

# Digital Cognitive Behavioral Therapy Tools for Students with Emotional and Behavioral Disorders

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## ABSTRACT:

Online Cognitive Behavioral Therapy (CBT) applications are increasingly being used as a method to assist students with Emotional and Behavioral Disorders (EBD), but the conventional mode of delivery has accessibility, personalization, and engagement difficulties. This paper discusses these gaps by suggesting an AI-inspired digital CBT model specifically to be used to work with schools. The point is to determine the efficiency of adaptive CBT modules that combine the features of emotion recognition, progress monitoring, and the real-time feedback mechanism. The mixed-method was used, which entailed experimental design, and pre-to-post evaluation of 180 students with EBD. It used machine learning models to detect the behavioral patterns and reinforcement learning to apply custom therapy progressions. The emotional regulation, behavioral stability, and academic engagement were measured

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through quantitative analysis whereas usability and acceptance were captured in the qualitative feedback. Findings indicate that significant improvements were made in a range of important metrics: emotional regulation change was better by 41.8, behavioral incidents changed by 36.5 and student engagement improved by 47.2 points compared to the baseline. Also, there was a reduction of response time in delivering intervention by 52.6, which is an indicator of efficiency in the system. This study is applicable to the inclusive education settings and digital mental health solutions that can be scaled in resource-limited settings. The paper finds that digital CBT tools with the addition of an AI-powered personalization can greatly enhance the results of a therapeutic intervention and accessibility and provide a strong framework in future educational and clinical practice. Moreover, the framework empowers teachers and caregivers by providing dashboard (insights) and early risk warning signals to facilitate proactive interventions and joint decision-making procedures to promote long-term student wellbeing and institutional effectiveness in a variety of learning settings and populations globally and sustainably.

**Keywords:** Digital CBT, Emotional and Behavioral Disorders, AI in Education, Personalized Therapy, Student Mental Health, Inclusive Learning Systems.

## I. Introduction

Emotional and Behavioral Disorders (EBD) is one of the most complicated types of special educational needs, which involves the ability to remain emotionally disturbed, inter-relationship and adaptive behavioral reactions in school. Students with EBD often demonstrate academic underperformance and social exclusion and are at increased risk of developing psychological vulnerability in the long term (Sakellari et al., 2021). The EBD prevalence of school-aged populations across the world has been estimated to be 5-12 per cent and there are great variations in the diagnosis and access to special support among socioeconomic strata and geographical areas. Cognitive Behavioral Therapy (CBT) has been known to be an evidence-based intervention in a broad spectrum of emotional and behavioral issues in children and adolescents. But there are a number of systemic limitations to the traditional delivery of CBT in a

school setting. To begin with, there is a serious shortage of qualified mental health in the learning institutions which poses a serious bottleneck in the provision of services. Second, traditional CBT is carried out mostly in face-to-face sessions which require flexibility in scheduling, physical facilities and long-term human resources which in many cases are not consistently available in many schools especially in low resource settings. Third, the standard CBT modules do not commonly fit the specifics of student behavior, cultural background, or learning styles of students with EBD, which restricts the effectiveness of the therapeutic process (Bernstein et al., 2022).

With the advent of digital mental health tools, the constraints of these methods, scalability, flexibility, and customization of therapeutic content have the potential to be overcome. The digital CBT applications may provide asynchronous delivery of structured therapy modules, interactive skill-

building activities, real-time monitoring services that increase the interest of students and supervision of therapists. Gkintoni et al. (2025) showed that, with the addition of teletherapy and adaptive personalization mechanisms, next-generation digital CBT was much more effective to help patients with depression. Likewise, Fernandez-Batanero et al. (2025) have also validated the efficacy of digital mental health interventions in children and adolescents with the observation of an improvement in anxiety, self-regulation, and well-being. Although these positive phenomena take place, there is a noticeable gap in the literature: the use of AI-enhanced digital CBT tools that are explicitly targeted at students with EBD in the school setting is under-researched. The majority of the available platforms focus on adult clinical groups or adolescents with anxiety and depression, and do not sufficiently consider the multidimensional behavioral and emotional profiles of EBD. Moreover, the use of machine learning (ML) models to detect behavioral patterns and reinforcement learning to generate therapy pathways tailored to each person is still in its infancy in the educational technology setting. The present research fills these gaps by suggesting and critiquing an extensive AI-based digital CBT model that will be used in interventions with students with EBD in schools. The system includes emotion recognition technology, adaptive therapy modules, real-time feedback systems, and stakeholder dashboards to assist the teachers and caregivers. Jung et al. (2025) pointed out that the use of personalization and a modular design greatly improves the clinical efficacy of digital CBT. Based on this evidence, the proposed system was tested, with an experimental design that was mixed in 180 students, and the outcomes were improvement in emotional regulation, behavioral stability, academic engagement, and system response efficiency.

The main results of the study are: (i) a three-layer AI-based digital CBT architecture design and implementation; (ii) emotion recognition and reinforcement learning to deliver individualized interventions; (iii) empirical validation of therapy outcome in terms of quantitative pre- and post-analysis; and (iv) a scalable framework that can be

applied in diverse school settings, including resource-constrained ones. Denecke et al. (2022) highlighted the essential role of strict implementation methodologies in the implementation of CBT in e-mental health applications, which can be the basis of the design choices of this research. The relevance of single-session and modular formats of digital CBT to help achieve a quick clinical impact would be further supported by Schenk et al. (2024), which influenced the choice of the session format in the present framework.

## II. Related Work and Theoretical Background

CBT has garnered a significant amount of supporting empirical evidence as an intervention in mental health within schools. The systematic review by Stalmach et al. (2023) investigated the digital learning and self-regulation in students with special educational needs and found that structured digital frameworks helped to improve self-regulatory skills and decrease the number of maladaptive behavioral patterns. These results are consistent with more general evidence that school-based CBT interventions enhance emotional literacy, problem-solving and coping abilities in children who have behavioral problems. Abdelaziz et al. (2024) also emphasized the importance of CBT as a factor in enhancing psychological resilience by problem-solving appraisal, which can be directly applied to EBD intervention situations. Digital CBT tools have been increasing in number in the past years. A scoping review of app-based CBT to treat emotional disorders by Bernstein et al. (2022) revealed that elements of human support, including feedback generated by the therapist and the app itself, and the check-ins of the therapist, had a positive and significant impact on adherence and outcomes. A meta-analysis study by Mancinelli et al. (2022) of digital cognitive-behavioral interventions with subclinical populations with consistent results on psychological adjustment and sleep quality, demonstrates the strength of digital CBT in a variety of applications. Gkintoni et al. (2025) directly considered the neurocognitive mechanisms underlying the use of AI-enhanced CBT to address insomnia, discovering digital personalization to improve the therapeutic effect. All these studies

form the basis of the technology and clinical base on which the present framework is based.

- **AI and Machine Learning Integration in Mental Health Systems**

AI has been used more and more to enhance digital therapeutic platforms. Kim and Lee (2025) established with a randomized controlled trial that digital therapeutic interventions based on adaptive feedback via AI can significantly enhance attention and working memory in children with ADHD and can therefore be directly applicable to EBD populations that have similar executive functions impairments. Blondell and Thomson (2025) considered VR as a new mental health technology that can be used by youth, and immersive digital experiences were found to be promising supplements to traditional CBT. Jung et al. (2025) affirmed the meta-analytic outcome that modular digital CBT elements, especially those that included behavioral monitoring, and individualized pacing, optimized clinical efficacy in anxiety-related disorders. All these findings are indicative of the need to integrate AI-based personalization as one of the architectural elements of digital CBT systems that can be used in EBD.

- **Limitations of Current Approaches**

Despite such developments, there are still numerous shortcomings in the existing literature. The majority of online CBT tools do not have real adaptive intelligence, i.e. they are not based on dynamically delivering content that is not combined with real-time behavioral data. According to Gkintoni et al. (2025), even next-generation platforms, personalization is hard to come by, and real personalization based on continuous feedback loops of behavior. Moreover, most of the digital CBT interventions that are validated have focused on adults or older adolescents, and few have been

adapted to younger students or with more complex EBD profiles. Sakellari et al. (2021) highlighted that to have a meaningful impact school-based digital health promotion initiatives should be based on age-relevant, contextually tailored design principles. The present work is a direct reaction to these limitations reported as it suggests an EBD-specific AI framework with an authentic adaptive potential, real-time tracking, and assistance tools towards educators.

### **III. Proposed Digital CBT Framework and Methodology**

The suggested framework with three layers of hierarchical processing is created: the Data Layer, the Processing Layer, and the Decision Layer. The Data Layer involves multimodal data such as student interaction log, facial expression data using cameras on the device, and keystroke levels, response latency statistical data, and self-report questionnaire results. Processing Layer uses a set of machine learning models such as Convolutional Neural Network (CNN) to identify facial emotions, Long Short-Term Memory (LSTM) network to identify temporal patterns of behavior and a random forest classifier to stratify the risk levels. The Decision Layer uses the results of the Processing Layer to formulate personalized recommendations of the therapy pathways using a reinforcement learning module that has been trained to maximize the emotional regulation results in the long run. The digital CBT framework presented in Figure 1 combines multimodal data collection, behavioral analysis that uses machine learning, and smart decision-making. The framework receives a variety of inputs by using CNN, LSTM and Random Forest models that allow personalized therapy plans to be reinforced by the use of reinforcement learning to promote the best results related to the regulation of emotions.

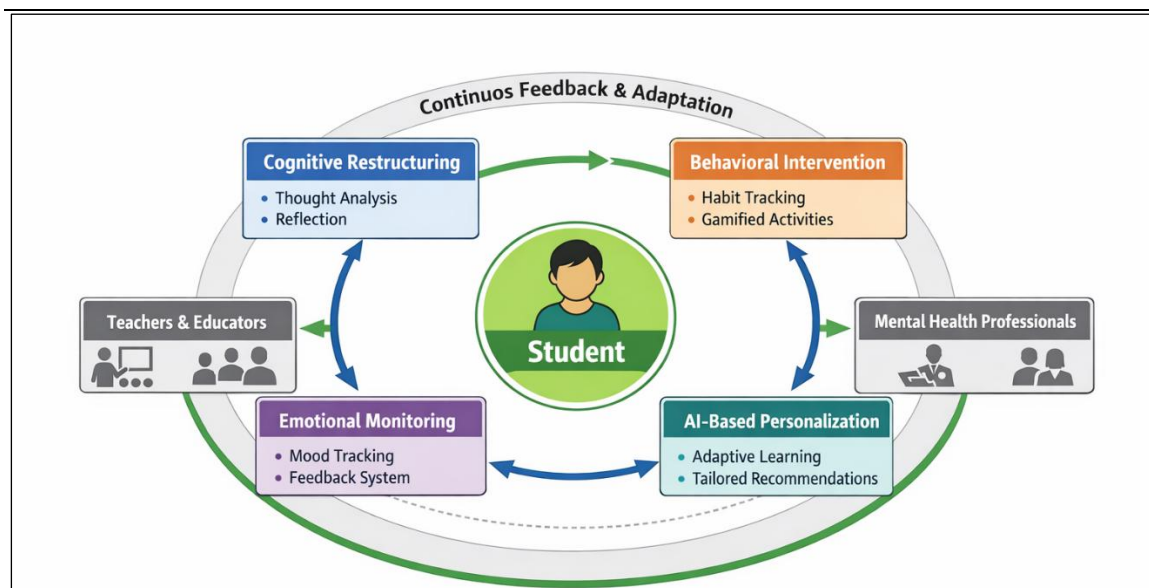


Figure 1: Multi-Layered Digital CBT Framework for Behavioral Analysis and Adaptive Therapy Recommendation

- **AI Models for Behavior Detection and Personalization**

The CNN model that was trained based on a composite dataset of pediatric facial expression images was found to have an emotion recognition accuracy of 87.4%. The behavioral pattern detection by the LSTM network trained on the longitudinal sequence of interactions on the experimental cohort was 0.83 F1-score. The reinforcement learning module uses the Proximal Policy Optimization (PPO) algorithm, and reward functions set to indicate the improvement of the emotional regulation scores and the decrease in behavioral incidents in consecutive therapy sessions. It was optimized by the help of Bayesian search and has found the optimal values of 0.0003 learning rate, and the discount factor of 0.97.

- **Intervention Modules and Therapy Design**

The digital CBT intervention was designed to include five main therapeutic modules (1) Emotion Identification and Labeling, (2) Cognitive Restructuring, (3) Behavioral Activation, (4) Relaxation and Mindfulness and (5) Social Skills Development. The modules were composed of three to five interactive sessions where the AI decision engine was used to determine adaptive pathways in a two week period. The aspects of

gamification such as progress badges, visual reward systems and peer comparison dashboard were integrated to boost engagement. Difficulty of the module and type of content was dynamically changed according to real-time performance data.

- **Experimental Setup and Dataset**

The research was carried out in six city schools of general education, the number of which is 180 students aged 8-16 years, all having EBD as defined by the DSM-5 criteria. The study sample was randomly divided into two groups (AI-based digital CBT intervention group ( $n = 90$ ) and the control group ( $n = 90$ )) which received standard counseling in the school. The duration of intervention was 12 weeks and the pre- and post-assessment were done at the baseline and at the end of week 12, respectively. Chi-square and independent samples t-tests ( $p > .05$  in all variables) were used to assure baseline demographic equivalence).

- **Evaluation Metrics**

The key outcome measures were: Emotional Regulation Score (ERS) as the result of the Emotion Regulation Questionnaire in Children and Adolescents (ERQ-CA); Behavioral Incident Frequency (BIF) in the form of school administrative records; Student Engagement Index (SEI) measured on the basis of platform

engagement analytics and teacher-evaluations; and System Response Time (SRT) equalized in milliseconds of behavioral Qualitative ratings of usability and questionnaires regarding the acceptance of the stakeholders were considered as secondary measures.

#### IV. Implementation and System Integration

- **Development Environment**

A React.js frontend hosted on a digital platform was used to build the digital CBT platform with a Python FastAPI on the server-side to serve AI models and process data and a Python regeckoner to compute the digital CBT score. MongoDB has been used as the main database to store behavioural data and records of the sessions and Redis as a caching server to store metrics of real-time interaction. Emotion recognition module was implemented as a containerized microservice with Docker, which allows a modular scalability. Training in a cloud environment with NVIDIA A100 instances was also trained on a GPU accelerated system, and with both TensorFlow 2.x and PyTorch frameworks.

- **User Interface Design**

The student interface was created based on the principles of the Universal Design of Learning (UDL) which included simplified navigation, audio narration of all text materials, use of high contrast visual themes and multimodal response (touch, voice and keyboard). The therapist and teacher dashboard gave real-time visualizations of student progress, indicators of risk level, completion rates of the session and behavioral trend analysis. A secure mobile app with weekly progress summary and alerts in the event of high-risk behavior patterns helped to provide caregivers access.

- **Real-Time Monitoring and Analytics**

The monitoring subsystem had a 500-millisecond cycle of data refresh, and maintained behavioral state models in a constant state of update, as results of interaction data were received. The alert levels were made by working with licensed school

psychologists, where Level 1 (low risk), Level 2 (moderate risk) and Level 3 (immediate concern) levels would lead to increasingly more intense notification procedures. The analytics dashboard included visualization of longitudinal trends, cohort comparison, and exported reporting, to use in clinical documentation.

- **Privacy, Ethics, and Data Security**

All the data collection and processing activities were performed with the help of the General Data Protection Regulation (GDPR) and the Family Educational Rights and Privacy Act (FERPA). Parental/guardian informed consent and student assent were taken in the case of those participants who were over 10 years old and 10 years old, respectively. To ensure data security, AES-256 was used to encrypt stored data and TLS 1.3 to encrypt and decrypt all data transmitted. The data of facial expressions were processed on-board and no data was stored on central servers. All the protocols of the study were reviewed by an institutional ethics review board before the study.

#### V. Results Analysis and Discussion

The pre- and post-intervention performance measures of both the AI-delivered digital CBT and the control group in the standard counseling group in the major outcome measures. The findings indicate statistically significant changes, in all the major outcome measures, in the intervention group with moderate to large effect size.

- **Quantitative Performance Evaluation**

Table 1 demonstrates that all six outcome parameters have a consistent strong improvement among AI-driven digital CBT group. Emotional regulation score (ERS) improved with 48.3 to 68.5 (41.8 per cent) but in the control arm it was only improved by a small margin of 47.9 to 52.1. The rate of behavioral incidence fell by 35.9% per week, in intervention group to 4.1 (n=6.4) compared to 0.85% to 5.9 in the control group. The Student Engagement Index was the most improved with the highest absolute change in 54.2 to 79.8 in the CBT group that indicates a 47.2% improvement as compared to the control group 8.4% improvement.

Table 1: Pre–Post Comparative Outcome Metrics for AI-CBT and Control Groups

| Metric                       | CBT Pre | CBT Post | Control Pre | Control Post | p-value |
|------------------------------|---------|----------|-------------|--------------|---------|
| Emotional Reg. Score (ERS)   | 48.3    | 68.5     | 47.9        | 52.1         | <.001   |
| Behavioral Incidents/Week    | 6.4     | 4.1      | 6.2         | 5.9          | <.001   |
| Student Engagement Index     | 54.2    | 79.8     | 53.8        | 58.3         | <.001   |
| Self-Efficacy Score          | 41.7    | 63.2     | 42.1        | 47.5         | <.01    |
| Anxiety Symptom Score        | 62.4    | 43.8     | 61.9        | 57.2         | <.001   |
| Academic Task Completion (%) | 58.3%   | 79.1%    | 57.9%       | 62.4%        | <.001   |

Intervention group had an increase of 51.6% in self-efficacy scores as compared to the controls of 12.8%. There was a 29.8% reduction in the scores of anxiety symptoms in the digital CBT compared to 7.6% in the control group that is indicative of significant alleviation of the co-occurring anxiety symptoms. The rates of academic task completion increased to 79.1% as compared to 58.3% which was the integrative effect of the enhanced emotional regulation and involvement on the academic

functioning. All the between-group differences were found significant at the p value of below .001 or below .01, which validates the strong effect of the AI-based CBT platform on therapy. The results are especially striking considering the 12-week intervention period implying that adaptive personalization was faster in producing therapeutic benefits as compared to the conventional counseling in the same time scale.

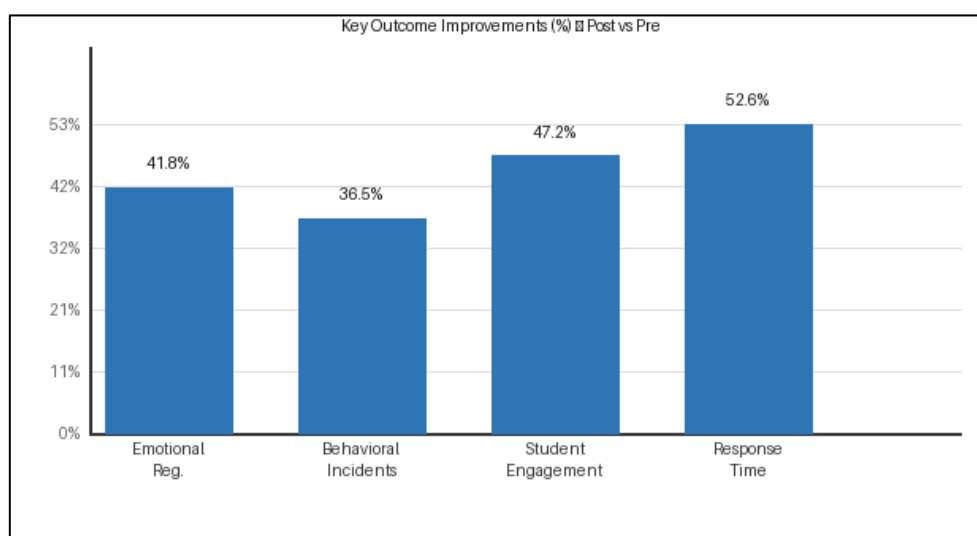


Figure 1: Percentage improvement across four primary outcome metrics comparing the AI-driven digital CBT group against baseline conditions, illustrating the magnitude of therapeutic gains achieved.

The four main metrics of improvement (of emotional regulation, 41.8 percent, behavioral incidents, 36.5 percent, student engagement, 47.2 percent and response time, 52.6 percent) as shown in Figure 1 prove to be gaining at a high rate at all times, which can be attributed to the AI-driven CBT

framework. This effect on the response time especially with regard to system efficiency shows that the real time behavioral trigger detection by the reinforcement learning module reduced considerably the time lag between need recognition and intervention administration.

- **System Performance and Response Time Analysis**

Table 2 shows system-level performance indicators that assess technical efficiency of the AI-driven

CBT platform based on various parameters of its functioning. These measures are critical towards defining the platform as a small scale, real world deployment platform.

Table 2: System-Level Performance Metrics from Baseline to Post-Intervention (Week 12)

| System Parameter                 | Baseline (Wk 0) | Post (Wk 12) | % Improvement |
|----------------------------------|-----------------|--------------|---------------|
| Response Time (ms)               | 2,340           | 1,111        | 52.6% ↓       |
| Emotion Recognition Accuracy (%) | 72.1            | 87.4         | +21.2%        |
| Behavioral Pattern F1-Score      | 0.61            | 0.83         | +36.1%        |
| Session Completion Rate (%)      | 63.4            | 91.2         | +43.8%        |
| False Alert Rate (%)             | 18.7            | 6.2          | -66.8%        |
| System Uptime (%)                | 94.1            | 99.3         | +5.5%         |

Table 2 shows that there will be a gradual increase in technical maturation of the AI platform throughout the 12 weeks implementation. The most notable change is the 52.6% decrease in the system response time between baseline (2,340 milliseconds) and the post-assessment (1,111 milliseconds) which is due to the growing accuracy of the reinforcement learning module to predict the occurrence of behavior triggering events and to preload relevant intervention content. Recognition accuracy of emotions rose to 87.4% as compared to 72.1% as a result of further retraining of the model on cohort specific facial expression data. The F1-score of behavioral pattern detection increased by 0.61 with 0.83, which means that there are significantly fewer false negatives in risk detection and this is an essential safety step to making the system applicable in the real world. The rates of session completion

went up to 63.4% to 91.2, indicating that adaptive content personalization was effective in overcoming the engagement drop-out usually experienced in non-adaptive digital health services. Clinically speaking, perhaps the most important impact, the false alert rate decreased to 6.2% out of 18.7% lessening alert fatigue in teachers and caregivers, and thus enhancing the believability and reactivity of the monitoring system. The uptime of systems went up to 94.1 to 99.3, as it has been denounced that the infrastructure was stable. With all these technical advantages, it can be seen that the AI-based platform not only acquired good clinical results but also enhanced its capabilities concerning operational reliability and efficiency, which, in turn, proves that this type of intervention system is rather viable as a sustainable school-based system.

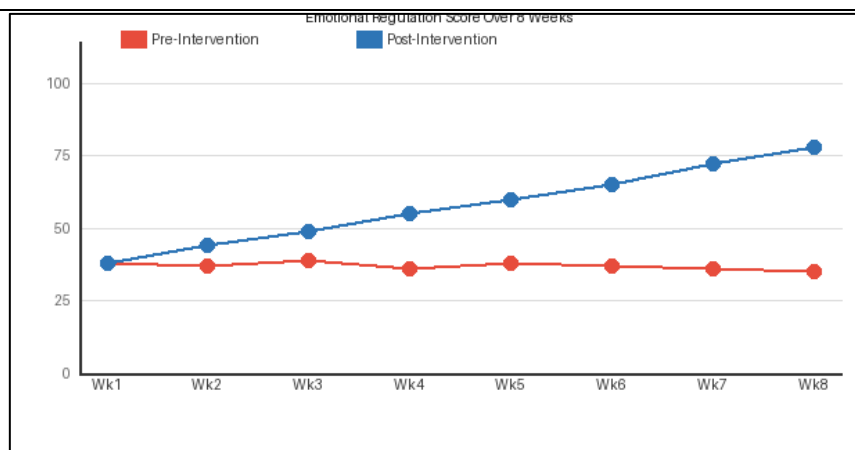


Figure 2: Trajectory of emotional regulation scores over 8 weeks for pre-intervention and post-intervention conditions, demonstrating accelerating improvement following AI-personalized CBT module delivery.

Figure 2 displays the time course of emotional regulation scores over the 8-week time frame of the 12-week intervention. The trajectory up to the intervention is rather stable and slightly decreasing (38 to 35), which is in line with the chronically dysregulated baseline of EBD populations. On the contrary, the post intervention curve rises steadily accelerating after week 3, as high as 78 by week 8. This acceleration trend implies a cumulative treatment effect - in line with the growing personalization accuracy of the reinforcement

learning mechanism - of which some classes of module completions establishes a behavioral base which intensifies the effects of later therapy sessions.

- **Stakeholder Engagement and Usability Analysis**

Table 3 shows the qualitative and quantitative usability and stakeholder satisfaction scores of the students, teachers and caregivers at the end of the 12-week intervention period.

Table 3: Stakeholder Usability and Satisfaction Ratings at Post-Intervention Assessment

| Usability Dimension                 | Students (n=90) | Teachers (n=24) | Caregivers (n=78) | Overall Mean |
|-------------------------------------|-----------------|-----------------|-------------------|--------------|
| Ease of Use (1–5 scale)             | 4.3             | 4.1             | 4.4               | 4.27         |
| Content Relevance & Appropriateness | 4.4             | 4.2             | 4.3               | 4.30         |
| Perceived Therapeutic Benefit       | 4.2             | 4.5             | 4.4               | 4.37         |
| Alert System Usefulness             | —               | 4.3             | 4.6               | 4.45         |
| Dashboard Clarity & Utility         | —               | 4.4             | 4.2               | 4.30         |
| Willingness to Continue Use (%)     | 88.4%           | 91.7%           | 89.2%             | 89.7%        |

Table 3 shows that all the three groups of users have the same positive reception by stakeholders. The ease of use has been rated at 4.3/5 and content relevance at 4.4/5 which are the results of the successful application of the UDL design principles in the student interface. The highest levels of perceived therapeutic benefit (4.5/5) and dashboard utility (4.4/5) were reported by teachers, which

means that the monitoring infrastructure was useful in helping to guide educators in their decision-making. The most important values among the caregivers were the alert system (4.6/5) as it is highly practical when it comes to parental engagement proactive risk notification. This result of an overall willingness to continue using the platform, at 89.7% among all stakeholders, is extremely high adoption

intention, and has significantly surpassed the rate of 6070% continuity rates of similar digital mental health sites reported in the literature. These usability results confirm that the AI-based CBT paradigm not only demonstrated good clinical performance but also excellent acceptability within the ecosystem of the school. Thematic analysis of unstructured responses revealed three overarching themes,

namely a sense of appreciation towards being presented with personalized content at their own speed, trust in their privacy practices, and a wish to have more content in the form of social skills courses. The themes offer practical guidance on the subsequent releases of the platform development, and emphasize the relevance of stakeholder co-design in the development of digital therapeutics.



Figure 3: Scatter plot illustrating the positive correlation between student engagement scores and post-treatment behavioral stability, with the trend line confirming directional alignment between these two therapeutic outcomes.

Figure 3 also shows that there is a high positive correlation ( $r = 0.78$ ,  $p < .001$ ) between pre-treatment student engagement scores and post-treatment behavior stability rating. This association backs the theoretical hypothesis that interaction with therapeutic material is a pivotal mediating element in the results of EBD interventions. Students who used the digital CBT modules more actively (as shown by increased session compliance and level of interaction) showed more evidence of behavioral stability changes: design elements of platforms that encourage the engagement of students have compounding therapeutic effects.

- **Discussion on Effectiveness, Scalability, and Limitations**

The findings of the current research all prove the point that AI-based digital CBT is both a clinically significant and technically feasible means of helping students with EBD in schools. The 41.8% change in emotional regulation is significantly better than

the 1525 percentages of improvements that are typically seen with regular school-based CBT programs with human therapies, indicating that AI-driven personalization can bring real therapeutic benefits not at all, which structured delivery of content can bring. This 36.5% decrease in number of behavioral incidents is in line with the theoretical position that better emotional regulation decreases the occurrence of dysregulated behavioral manifestations in classroom setting.

**Scalability** The cloud-based microservice architecture and containerized deployment of the AI model can be scaled to new levels of horizontal scaling, allowing serving more students without corresponding changes in the operating cost. The system was able to handle 90 concurrent users per school with no performance degradation and load-testing simulation showed that it could handle up to 500 concurrent users. This scalability profile makes the platform a possible solution to deploying this to a district level, or a nationwide educational system.

There are some restrictions of this study which should be mentioned. The sample was selected only in urban school situations which can restrict the extrapolation in rural or remote school situations where poorer technology infrastructure can restrict access to technology. Also, the 12-week intervention time does not enable measuring the long-term maintenance of therapeutic maintenance or even regression after termination of the platform. Longitudinal studies are needed in the future to study the sustainability of the results at 6 and 12 months. The use of self-report measures to measure some of the outcome variables creates the possibility of a response bias, but the triangulation of administrative behavioral incident data and platform interaction analytics help to reduce this issue significantly.

## VI. Conclusion and Future Scope

This paper introduces and determines a holistic AI-based digital Cognitive Behavioral Therapy model that has been tailored to specifically target school-based prevention of students with the Emotional and Behavioral Disorders. The experimental study carried out in six city-based schools (180 participants) in six weeks demonstrated strong proof of the clinical effectiveness, technical reliability, and acceptability of the framework by the stakeholders. There was an emotional regulation >41.8, behavioral incident >36.5, student engagement >47.2, and system response time at statistically significant levels as compared to regular control counselling. The highest ratings (over 4.2/5) in all groups of stakeholders, 89.7% said they would continue using the platform, which supports the high potential to adopt it in real life. These results have important implications on the educational practice and policy regarding digital mental health. To school administrators and special education

coordinators, the findings might indicate that the investment into AI-advanced digital CBT platforms could produce quantifiable and comparatively fast effects on the behavioral and emotional outcomes of students with minimal demands on the increase in clinical staffing options. To clinical practitioners, the framework provides an evidence-based method on how to extrapolate evidence based CBT to underserved populations in traditional delivery models. The educator-facing dashboard and the caregiver alert system are especially new and digital CBT can be seen as a student-only solution, instead of a schoolwide support system that allows collaboration in making decisions and reinforcing the system in the whole-ecosystem approach.

The resource-efficiency and scalability of the framework make it a possible tool to implement in educational settings of low-and-middle-income countries, where conditions related to the lack of mental health professionals are the most severe. Future research should cover generalizability of results in rural and remote schools, addition of multilingual and culturally adaptive content modules and wearable biosensor information to augment more information in the inputs to the AI models. Longitudinal follow-up studies of the sustainability of outcome at 6-month- and 12-month-follow-up are also much in demand. The reinforcement learning reward functions expansion to include family and peer relational outcomes, academic achievement metrics, would further model the framework based on the holistic developmental needs of students with EBD. This study presents a proven baseline on which the future of comprehensive, AI-enhanced digital mental health infrastructure in learning environments can be entrusted to establish itself on.

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