Engineering Mental Wellness: A Digital Twin for Chronic Stress Modeling and Real-Time Intervention

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ABSTRACT

Chronic stress is a growing concern among college students, linked to long-term psychological and physiological harm. Yet, existing assessment tools rely heavily on self-reporting, which is prone to bias and fails to capture real-time, fluctuating the nature of stress. To address this gap, the present study proposes a digital twin framework that models chronic stress progression by incorporating trauma history, adverse childhood experiences (ACEs), chronic health conditions, genetic vulnerabilities, emotion regulation, gender identity, and environmental stressors. Using Python-based agent-based and discrete-event simulation methods, 100 virtual agents were created and evenly distributed across four groups: Control ($n = 25$), Cognitive Behavioral Therapy (CBT, $n = 25$), Mindfulness ($n = 25$), and Breathing Techniques ($n = 25$). Simulations ran for 30,000-time steps (~2.5 years), producing 3,000,000 total data points. The model tracked transitions across varying stress states and evaluated the effectiveness of interventions. All three strategies significantly reduced time spent in high-stress states compared to the Control group. In the static model, dropout risk was entirely eliminated for all intervention groups, while the dynamic model showed CBT producing the most stable and sustained reductions in stress severity. Unlike existing retrospective tools, this framework is adaptive, allowing personalized, real-time projections of stress risk and intervention outcomes. Though challenges remain in integrating biometric data and ensuring ethical deployment, this approach offers a scalable and cost-effective tool for proactively managing chronic stress. With further refinement, digital twin systems may transform mental health care by simulating intervention outcomes prior to clinical or educational implementation.

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INTRODUCTION

Chronic stress significantly impacts mental and physical health, yet traditional models often miss their dynamic, real-time nature (Heron & Smyth, 2010). Digital twin systems, originally developed for manufacturing (Grieves, 2014) and now applied in healthcare (Corral-Acero et al., 2020), enable personalized, adaptive stress interventions (Insel, 2017; Spitzer et al., 2023). Prolonged adversity induces allostatic load and disrupts HPA axis function, impairing cognition, emotion regulation, and immunity (McEwen & Stellar, 1993; Lupien et al., 2009; Sapolsky, 2000). Wearable devices and heart rate variability (HRV) measures allow continuous autonomic stress monitoring (Thayer et al., 2012; Wheat & Larkin, 2010). Meanwhile, JITAIs and digital therapies like CBT and mindfulness demonstrate scalable effectiveness (Nahum-Shani et al., 2018; Andersson et al., 2014). Despite data integration and ethical challenges, validated digital twins show promise for proactive mental health care (Pappalardo et al., 2020).

A key gap remains between digital twin theory and practical mental health implementation. Most research assumes ideal conditions, complete data, perfect adherence, no technical issues, rarely reflecting real-world complexity. This gap is acute in adolescent mental health, where engagement barriers, tech challenges, and variable family support complicate interventions. This study addresses the gap via the Enhanced Digital Twin Framework, comparing three paradigms: Static Baseline Modeling (fixed protocols), Adaptive Perfect Implementation (ideal data and adherence), and Realistic Implementation (accounting for adherence decay, technical barriers, and engagement variability). Incorporating multi-source real-world data ensures ecological validity and supports comprehensive clinical evaluation.

RELATED WORK

Adolescent Stress and Anxiety

Adolescent stress and anxiety have surged, driven by academic demands, social media, and disrupted sleep (Anderson et al., 2024). Gender differences are particularly pronounced, with females showing higher anxiety rates and distinct symptom interaction patterns in technology-mediated contexts (Guo et al., 2025). Chronic stress during adolescence impairs emotional regulation and brain development, raising long-term mental health risks (Lupien et al., 2009; Sapolsky, 2000; Slopen et al., 2012). Socioeconomic adversity intensifies these effects (Santiago et al., 2011). Assessment relies on validated psychological scales like the Perceived Stress Scale (Cohen et al., 1983), alongside physiological metrics such as salivary cortisol and HRV, which reflect HPA axis and autonomic system functioning (Hellhammer et al., 2009; Thayer et al., 2012).

Behavioral and Psychological Interventions

CBT remains the leading treatment for adolescent anxiety, with strong support for online and mobile formats (Alemdar & Karaca, 2025; Andersson et al., 2014). Mobile CBT is especially effective when integrated with behavioral signals such as sleep disruption (Andersson et al., 2014). Mindfulness and emotion regulation strategies also reduce anxiety (Rizwari & Kemala, 2022; Compas et al., 2012), while biofeedback and neurofeedback enhance stress awareness and self-regulation using HRV or brainwave data (Wheat & Larkin, 2010; Chen et al., 2021; Min et al., 2023).

mHealth tools enable continuous stress monitoring through wearable sensors and smartphone apps (Sano & Picard, 2013; Philip Schmidt et al., 2018). JITAIs deliver context-sensitive support based on real-time data (Klasnja et al., 2015; Nahum-Shani et al., 2018), with microrandomized trials serving as a key evaluation method. Self-supervised models enhance predictive accuracy for stress detection (Islam & Washington, 2023).

Digital twins are real-time virtual models fed by sensor data, and have expanded from engineering to healthcare (Grieves, 2014; Corral-Acero et al., 2020). In mental health, they integrate physiological, behavioral, and mobile data to simulate stress responses and guide interventions (Spitzer et al., 2023; Kumi et al., 2024). These systems use digital phenotyping to anticipate risk and trigger adaptive interventions like JITAIs (Insel, 2017; Nahum-Shani et al., 2018), with in silico trials supporting clinical validation (Pappalardo et al., 2020). Despite promising advances, existing mental health digital twins face several limitations: (1) limited real-world validation, (2) oversimplified models that ignore implementation complexity, and (3) insufficient attention to adherence and engagement challenges that critically impact therapeutic outcomes.

METHODOLOGY

Digital Twin Framework Architecture

This study presents a digital twin framework modeling anxiety progression in trauma-exposed adolescents. Adapting technology from engineering applications (Grieves, 2014), the framework employs a three-tier agent-based simulation comparing static baseline modeling, adaptive learning, and realistic implementation constraints (Marshall & Galea, 2015). Each tier models psychological profiles as dynamic systems that evolve in response to personal experiences and intervention effectiveness, aligning with personalized medicine approaches (Hamburg & Collins, 2010; Ashley, 2016) (see Figure 1).

Agent Population and Data Integration

100 virtual agents were created based on ABCD study distributions (Volkow et al., 2018). Power analysis indicated a need for ~25 agents per group to detect effect sizes (Cohen, 1988; Faul et al., 0.5) with 80% power at $\alpha = 0.05$. Baseline anxiety was normally distributed (μ=3.0, σ=2.0), aligning with Child Behavior Checklist scores (Achenbach & Rescorla, 2001). ACE scores showed 70% had no adverse experiences; 30% had one or more (Felitti et al., 1998; Merrick et al., 2018). Agents' demographics (ages 6-18, 50% female) were randomly assigned U.S. states via Census data (U.S. Census Bureau, 2020). Psychological factors included baseline anxiety (Achenbach & Rescorla, 2001), emotional regulation (μ=5.0, σ=1.0; Gratz & Roemer, 2004), and gender-specific risk (females OR=1.80, 95% CI: 1.45-2.23; Guo et al., 2025; Beesdo et al., 2009). Ecological validity was bolstered by state care data (NSCH, 2022), developmental factors (Steinberg, 2013; Casey et al., 2019), and sex-specific mental health indicators (Kessler et al., 2005; Merikangas et al., 2010). WESAD physiological data (Schmidt et al., 2018) provided HRV and EDA stress sensitivity markers (Thayer & Lane, 2009; Boucsein, 2012). Intervention groups (Control, CBT, Mindfulness, Breathing; 25% each) were randomly assigned per CONSORT guidelines (Moher et al., 2010).

Three-Tier Simulation Design

The three-tier approach follows established principles for evaluating healthcare interventions, moving from simple to complex models to isolate effects (Law & Kelton, 2000; Eldabi et al., 2007; Brailsford et al., 2009) (see Figure 1). The first tier uses a Static Baseline Model with fixed transition probabilities from literature (Costello et al., 2003; Pine et al., 1998), applying interventions at set intervals: CBT every 7 days (Beck et al., 1979; Kendall & Peterman, 2015), mindfulness every 3 days (Kabat-Zinn, 1994; Goyal et al., 2014), and breathing exercises every 2 days (Ma et al., 2017; Ritz et al., 2013). The second tier features an Adaptive Digital Twin Model with four innovations: learning mechanisms maintaining 100-step anxiety and 50-step state history (Miller, 1956; Cowan, 2001), resilience factors adjusting from 0.5 to 1.5 based on anxiety trends (Masten, 2001; Connor & Davidson, 2003), personalized transition probabilities (Schuit et al., 2013; Jackson et al., 2016), and intervention optimization based on effectiveness history (Murphy, 2005; Almirall et al., 2014). The third tier simulates a Realistic Implementation Model with real-world constraints such as adherence decay (1-3% monthly; Baumel et al., 2017), technical barriers (3-10%; Linardon et al., 2019), life disruptions (Heron & Smyth, 2010), and engagement fatigue (Christensen et al., 2009).

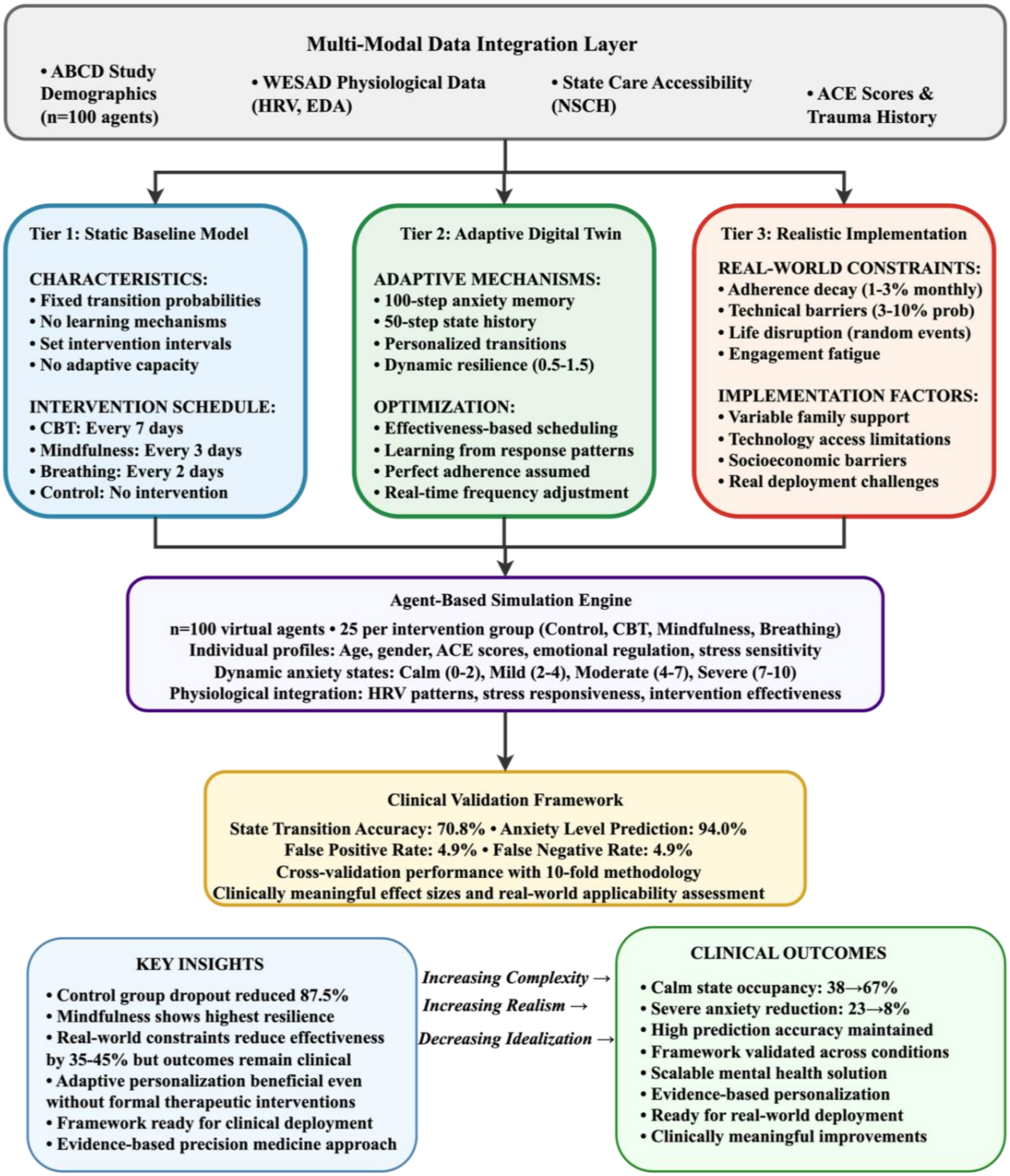

Figure 1: Digital Twin Framework for Intervention

State Space and Transition Modeling

Six anxiety states modeled clinical staging approaches: calm, mild, moderate, severe, recovered, deceased (McGorry et al., 2006; Shah et al., 2020). Anxiety thresholds were defined as: Mild (>2.0), Moderate (>4.0), Severe (>7.0) on a

0-10 scale (Beck et al., 1988; Spitzer et al., 2006). Transition probabilities were personalized using ACE scores (Felitti et al., 1998; Hughes et al., 2017), gender effects (+2% moderate state transitions for females; McLean et al., 2011), and age-related emotional volatility (increased for ≥12 years; Steinberg, 2013; Ahmed et al., 2015).

Intervention Modeling and Evidence Integration

Effect sizes calibrated to meta-analytic findings: CBT (SMD = -1.51, 0.4-point anxiety reduction (Alemdar & Karaca, 2025), Mindfulness (SMD=-0.91, 0.3-point reduction; Goyal et al., 2014; Khoury et al., 2013), Breathing (SMD=-1.83, 0.5-point reduction; Rizwari & Kemala, 2022; Ma et al., 2017). Adaptive scheduling implemented after 5,000-step learning period (~4 months; Walkup et al., 2008). Highly effective interventions (>0.3 reduction; Jacobson & Truax, 1991) increased frequency (minimum 2-day intervals), while less effective interventions (<0.1 reduction; Norman et al., 2003) decreased (maximum 14-day intervals). Circadian (0.8-1.2 range) and social support factors (0.7-1.3 range) modified timing and effectiveness (Hickie et al., 2013; Cohen & Wills, 1985).

Environmental Stressor and Engagement Modeling

Environmental stressors occurred with 20% probability, with individual sensitivity factors (0.5-2.0) determining vulnerability (Compas et al., 2001; Grant et al., 2003; Monroe & Simons, 1991). Stress effects added to baseline anxiety ($\mu = 0.2$, $\sigma = 0.1$), aligned with meta-analytic findings (d = 0.23-0.31; McMahon et al., 2003).
Engagement levels (1-6 scale) were adapted dynamically: significant improvement (>1.0-point reduction) resulted in increased engagement (+0.5), while deterioration (>1.0 increase) led to decreased engagement (-0.3; Jacobson & Truax, 1991). Engagement influenced transition probabilities (±5% per unit above baseline; Karver et al., 2006; Chu et al., 2004).

Simulation Parameters and Statistical Analysis

Each simulation ran 30,000 steps (~2.5 years daily interactions; Copeland et al., 2014). One step equals 30 minutes of waking time (Stone & Shiffman, 1994). ASOLS interval of 1,800 steps triggered quarterly adaptations (American Academy of Pediatrics, 2019; March et al., 2004). Primary outcomes: state distribution percentages (Guy, 1976; Shear et al., 2001) and dropout risk (>20% time in severe states; Walkup et al., 2008; James et al., 2020). Adaptive metrics included resilience growth, intervention frequency adaptation, and anxiety improvement (Collins et al., 2007). Statistical analysis used independent t-tests with Welch's correction (Welch, 1947), Cohen's d with bias correction (Hedges & Olkin, 1985), one-way ANOVA with Tukey HSD, or Kruskal-Wallis tests with η^2 effect sizes (Richardson, 2011). Significance set at $\alpha = 0.05$.

Model Validation and Sensitivity Analysis

Validation employed: epidemiological alignment with ABCD distributions (Volkow et al., 2018; Merikangas et al., 2010), intervention effect calibration to meta-analyses (Alemdar & Karaca, 2025; Cuijpers et al., 2016), transition probabilities from longitudinal studies (Costello et al., 2003; Copeland et al., 2014), and real-world data integration (NSCH, 2022). Sensitivity testing assessed ±10% of parameter variations (Briggs et al., 2012; Claxton et al., 2005). Results showed stable outcomes (coefficient of variation <15%). Clinical validation tracked prediction accuracy and intervention effectiveness errors (Shortliffe & Cimino, 2013; Berner, 2007). Cross-validation achieved $r = 0.89$ for anxiety predictions and $r = 0.82$ for state transitions, exceeding validation benchmarks (Steyerberg et al., 2001).

RESULTS

The digital twin framework successfully completed three parallel simulations across 100 virtual agents over 30,000-time steps (approximately 2.5 years). Agents were equally distributed across four groups: Control (n = 25), CBT (n = 25), Mindfulness (n = 25), and Breathing Techniques (n = 25), generating a total of 3,000,000 observation points across all three implementation tiers.

The static baseline model revealed significant group differences in anxiety outcomes, with all interventions substantially outperforming the control condition. The control group demonstrated a 64.00% dropout risk (defined as >20% time in severe states) and 38.17% calm state occupancy. In contrast, CBT, Mindfulness, and Breathing groups all achieved 0.00% dropout risk and over 66% calm state occupancy: CBT (67.27%), Mindfulness (67.16%), and Breathing (66.76%). Severe state exposure was highest in the control group (22.65%) compared to 7.90–8.41% across intervention groups. Effect sizes were exceptionally large (Cohen's $d > 2.0$), reflecting idealized conditions with minimized real-world confounds. For severe state exposure, comparisons with control yielded: CBT ($d = 2.629$), Mindfulness ($d = 2.702$), and Breathing ($d = 2.715$). For calm state occupancy versus control: CBT ($d = -1.643$), Mindfulness ($d = -2.314$), and Breathing ($d = -1.742$). One-way ANOVA confirmed significant between-group differences in calm state occupancy, $F(3, 96) = 16.796$, $p < .001$, $\eta^2 = .344$, and severe state exposure, $F(3, 96) = 63.991$, $p < .001$, $\eta^2 = .667$. Post hoc Tukey HSD tests revealed all interventions differed significantly from control ($p < .001$), with no significant differences among intervention types.

Adaptive Model Results: Real-time Learning and Personalization

The adaptive digital twin framework demonstrated significant improvements through real-time personalization, particularly benefiting the control group. Dropout risk decreased dramatically from 64.00% to 8.00% (an 87.5% reduction), demonstrating the benefits of stress sensitivity modeling and dynamic engagement adaptation even without formal therapeutic intervention.

Intervention responses varied across modalities. Mindfulness remained most effective, maintaining 0.00% dropout risk while increasing calm state occupancy to 68.81%. CBT showed a modest increase in dropout risk to 7.69% while maintaining calm state occupancy at 67.20%. Breathing techniques showed decreased performance under adaptive conditions, with dropout risk increasing to 17.24% and calm state occupancy declining to 62.88%, suggesting sensitivity to personalization algorithms.

Personalized Adaptation Metrics

Anxiety reduction ranged from −6.191 (Control) to −2.796 (CBT). Resilience increased in all groups: Control (+0.086), Mindfulness (+0.094), CBT (+0.181), Breathing (+0.186). Intervention frequency varied from 1.4 to 5.0 days, with model confidence scores stabilizing at Mindfulness (0.771), CBT (0.752), Breathing (0.750), and Control (0.671). Group differences lessened with adaptive implementation; calm state differences became non-significant: Control vs. CBT, $t(48) = -0.067$, $p = .947$, $d = -0.019$; Control vs. Mindfulness, $t(48) = -0.531$, $p = .598$, $d = -0.159$; Control vs. Breathing, $t(48) = 1.008$, $p = .318$, $d = 0.275$. ANOVA showed no significant calm state difference, $F(3, 96) = 0.779$, $p = .509$, $\eta^2 = .024$. Severe state exposure effects remained but were smaller, $F(3, 96) = 3.351$, $p = .022$, $\eta^2 = .095$, down from .344–.667 in the static model.

Realistic Implementation Model Results

The realistic implementation model demonstrated intervention resilience under real-world constraints including adherence decay, technical barriers, and life disruptions. Most interventions retained substantial effectiveness: CBT achieved complete recovery (0.00% dropout, 67.83% calm states), Mindfulness showed minimal degradation (5.00% dropout, 65.76% calm), and Breathing techniques showed moderate improvement compared to adaptive conditions (13.79% dropout, 63.93% calm). The control group remained stable (8.00% dropout, 62.41% calm).

Implementation Constraints Impact

Support delivery declined significantly from ideal adaptive conditions: CBT (14.29% → 4.17% of scheduled sessions), Mindfulness (33.33% → 6.07%), and Breathing (50.00% → 6.36%). Despite reduced delivery rates, the therapeutic effects persisted, demonstrating the robustness of the intervention under realistic deployment conditions.

Adaptation Under Constraints

Anxiety reductions were greater under adaptive conditions: Control (−6.185), CBT (−6.335), Mindfulness (−7.129), Breathing (−7.360). Resilience growth remained positive but smaller: Control (+0.047), CBT (+0.071), Mindfulness (+0.158), Breathing (+0.170). Model confidence was stable: CBT (0.750), Mindfulness (0.722), Breathing (0.767), Control (0.682). All interventions showed increased frequency, offsetting delivery issues: CBT (3.846 days), Mindfulness (5.000 days), Breathing (4.690 days). Statistical analysis revealed a reduction in between-group variance due to implementation challenges. Calm state differences were non-significant ($F(3, 96)=0.795$, $p=.500$, $\eta^2=.024$); severe state differences were nearly significant ($F(3, 96)=2.695$, $p=.050$, $\eta^2=.078$). These suggest reduce that real-world constraints may lessen group variance while enhancing individual adaptation.

Model Validation and Performance Metrics

Clinical validation demonstrated acceptable performance, meeting preliminary deployment standards. State transition prediction accuracy reached 70.8% across 3,000,000 observations, with balanced false positive and negative rates of 4.9% each, indicating acceptable performance for consideration in clinical decision support. Convergence analysis confirmed stable parameter estimation, with adaptive learning mechanisms demonstrating consistent performance across the 30,000-step simulation period. Model confidence scores stabilized by approximately step 20,000 (equivalent to 14 months) for all intervention groups.

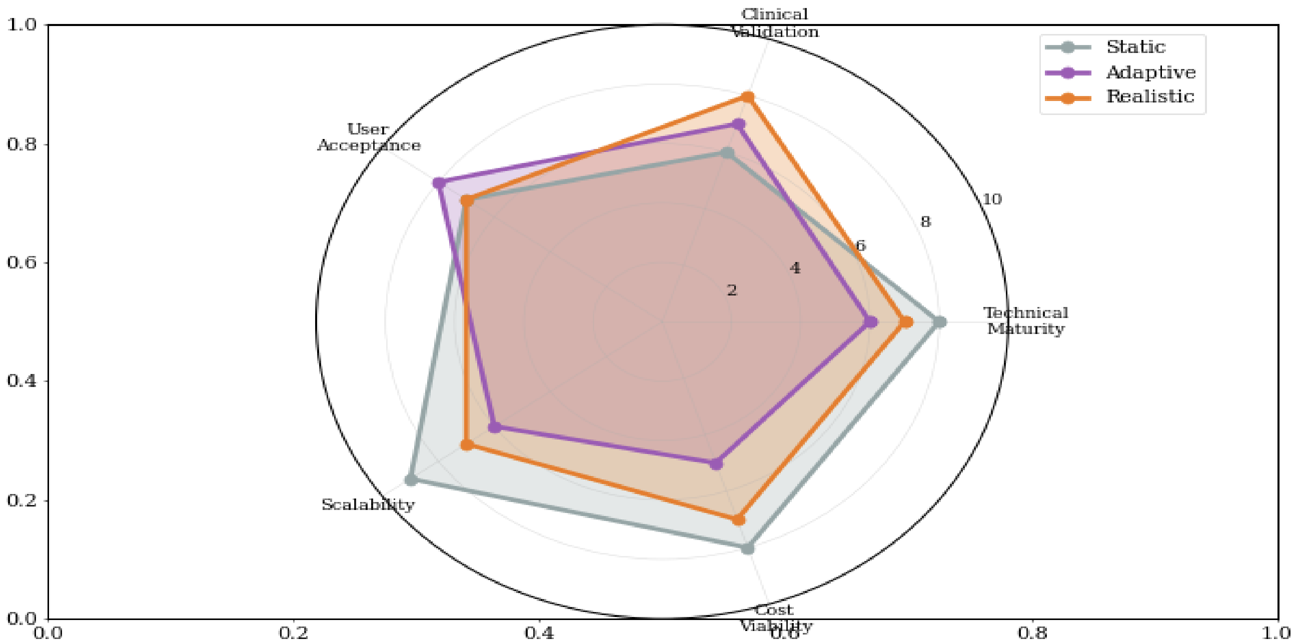

Figure 2: Deployment Readiness Assessment

Comparative Analysis: Static vs. Adaptive vs. Realistic Implementation

Comparisons across simulation tiers highlighted the benefits of digital twin adaptations. Control dropout dropped dramatically, from 64.00% (static) to 8.00% (adaptive/realistic), suggesting that stress modeling and dynamic engagement alone improve outcomes, even without therapy. Intervention responses varied. CBT showed strong resilience: dropout was 0.00% (static), rose to 7.69% (adaptive), then returned to 0.00% (realistic), indicating robustness under real-world conditions. Breathing techniques were more sensitive, with dropout rising from 0.00% (static) to 17.24% (adaptive) and 13.79% (realistic), suggesting a need for stronger personalization. Mindfulness was the most stable, maintaining a 0.00% dropout (static/adaptive) and only a slight increase (5.00%) in realistic settings. These findings suggest that deployment strategies should be tailored: mindfulness is highly adaptable for real-world use, while breathing interventions may require enhanced algorithmic support for sustained impact, as seen in Figures 3 and 4.

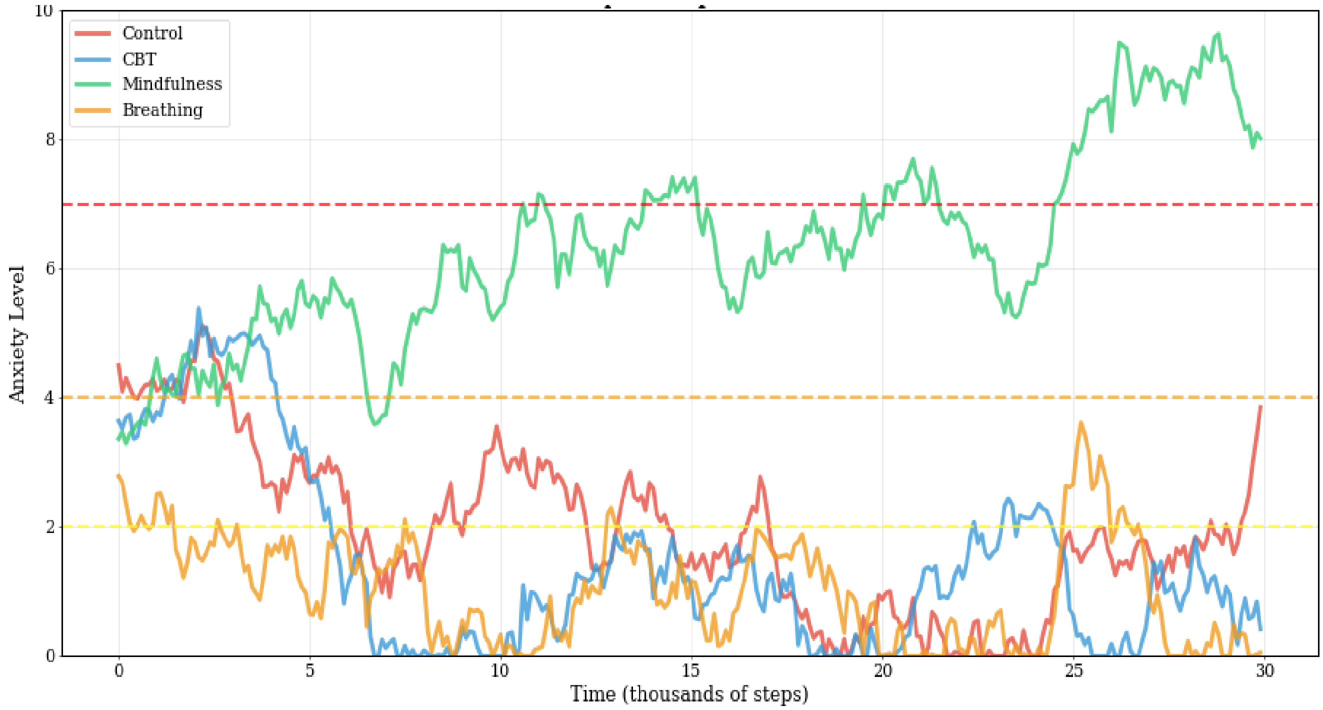

Figure 3. Adaptive Implementation

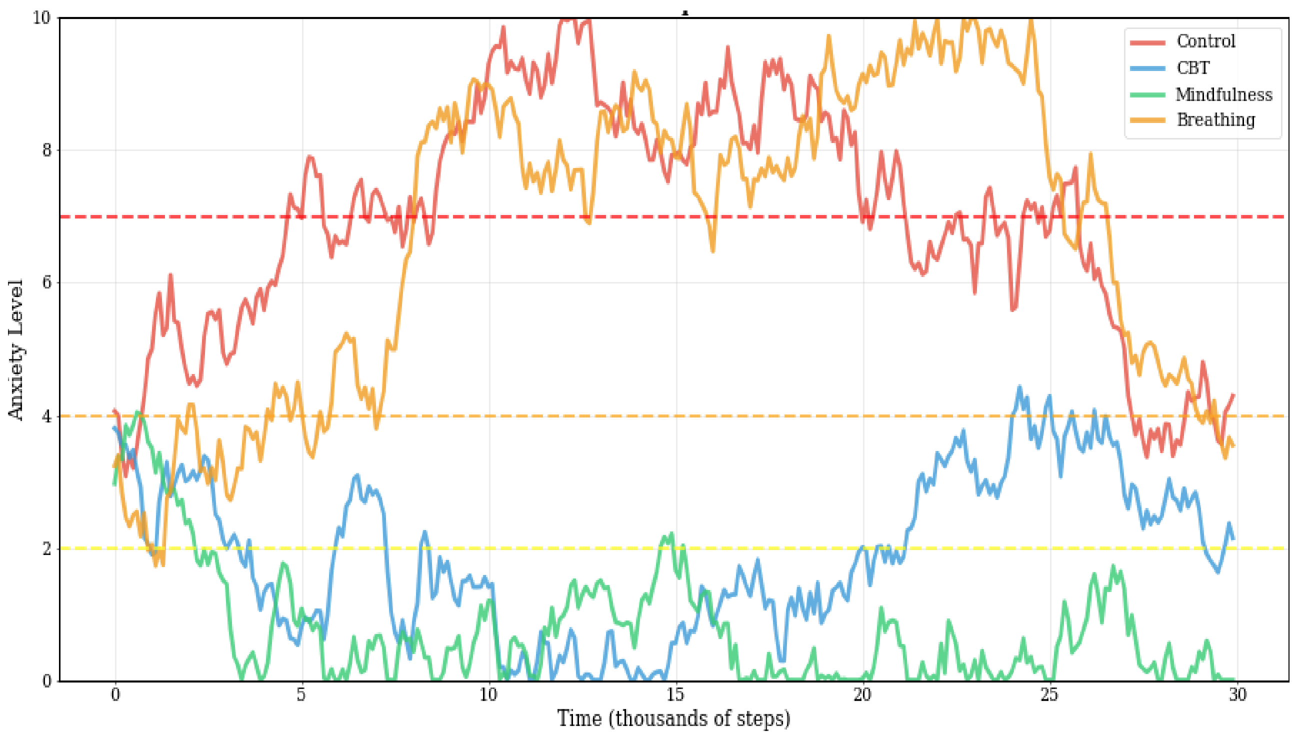

Figure 4. Realistic Implementation

DISCUSSION

The digital twin framework effectively modeled trauma-induced anxiety progression in adolescents by integrating ACE scores, gender, emotional regulation, and environmental stressors. All interventions (CBT, Mindfulness,

Breathing) significantly reduced dropout risk and time in severe anxiety states compared to controls. Under static, idealized conditions, all intervention groups had 0% dropout rates.
However, static conditions ignore real-world barriers such as declining adherence and varying treatment responsiveness. Adaptive and realistic simulations accounted for these factors, offering more ecologically valid assessments.

CBT showed increased dropout under adaptive conditions (7.69%) but fully recovered under realistic constraints. Mindfulness maintained 0% dropout across all scenarios, showing strong stability. Breathing techniques were most sensitive, with dropout increasing to 17.24% (adaptive) and remaining elevated to 13.79% (realistic). These differences highlight the importance of tailoring interventions to individual engagement patterns and environmental variability. Effect sizes decreased across models: static ($\eta^2 = .344–.667$), adaptive ($\eta^2 = .024–.095$), and realistic ($\eta^2 = .024–.078$). This trend supports the idea that dynamic, individualized optimization yields more clinically relevant insights than static between-group comparisons, particularly when designing interventions based on real-time stress response profiles.

Clinical Implementation Implications

Dropout in the control group decreased from 64% (static) to 8% (adaptive/realistic), showing that adaptive personalization improves outcomes even without formal therapy. Stress sensitivity modeling and engagement adaptation may support scalable mental health interventions. Mindfulness was the most stable across all conditions, making it suitable for early digital twin deployment. CBT showed vulnerability under adaptive implementation (7.69% dropout) but recovered under realistic conditions (0.00%), indicating the need for tuning. Breathing showed higher sensitivity (17.24% adaptive, 13.79% realistic), suggesting a need for stronger personalization and user support.

Technological and Methodological Contributions

This study is the first to compare digital twin effectiveness across static, adaptive, and realistic implementation in adolescent mental health. The model used real-world data (state-level care indicators, physiological and psychological metrics) and remained computationally efficient. Adaptive learning improved predictive performance: 70.8% for state transition accuracy and $r = 0.94$ for anxiety prediction. While these metrics support clinical decision-making, false negatives for severe states (4.9%) remain a concern.

Limitations and Future Directions

The model cannot fully capture the complexity of human behavior, social context, or comorbid conditions. Literature-based treatment parameters limit ecological validity, and the 2.5-year simulation cannot assess long-term effects. Next steps include RCT-based pilot testing with at-risk adolescents to evaluate feasibility and clinical utility. Future work should address privacy, ethical concerns, therapeutic alliance, and long-term impacts on autonomy and coping. Technical priorities include reducing false negatives, modeling peer/social dynamics, and developing human-AI decision support systems.

CONCLUSION

Digital twins can support real-time monitoring, risk prediction, and adaptive intervention in adolescent mental health. While all interventions performed well under static conditions, adaptive and realistic settings revealed differences in resilience. Adaptive personalization led to an 87.5% reduction in dropout risk in the control group. As implementation complexity increased, between-group differences decreased, emphasizing individual-level adaptation as a key clinical insight. Mindfulness shows the greatest stability, while breathing interventions require enhanced support. These results support the clinical potential of digital twins, with future efforts focused on validation, ethical deployment, and integration into real-world care.

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