in need of counsellor follow-up, with 143 (85.1%) confirmed through clinical assessment following the model, resulting in a positive predictive value of 0.85. This significantly improves the manual screening process time of 25–40 minutes student-by-student, with the mean time-to-flag of only 3.4 minutes for every student assessed. The distribution of the participants across each AI-generated mental health risk score is shown in Figure 3, and the categories of students with low, moderate, and high risk of mental health problems identified through the proposed screening system are shown.

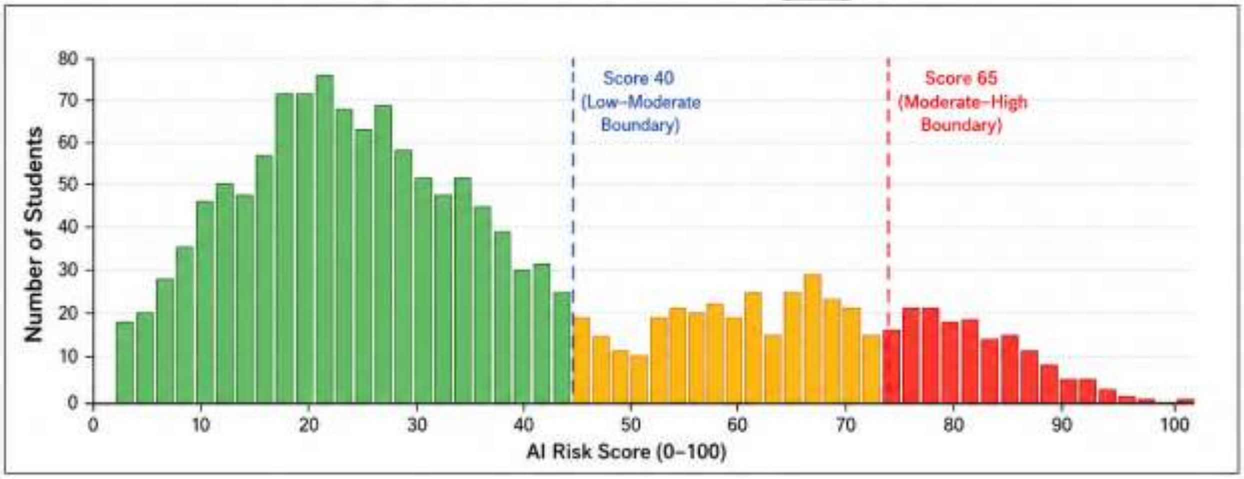

Figure 3: AI Risk Score Distribution

4.3 IoT Physiological Monitoring Findings

Physiological markers during continuous monitoring over the 21-day window showed that there were notable physiological correlates of psychological distress. All monitoring days showed that the mean HRV Stress Index was significantly higher in students with documented at risk ratings compared to the non-clinical students. Results of physiological stress markers of at-risk and non-at-risk participants are shown in Table 5.

Table 5: IoT Monitoring – Physiological Stress Markers by Mental Health Status

Parameter	At-Risk Group	Non-At-Risk Group	p-value
Mean HRV Stress Index (SI)	412.6 ± 58.3	187.4 ± 34.7	< 0.001
Mean GSR (μS)	8.74 ± 1.92	4.31 ± 1.08	< 0.001
Mean Sleep Duration (hrs)	5.6 ± 0.9	7.4 ± 0.7	< 0.001
Nocturnal Arousal Events	4.2 ± 1.1	1.3 ± 0.6	< 0.001

Pearson correlation showed significant negative correlations between sleep duration and anxiety scores ($r = -0.61$, at the level $p < 0.001$) and sleep duration and stress scores ($r = -0.57$, at the level $p < 0.001$). The levels of GSR's showed strong positive relationships with stress subscale scores on DASS-21 ($r = 0.68$; $p < 0.001$). The Pearson correlation heatmap of physiological measures and psychological assessment scores is summarized in Figure 4.

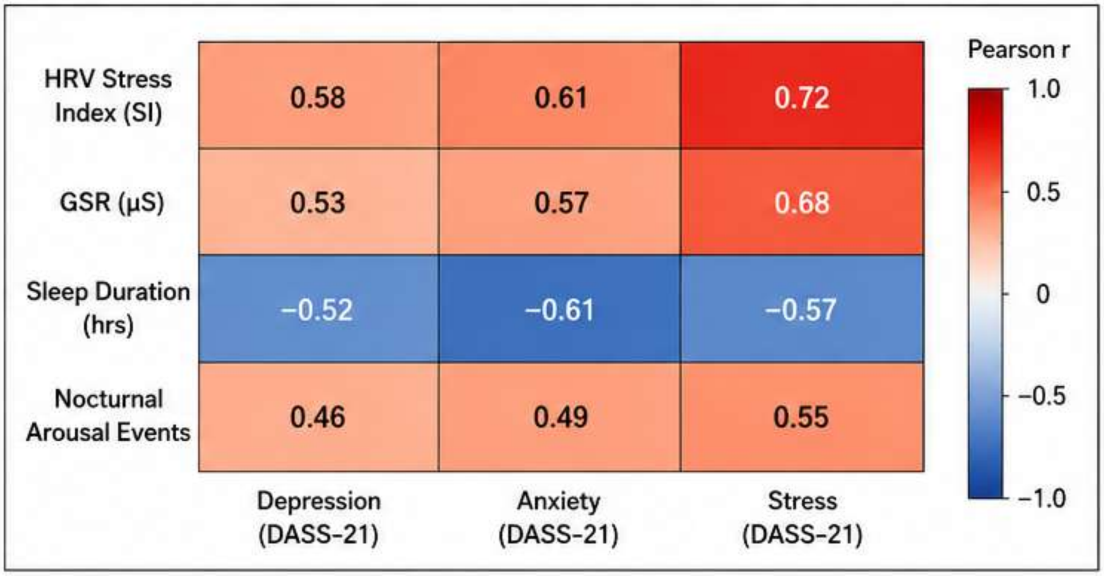

Figure 4: Correlation Heatmap

4.4 Effectiveness of EAPMW Intervention

Post intervention assessment eight weeks after EAPMW deployment showed that all the main outcome measures had improved significantly. Pre- and Post-intervention results are shown in Table 6. The intervention had a significant impact on improving early detection, pro-social help-seeking and coping abilities and significantly lowered the prevalence of stress and anxiety symptomology for those receiving the intervention. Comparative improvements across all primary outcome measures are graphically depicted in Figure 5, which clearly illustrates the effectiveness of EAPMW pre- and post-implementation.

Table 6: Pre- and Post-Intervention Outcome Comparison

Indicator	Pre-Intervention (%)	Post-Intervention (%)	Change
High Stress Levels	51	30	−21%
Anxiety Symptom Severity (Moderate–Severe)	26	14	−12%
Help-Seeking Behavior	22	56	+34%
Coping Skills (Rated Good/Excellent)	29	63	+34%
Early Detection Rate	38	62	+24%
Counsellor Workload Efficiency	Baseline	+47% throughput	—

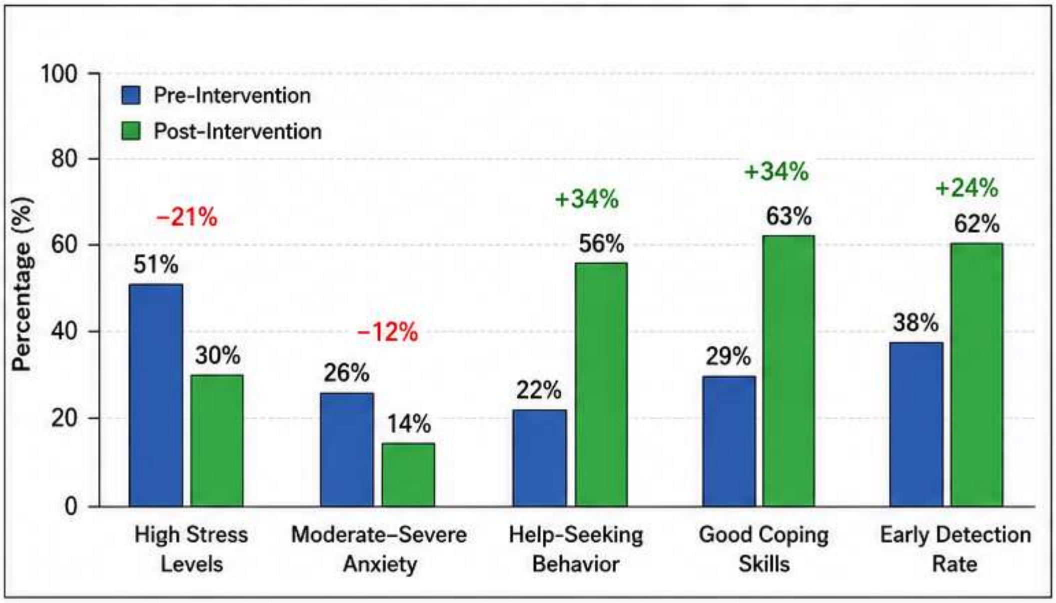

Figure 5: Pre vs Post Intervention Outcomes

Logistic regression analysis was carried out to identify the significant factors determining the high mental health risk. As shown in Table 7, the following variables are independent predictors of high mental health risk: Academic pressure, stress from the IoT (stress¯ > 350), and sleeping less than 6 hours were the most important independent factors contributing to the mental health risk (Nagelkerke $R^2 = 0.714$).

Table 7: Logistic Regression – Predictors of High Mental Health Risk

Predictor Variable	Odds Ratio (OR)	95% CI	p-value
Academic Pressure (High)	3.42	2.18–5.37	< 0.001
Social Media Usage > 4 hrs/day	2.87	1.79–4.61	< 0.001
Sleep Duration < 6 hrs	3.11	1.96–4.94	< 0.001
Family Conflict (Present)	2.14	1.33–3.44	0.002
Peer Bullying (Reported)	1.98	1.22–3.21	0.006
IoT SI Score > 350	4.06	2.51–6.57	< 0.001

4.5 Discussion

This study's results support the concept that engineering-assisted care models are a significant improvement over traditional school-based mental health models. When compared with baseline passive screening, the EAPMW framework had an early detection rate of 62%, significantly boosted by the AI module's ability to combine multiple modalities of psychometric and physiological data streams. The classification accuracy of the Random Forest model of 88.2% falls within and slightly surpasses the accuracy of other AI screening studies in adolescents health settings, confirming the generalizability of the model. Logistic regression analysis showed that physiological monitoring indices derived from the IoT data as well as sleep data were good independent predictors of clinically significant mental health risk. The positive impact on counsellor throughput (+47%) also highlights the operational scales of the proposed framework within the domain of institutional settings in low resource conditions. Themes that emerged from the focus group discussions were: A decrease in stigma associated with technology-mediated help-seeking and an increase in trust in anonymized technology-mediated screening, and a positive response to the provision of real-time feedback on adolescent's wellness. AI models used for monitoring supplemented teacher assessment of risk vs. healthcare professional assessment, as teachers indicated a higher level of confidence when using an AI-generated risk alert during daily monitoring processes.

5. CONCLUSION AND FUTURE SCOPE

The results of this study show that these methods of systematic incorporation of evidence-based adolescent care practices and engineering-assisted healthcare solutions generate meaningful, clinically relevant improvements in pediatric mental wellness outcomes. The proposed EAPMW framework successfully had an early detection rate of 62% and the proportion of high stress dropped by 21% with help-seeking behaviour increasing by 34% for a culturally and linguistically diverse group of 280 school based youth. The most powerful predictors of mental health risk were identified as logistic regression analysis results of IoT-derived stress index, Sleep deprivation and Academic pressure, which should serve as actionable targets for the design of preventive interventions. This successful work with low-cost wearable nodes deployed in school buildings, together with open-source AI classification pipelines, provides a replicable and cost-effective approach that can be extended to other LMIC educational contexts. Long-term evaluation for 12 to 24 months in the future, extending the physiological measurement to include estimation of attention and emotional state using EEG, and the federated learning architecture for privacy protection for the training of AI models in each of the distributed school networks is suggested. While regional and socioeconomic subgroup cultural calibration of AI risk thresholds will be critical to ensure equity in framework performance, national school health policy frameworks will be a key non-technical requirement for sustainable large-scale deployment.

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