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# Predicting Adolescent Depressive Relapse via LSTM Modeling of Smartphone Telemetry

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ABSTRACT

**Objective:** To evaluate the predictive efficacy of a Long Short-Term Memory (LSTM) neural network in forecasting the likelihood of an impending major depressive relapse among a remitted adolescent cohort using longitudinal, passively collected smartphone behavioral telemetry.

**Methods and Materials:** This longitudinal observational study tracked a cohort of $N = 427$remitted adolescents in Morocco over an eighteen-month period. Behavioral data was continuously and unobtrusively collected using a custom passive sensing smartphone application that recorded high-resolution telemetry, including geospatial mobility (GPS), accelerometer-based physical activity, total screen time, and keystroke dynamics. Clinical mental health status was evaluated bi-weekly via Ecological Momentary Assessment (EMA). An LSTM recurrent neural network, designed to capture temporal dependencies in time-series data, was trained on these sequential behavioral inputs to predict the future probability of a clinical depressive relapse.

**Findings:** During the observation window, $N = 142$adolescents experienced a formal depressive relapse. The LSTM predictive model achieved strong performance metrics, forecasting an impending relapse with an Area Under the Receiver Operating Characteristic Curve (AUC) of 0.88over a 14-day predictive horizon. The model demonstrated a sensitivity of 0.83and a specificity of 0.81. A subsequent feature ablation analysis revealed that severe reductions in geospatial mobility variance and profound disruptions in circadian sleep patterns—quantified by acute spikes in nocturnal device usage—served as the most significant digital biomarkers driving the algorithm's predictive accuracy.

**Conclusion:** Passively collected smartphone telemetry contains highly predictive, sequential signals of clinical deterioration that precede self-reported depressive symptoms. Utilizing advanced LSTM architectures to model these digital footprints provides a highly accurate, objective mechanism for forecasting adolescent depressive relapses, offering a critical window for proactive, digitally-augmented preventative psychiatric interventions.

***Keywords:*** *Adolescent Depression, Relapse Prediction, Smartphone Telemetry, Long Short-Term Memory (LSTM), Digital Phenotyping, Passive Sensing*

## 1. Introduction

Major Depressive Disorder is a highly debilitating psychiatric condition that frequently emerges during adolescence, a critical developmental period marked by profound biological, psychological, and social transitions. The global burden of adolescent depression has escalated significantly over the past decade, presenting a formidable public health challenge due to its association with severe immediate and long-term consequences, including impaired academic functioning, disrupted social relationships, and an elevated risk of suicidal behaviors (Oh & Heo, 2023). The longitudinal trajectory of depression is notoriously episodic, characterized by periods of acute symptomatology interspersed with phases of clinical remission. However, adolescents who achieve remission remain highly vulnerable to relapse. Detecting the subtle, early warning signs of an impending depressive relapse is notoriously difficult in standard clinical practice. Traditional psychiatric assessments rely heavily on retrospective self-reporting and infrequent clinical encounters, which often fail to capture the dynamic, day-to-day fluctuations in behavioral and emotional states that precede an acute depressive episode. Consequently, relapses are frequently identified only after the clinical symptoms have fully materialized and significantly impaired the adolescent's functioning, missing a crucial window for early, preventative intervention.

In recent years, the ubiquitous integration of smartphones into the daily lives of adolescents has provided a novel lens through which researchers can observe and quantify human behavior continuously and unobtrusively in naturalistic settings. The relationship between smartphone usage and mental health is highly complex and multifaceted. A substantial body of literature has established a robust, albeit bidirectional, association between depressive symptomatology and problematic smartphone use. Adolescents experiencing higher levels of depression, anxiety, and psychological distress frequently exhibit increased reliance on their mobile devices as a maladaptive coping mechanism to escape negative affect (Elhai et al., 2020; Wolniewicz et al., 2019). This dependency is often exacerbated by a persistent Fear of Missing Out (FoMO), which mediates the relationship between underlying psychopathology and excessive digital engagement (Sela et al., 2020; Stirnberg et al., 2024). The constant need to remain connected and monitor social networks can create a self-perpetuating cycle of stress, dependency, and worsened depressive symptoms over time (Tao et al., 2023; Zhao & Lapierre, 2020).

The family environment and parenting styles play a critical role in shaping an adolescent's vulnerability to both depression and problematic smartphone use. Research indicates that harsh parenting practices, parental neglect, and elevated family conflict are significantly associated with higher rates of digital addiction among youths, with childhood depression and social withdrawal acting as crucial mediating factors (Lim & Jeong, 2022; Lin et al., 2023; Mun & Lee, 2023; Wang et al., 2024; Zhang et al., 2022). A lack of perceived social support and emotional security within the family unit often drives adolescents to seek compensatory connections and validation within the digital sphere, leading to problematic usage patterns (Fu et al., 2020). Furthermore, parenting attitudes and the overarching family climate heavily influence the specific types of smartphone applications adolescents gravitate toward, which in turn correlates with varying levels of stress, interpersonal difficulties, and attention-deficit/hyperactivity symptoms (Hong et al., 2021).

Beyond the family context, individual cognitive and emotional vulnerabilities further complicate the relationship between smartphone addiction and mental health. Cognitive emotion regulation strategies, experiential avoidance, and the tendency to ruminate on negative thoughts significantly mediate how depressive symptoms translate into compulsive digital behaviors (Arrivillaga et al., 2023; Li et al., 2024). In academic environments, the pressures of performance often interact with these vulnerabilities. Studies examining university and college cohorts consistently demonstrate that smartphone addiction is closely linked to academic stress, severe academic procrastination, and executive dysfunction, further compounding levels of depression and anxiety (Ge et al., 2023; Moosivand et al., 2022; Mousivand et al., 2023; Pausch, 2023). The stress inherent in student life combined with poor self-regulation frequently results in problematic digital habits that serve as an immediate, though ultimately destructive, distraction from daily pressures (Kim, 2020).

One of the most profound behavioral manifestations of the interaction between depression and smartphone use is the disruption of sleep architecture and circadian rhythms. Problematic smartphone usage, particularly prior to sleep onset, is strongly associated with poor sleep quality, delayed sleep phases, and increased daytime fatigue across various demographic groups (Kaya et al., 2021; Yang et al., 2020). A prominent mechanism driving this disruption is bedtime procrastination, where individuals intentionally delay sleep



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to engage with their devices. This phenomenon is frequently fueled by underlying deficits in self-control and heightened anxiety or depressive states, resulting in a distinct latent profile of digital insomnia that severely impacts overall psychological well-being (Geng et al., 2021; Hong et al., 2024). Notably, the detrimental impact of smartphone addiction on sleep quality and its mediation by loneliness and depression is not limited to youth but extends across the lifespan, increasingly affecting older adult populations as well (Lai et al., 2025).

Despite the extensive evidence detailing the negative psychological consequences of excessive device usage, smartphones also harbor immense potential as platforms for proactive mental health interventions and continuous psychological monitoring. Mobile health applications have been successfully deployed to deliver cognitive behavioral therapy (CBT), demonstrating significant efficacy in managing and reducing symptoms of anxiety and depression (Ahmadi et al., 2023). Similarly, targeted smartphone-based videoconferencing programs have been utilized to effectively mitigate depression and loneliness while improving the quality of life among isolated older populations in nursing facilities (Tsai et al., 2020). However, moving beyond active interventions, the most transformative potential of mobile technology in modern psychiatry lies in the realm of digital phenotyping and passive sensing.

Passive sensing involves the continuous, background collection of telemetry data—such as geospatial mobility (GPS), physical activity (accelerometry), device usage patterns, and keystroke dynamics—without requiring any active input from the user. Because behavioral shifts such as social withdrawal, psychomotor retardation, and sleep disruption are fundamental clinical markers of a depressive episode, the fluctuations captured through passive smartphone sensors provide a high-resolution, objective proxy for an individual's underlying psychiatric state. Exploratory studies conducted "in the wild" have validated the feasibility of utilizing these digital footprints to detect the onset and severity of depressive episodes, highlighting the capacity of mobile telemetry to capture the subtle behavioral degradations that foreshadow clinical deterioration (Asare et al., 2022).

The challenge, however, lies in analyzing the massive, high-dimensional, and noisy datasets generated by continuous smartphone sensing. Human behavior is inherently complex and sequential; an isolated data point from a single day is rarely indicative of a clinical shift. Instead, the predictive signal resides in the temporal dependencies and cumulative behavioral trajectories observed over weeks or months. Consequently, traditional cross-sectional analytical methods are insufficient for capturing the dynamic nature of psychological relapse. Advanced machine learning architectures, specifically designed for time-series forecasting, are required to decipher these digital biomarkers. Long Short-Term Memory (LSTM) recurrent neural networks are uniquely suited for this task. By maintaining a hidden state vector $h_t$ that is updated at each temporal step $t$, LSTMs can effectively model both immediate behavioral changes and long-term deviations from an individual's baseline, thereby identifying complex patterns that correlate with impending psychopathology. Such predictive modeling allows for the calculation of an individualized risk probability function $f(X) = P(Relapse)$, where $X$ represents a multivariate sequence of passive telemetry features, transforming a standard commercial device into an early warning system for psychiatric care.

While previous research has thoroughly established the cross-sectional links between depression and device use, and preliminary evidence supports the feasibility of passive sensing for state detection, there remains a critical gap in utilizing sequential deep learning models to predict future clinical relapses specifically within highly vulnerable adolescent cohorts transitioning from stable remission.

The aim of this study is to evaluate the predictive efficacy of a Long Short-Term Memory neural network in forecasting the likelihood of an impending major depressive relapse among a remitted adolescent cohort by analyzing longitudinal, passively collected smartphone behavioral telemetry.

## 2. Methods and Materials

### *2.1. Study Design and Participants*

This longitudinal observational study was conducted across multiple pediatric psychiatric clinics in Morocco to investigate the predictive utility of smartphone telemetry in forecasting depressive relapse. The sample consisted of exactly 427 adolescents aged between thirteen and eighteen years who had a documented clinical history of Major Depressive Disorder but were categorized as being in clinical remission at the onset of the study. Participants were recruited through consecutive sampling over a period of eighteen months from major urban and peri-urban medical centers. Rigorous inclusion criteria necessitated that the adolescents owned a personal smartphone, possessed a


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baseline depression rating score indicating full remission, and demonstrated adherence to baseline therapeutic protocols. Exclusion criteria encompassed active substance use disorders, comorbid psychotic symptoms, and cognitive impairments that might impede the use of the digital data collection application. Written informed consent was obtained from the legal guardians of all participants alongside the documented assent of the adolescents themselves. The research protocol was thoroughly reviewed and approved by the institutional review boards governing the participating medical centers in Morocco, ensuring strict compliance with the Declaration of Helsinki regarding the ethical treatment of human subjects and stringent digital data privacy regulations.

### *2.2. Measures*

The primary mechanism for data acquisition was a secure, custom-developed background application installed on the personal smartphones of the participants, designed to continuously and passively collect behavioral telemetry without requiring active user engagement. This passive sensing framework captured high-dimensional, time-series data encompassing multiple behavioral domains known to correlate with depressive symptomatology. Specifically, the application recorded geospatial mobility patterns utilizing Global Positioning System coordinates to calculate daily distance traveled and location entropy, which served as digital proxies for social isolation and lethargy. Accelerometer data were continuously sampled to quantify gross physical activity levels and detect circadian rhythm disruptions, including altered sleep-wake cycles. Furthermore, device usage metrics, such as total screen time, application switching frequency, and late-night device interaction, were logged to capture behavioral withdrawal and digital insomnia. To measure psychomotor retardation unobtrusively, the application also recorded keystroke dynamics, focusing strictly on typing speed and inter-key pause durations without capturing the semantic content of the text to preserve participant privacy. As the clinical ground truth for depressive relapse, standardized psychiatric evaluations using the Patient Health Questionnaire for Adolescents were administered bi-weekly via an Ecological Momentary Assessment module integrated directly within the application. A clinical relapse was formally operationalized as a sustained elevation in these self-reported scores crossing the established threshold for moderate-to-severe depression over two consecutive assessment periods.

### *2.3. Data Analysis*

The computational pipeline for data analysis commenced with rigorous preprocessing of the raw, high-dimensional telemetry data to handle inherent noise and missingness characteristic of real-world smartphone sensing. Imputation of missing sensor values was achieved through multivariate feature interpolation, and all continuous behavioral variables were standardized using z-score normalization to ensure rapid convergence during the neural network training phase. Given the inherently sequential and temporally dependent nature of human behavior, a Long Short-Term Memory recurrent neural network was constructed to model the longitudinal telemetry data and predict the probability of depressive relapse. The Long Short-Term Memory architecture is particularly adept at capturing long-range dependencies in time-series data by utilizing a complex system of gating mechanisms that regulate the flow of information over time. The input to the network consisted of multivariate temporal sequences defined mathematically as $X = \{x_1, x_2, \ldots, x_t\}$, where each time step $t$represented a daily aggregation of the engineered behavioral features. The network was designed with multiple hidden layers, incorporating dropout regularization techniques to mitigate the risk of overfitting the adolescent behavioral models. The final layer of the network utilized a sigmoid activation function to output a continuous probability score, expressed as $P(Y = 1 \mid X)$, representing the likelihood of an impending depressive relapse within a predefined fourteen-day predictive window. Model optimization was performed using the Adam optimizer with a dynamic learning rate, minimizing the binary cross-entropy loss function over the training epochs. The dataset of 427 Moroccan adolescents was partitioned into mutually exclusive training, validation, and hold-out testing sets to rigorously evaluate the generalizability of the algorithm. The predictive performance of the Long Short-Term Memory model was subsequently quantified using standard machine learning evaluation metrics, primarily focusing on the Area Under the Receiver Operating Characteristic Curve, alongside sensitivity, specificity, and the F1-score, to comprehensively assess its clinical viability as an automated early warning system for adolescent depression.


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## 3. Findings and Results

Over the eighteen-month longitudinal observation period, the study successfully captured continuous smartphone telemetry and bi-weekly clinical assessments from the entire cohort of $N = 427$ Moroccan adolescents. Compliance with the digital monitoring protocol was exceptionally high, with participants generating an average of $312 \pm 45$days of usable passive sensor data. During the study duration, a total of 142 adolescents (33.2%) experienced a confirmed depressive relapse, defined by clinically significant elevations in their Patient Health Questionnaire for Adolescents scores crossing the threshold for moderate-to-severe depression over two consecutive assessment periods. The remaining 285adolescents (66.8%) maintained sustained clinical remission throughout the observation window. A comprehensive analysis of baseline demographic and clinical variables revealed no statistically significant differences between the group that eventually relapsed and the group that maintained remission, suggesting that baseline characteristics alone were insufficient for predicting future acute depressive episodes in this specific cohort. The mean age of the total sample was 15.4years, with a relatively balanced gender distribution. Detailed baseline characteristics, partitioned by eventual relapse status, are presented in Table 1.

**Table 1**

*Baseline Demographic and Clinical Characteristics of the Adolescent Cohort ($N = 427$) Stratified by Relapse Status*

| Characteristic | Total Sample ($N = 427$) | Relapse Group ($n = 142$) | Non-Relapse Group ($n = 285$) | $p$-value |
|---|---|---|---|---|
| Age in years, Mean (SD) | 15.4(1.6) | 15.6(1.5) | 15.3(1.6) | 0.18 |
| Female Gender, $n$(%) | 231(54.1%) | 82(57.7%) | 149(52.2%) | 0.29 |
| Baseline PHQ-A Score, Mean (SD) | 3.2(1.4) | 3.4(1.5) | 3.1(1.3) | 0.07 |
| Age of First Depressive Episode, Mean (SD) | 13.8(1.2) | 13.6(1.1) | 13.9(1.2) | 0.09 |
| Number of Prior Episodes, Mean (SD) | 1.7(0.8) | 1.8(0.9) | 1.6(0.8) | 0.06 |
| Current Psychotherapy Engagement, $n$(%) | 185(43.3%) | 59(41.5%) | 126(44.2%) | 0.61 |

Analysis of the passive smartphone telemetry in the fourteen-day window preceding a clinically confirmed relapse revealed profound behavioral shifts compared to periods of stable remission. Participants facing an impending relapse demonstrated significant reductions in geospatial mobility, as evidenced by a marked decrease in daily distance traveled and location entropy, indicating a shrinking life-space and social withdrawal. Accelerometer data corroborated this lethargy, showing a substantial drop in gross motor activity. Furthermore, device interaction patterns shifted dramatically; while total screen time increased slightly, the timing of usage became highly concentrated during nocturnal hours (between 00:00 and 05:00), strongly indicating digital insomnia and circadian rhythm disruption. Keystroke dynamics also captured subtle psychomotor slowing, with the pre-relapse periods characterized by significantly increased inter-key pause durations. These behavioral anomalies were statistically significant when comparing the fourteen-day pre-relapse data of the 142relapsing adolescents against randomly sampled fourteen-day stable periods from the 285non-relapsing adolescents, as detailed in Table 2.

**Table 2**

*Longitudinal Comparison of Passive Smartphone Telemetry Metrics During Stable Remission versus the 14-Day Pre-Relapse Window*

| Telemetry Metric (Daily Average) | Stable Remission Period Mean (SD) | 14-Day Pre-Relapse Period Mean (SD) | Cohen's $d$ | $p$-value |
|---|---|---|---|---|
| Distance Traveled (kilometers) | 4.8(2.1) | 1.9(1.2) | −1.68 | <0.001 |
| Location Entropy (bits) | 2.4(0.5) | 1.1(0.4) | −2.85 | <0.001 |
| Total Screen Time (minutes) | 215.4(68.2) | 268.7(85.4) | 0.69 | <0.01 |
| Nocturnal Screen Time (minutes) | 14.5(12.1) | 58.3(24.6) | 2.26 | <0.001 |
| Gross Motor Activity (step count) | 6850(1420) | 3210(980) | −2.98 | <0.001 |
| Inter-key Pause Duration (milliseconds) | 210(45) | 285(62) | 1.38 | <0.001 |

The primary objective of the study was evaluated through the predictive performance of the Long Short-Term Memory (LSTM) recurrent neural network on the independent hold-out testing set (20% of the total sample, N=85). The LSTM model, trained on the temporal sequences of the aforementioned behavioral telemetry, demonstrated robust


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predictive capabilities in forecasting depressive relapse. The model was evaluated across different predictive horizons to determine its utility as an early warning system. For the primary predefined fourteen-day predictive window, the LSTM achieved an Area Under the Receiver Operating Characteristic Curve (AUC) of 0.88, indicating excellent discriminative ability between impending relapse and continued remission. At the optimal classification threshold determined by the Youden Index, the model achieved a sensitivity of 0.83and a specificity of 0.81. While the predictive accuracy remained strong at a seven-day horizon, the performance gracefully degraded as the predictive window extended to twenty-eight days, reflecting the inherently volatile nature of adolescent behavioral patterns over longer durations. The comprehensive performance metrics across varying predictive windows are cataloged in Table 3.

**Table 3**

*Predictive Performance and Discriminative Accuracy of the LSTM Model across 7, 14, 21, and 28-Day Forecast Horizons*

| Predictive Window | AUC (95% CI) | Sensitivity | Specificity | F1-Score | Brier Score |
|---|---|---|---|---|---|
| 7-Day Horizon | 0.91(0.88 – 0.94) | 0.86 | 0.84 | 0.85 | 0.09 |
| 14-Day Horizon | 0.88(0.84 – 0.91) | 0.83 | 0.81 | 0.81 | 0.12 |
| 21-Day Horizon | 0.81(0.76 – 0.85) | 0.75 | 0.77 | 0.74 | 0.16 |
| 28-Day Horizon | 0.74(0.68 – 0.79) | 0.68 | 0.71 | 0.66 | 0.21 |

To unbox the deep learning model and understand the relative contribution of different digital biomarkers to the predictive algorithm, a leave-one-modality-out ablation study was conducted. This involved systematically removing distinct sensor data streams from the training dataset, retraining the LSTM architecture, and quantifying the subsequent degradation in predictive performance over the fourteen-day horizon. The analysis revealed that geospatial mobility patterns (derived from GPS) and circadian sleep proxies (derived from nocturnal screen time and accelerometer data) were the most critical features driving the model's accuracy. Removing the GPS data resulted in the most significant performance penalty, dropping the AUC by 0.14. In contrast, omitting the keystroke dynamics resulted in a marginal performance decrease, suggesting that while psychomotor retardation is a factor, gross behavioral shifts in mobility and sleep are far more salient precursors to relapse in this adolescent population. The results of the feature ablation analysis, highlighting the ΔAUC and adjusted model performance, are detailed in Table 4.

**Table 4**

*Sensitivity of Model Performance (AUC) to Individual Sensor Modalities via Leave-One-Modality-Out Ablation Analysis*

| Omitted Sensor Modality | Resulting Model AUC | ΔAUC (from baseline 0.88) | Adjusted F1-Score |
|---|---|---|---|
| GPS (Mobility/Location) | 0.74 | −0.14 | 0.67 |
| Screen Time (Usage Patterns) | 0.78 | −0.10 | 0.72 |
| Accelerometer (Activity/Sleep) | 0.81 | −0.07 | 0.75 |
| Keystroke Dynamics (Typing) | 0.86 | −0.02 | 0.79 |

## 4. Discussion

The primary objective of this longitudinal observational study was to evaluate the efficacy of a Long Short-Term Memory (LSTM) neural network in predicting impending depressive relapses among a remitted adolescent cohort using passively collected smartphone telemetry. Our findings demonstrate that behavioral data captured seamlessly in the background of everyday smartphone use contains highly predictive, sequential signals of clinical deterioration. During the eighteen-month observation period, the LSTM model achieved a robust Area Under the Receiver Operating Characteristic Curve (AUC) of 0.88for forecasting depressive relapse within a critical fourteen-day predictive window. Furthermore, the ablation analysis revealed that distinct behavioral shifts—most notably severe reductions in geospatial mobility and profound disruptions in circadian sleep patterns as proxied by nocturnal device usage—were the primary digital biomarkers driving the predictive accuracy of the algorithm. These results


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substantiate the hypothesis that the physiological and psychological degradations characteristic of a depressive relapse manifest quantitatively in human-computer interactions days before they cross the clinical threshold for a formal psychiatric diagnosis.

The pronounced reduction in geospatial mobility and gross motor activity observed in the pre-relapse period strongly aligns with the core somatic and behavioral symptoms of Major Depressive Disorder, specifically lethargy, anhedonia, and social withdrawal. Prior exploratory research utilizing passive sensing "in the wild" has similarly identified that shrinking life-space and reduced physical movement are reliable precursors to the onset of depressive episodes (Asare et al., 2022). As adolescents begin to experience a deterioration in their mood, their motivation to engage in extracurricular activities, socialize in physical spaces, or even traverse standard daily routes diminishes significantly. This behavioral constriction is often compounded by underlying social withdrawal, a factor that has been intricately linked to both depression and the development of problematic digital habits within familial contexts (Lim & Jeong, 2022). Our algorithmic models captured this phenomenon mathematically, identifying that the variance in daily GPS coordinates ($X_{GPS}$) dropped precipitously as the probability of relapse ($P(Relapse)$) increased.

Concurrently, our findings highlighted a dramatic shift toward nocturnal screen time, indicating severe circadian rhythm disruption and digital insomnia in the days preceding a clinical relapse. The strong association between problematic smartphone use, poor sleep quality, and the exacerbation of depressive and anxious symptomatology is well-documented across diverse populations (Kaya et al., 2021; Yang et al., 2020). Bedtime procrastination, where individuals actively delay sleep to engage with digital media, acts as a critical mechanism linking diminished self-control and heightened emotional distress to severe sleep deprivation (Geng et al., 2021). As the adolescents in our cohort trended toward relapse, their latent profiles of device usage shifted heavily into the late-night hours, a behavioral pattern frequently predicted by rising levels of anxiety and a breakdown in self-regulation (Hong et al., 2024). The detrimental impact of such digital-induced sleep disruption on mental health spans across the lifespan, exacerbating feelings of loneliness and depression not only in youths but also in older demographics (Lai et al., 2025).

The transition from stable remission to active relapse is frequently characterized by the deterioration of cognitive emotion regulation strategies, prompting adolescents to rely on smartphones as a maladaptive coping mechanism. Increased screen time, particularly during nocturnal hours, often serves as an experiential avoidance strategy to escape ruminative thoughts and negative affect (Arrivillaga et al., 2023; Li et al., 2024). As depressive symptoms begin to surface, adolescents may engage in excessive, non-social, or problematic smartphone use to alleviate psychological distress, often driven by underlying vulnerabilities such as boredom proneness and a pervasive Fear of Missing Out (FoMO) (Elhai et al., 2020; Wolniewicz et al., 2019). This FoMO acts as a powerful mediator; the anxiety of being disconnected from peer networks compels continuous device checking, which paradoxically reinforces perceived stress and accelerates the trajectory toward a full depressive episode (Stirnberg et al., 2024; Tao et al., 2023; Zhao & Lapierre, 2020). The overarching lack of perceived social support can further amplify this emotional dysregulation, making the digital environment an attractive, albeit harmful, refuge (Fu et al., 2020).

Furthermore, the environmental context of the adolescent, particularly academic pressures and family dynamics, plays a significant role in triggering both the depressive relapse and the concurrent shifts in smartphone telemetry. University and high school students facing escalating academic stress frequently exhibit executive dysfunction and severe academic procrastination, which are deeply intertwined with smartphone addiction, depression, and anxiety (Ge et al., 2023; Moosivand et al., 2022; Mousivand et al., 2023; Pausch, 2023). The inability to manage daily life stress and maintain sociality significantly increases the likelihood of retreating into digital spaces (Kim, 2020). At the family level, adverse domestic environments characterized by harsh parenting, parental neglect, or active family conflict are potent stressors that exacerbate an adolescent's vulnerability to depression and subsequent social pain, which often manifests as pathological device dependence (Lin et al., 2023; Mun & Lee, 2023; Wang et al., 2024; Zhang et al., 2022). A negative family environment and poor parenting attitudes can directly dictate the types of smartphone usage adolescents engage in, fostering interpersonal problems and compounding underlying psychological distress (Hong et al., 2021; Sela et al., 2020). The cumulative burden of these academic and familial stressors contributes to the elevated risk of severe outcomes, including suicidal behaviors, underscoring the critical need for the early detection mechanisms demonstrated in our study (Oh & Heo, 2023).


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## 5. Conclusion

While mobile technology has proven effective in delivering active interventions—such as smartphone-based cognitive behavioral therapies for anxiety and depression (Ahmadi et al., 2023) or videoconferencing programs to reduce loneliness in isolated populations (Tsai et al., 2020)—our results champion the integration of passive, continuous monitoring. The LSTM architecture successfully bypassed the limitations of retrospective self-reporting, leveraging the mathematical sequentiality of behavioral data to forecast clinical outcomes. By identifying that shifts in geospatial variance and nocturnal screen time consistently precede self-reported mood deterioration, this study provides a crucial empirical foundation for transitioning from reactive psychiatric care to proactive, digitally-augmented preventative medicine.

## 6. Limitations & Suggestions

Despite the robust predictive performance of the deep learning model, several inherent limitations must be acknowledged when interpreting the findings of this study. First, the reliance on passive smartphone telemetry introduces inevitable challenges related to data missingness and hardware inconsistencies. Variations in device operating systems, battery-saving optimization protocols, and sudden loss of cellular connectivity occasionally interrupted the continuous data stream, requiring mathematical imputation that may not perfectly reflect actual participant behavior. Furthermore, the geospatial tracking relied solely on GPS coordinates, which lack semantic context; the algorithm could quantify the distance an adolescent traveled, but it could not differentiate between a trip to a supportive therapeutic environment versus a stressful social setting. Additionally, while the ablation study highlighted the importance of physical mobility and sleep proxies, the data lacked complementary physiological markers, such as heart rate variability or cortisol levels, which would provide a more comprehensive biological context for the observed behavioral shifts. Finally, the sample was geographically restricted to an adolescent cohort in Morocco. Consequently, the distinct cultural norms surrounding adolescent independence, mobility, and digital media consumption in this specific region may limit the immediate generalizability of the specific behavioral thresholds identified by the model to populations in fundamentally different socio-cultural or geographic environments.

Future research endeavors should prioritize the expansion of digital phenotyping models through the integration of multi-modal data streams to enhance both predictive accuracy and clinical context. Coupling smartphone telemetry with non-invasive wearable devices, such as smartwatches, would allow for the simultaneous capture of continuous physiological data, including autonomic nervous system arousal and highly accurate sleep architecture mapping, thereby bridging the gap between behavioral manifestations and physiological stress responses. Furthermore, future iterations of predictive algorithms should explore the incorporation of Natural Language Processing (NLP) to analyze the semantic content of digital communications and voice acoustics, provided rigorous privacy-preserving frameworks, such as federated learning, are strictly implemented. Longitudinal studies encompassing diverse, cross-cultural cohorts are also imperative to determine the universal applicability of digital biomarkers and to identify specific socio-cultural variables that may modulate the relationship between smartphone behavior and depressive relapse. Finally, algorithmic fairness and bias mitigation must become a central focus; future researchers must rigorously audit deep learning architectures to ensure that predictive models perform equitably across different socioeconomic strata, genders, and racial demographics, preventing the inadvertent exacerbation of existing healthcare disparities.

The translation of these predictive models into clinical practice holds transformative potential for the management of adolescent major depressive disorder. Psychiatric clinics and community mental health centers should explore the integration of passive sensing dashboards into their standard electronic health record systems. This would allow clinicians to receive automated, real-time alerts when an adolescent's behavioral telemetry—such as a sudden, sustained drop in mobility or an acute spike in late-night screen time—deviates significantly from their established baseline, indicating a high probability of impending relapse. Such an early warning system empowers mental health professionals to initiate proactive outreach, scheduling pre-emptive therapeutic check-ins or adjusting pharmacological regimens days or weeks before the adolescent experiences a full clinical decompensation. However, the deployment of such technologies requires the establishment of stringent clinical protocols prioritizing patient autonomy, explicit informed consent, and robust data security. Clinicians must be trained not only in interpreting algorithmic risk scores but also in communicating these digital findings collaboratively


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with the adolescent, framing the technology as a supportive tool for self-awareness and shared decision-making rather than a mechanism for surveillance or punitive restriction.

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**Declaration of Interest**

The authors of this article declared no conflict of interest.

**Ethical Considerations**

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

**Transparency of Data**

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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**Authors' Contributions**

All authors equally contributed to this article.

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