

Detecting Adolescent Emotional Distress from Daily Smartphone Behavioral Patterns Using Long Short-Term Memory Networks

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ABSTRACT

Objective: This study aimed to determine whether daily smartphone-derived behavioral patterns could accurately detect high emotional distress among Colombian adolescents using Long Short-Term Memory (LSTM) networks and whether sequential deep learning outperformed alternative predictive models.

Methods and Materials: A prospective longitudinal observational study was conducted among 312 adolescents aged 13–18 years recruited from public and private secondary schools in Bogotá, Medellín, and Cali, Colombia. Participants were monitored for eight consecutive weeks using a custom Android smartphone application that passively recorded non-content behavioral metadata related to screen activity, application use, communication, mobility, and temporal routines. Daily emotional distress was assessed through ecological momentary assessment. After preprocessing, 15,884 valid participant-days and 13,912 seven-day behavioral sequences were available for analysis. Data were divided at the participant level into training, validation, and independent test sets. An LSTM model was developed and compared with logistic regression, random forest, gradient boosting, and feed-forward neural network models.

Findings: The LSTM model achieved a ROC-AUC of 0.886, PR-AUC of 0.774, accuracy of 82.3%, sensitivity of 81.1%, specificity of 82.8%, balanced accuracy of 81.9%, and F1 score of 0.737 in the independent test set. It outperformed logistic regression (ROC-AUC = 0.724), random forest (0.801), gradient boosting (0.827), and feed-forward neural network (0.842). Temporal-routine features showed the strongest single-domain predictive performance, followed by mobility features. The seven-day sequence yielded better discrimination than three-day, five-day, and ten-day alternatives. Increased nighttime use, later final smartphone interaction, reduced mobility, greater time spent at the primary location, and reduced routine regularity were among the most influential predictive features.

Conclusion: Daily smartphone behavioral patterns provide a meaningful, privacy-preserving signal for detecting adolescent emotional distress, and LSTM networks offer superior performance by capturing temporal dependencies across multiple behavioral domains.

Keywords: adolescents; emotional distress; smartphone behavior; digital phenotyping; Long Short-Term Memory

1. Introduction

Adolescence is a developmental period characterized by rapid biological maturation, expanding social worlds, increasing autonomy, heightened sensitivity to peer evaluation, and substantial changes in emotional regulation. These processes unfold at the same time that smartphones and digitally mediated communication have become deeply embedded in everyday adolescent life, creating a behavioral environment in which social interaction, entertainment, education, information seeking, and self-expression increasingly occur through mobile devices. Smartphones therefore occupy an unusual position in contemporary developmental research: they are simultaneously potential contributors to psychosocial strain and exceptionally rich sensors of daily behavior. Concerns regarding excessive or dysregulated digital media use have intensified because adolescents may be particularly vulnerable to sleep disruption, attentional fragmentation, compulsive checking, social comparison, displacement of offline activities, and persistent exposure to emotionally salient online interactions. Reviews of adolescent and youth digital behavior have linked problematic patterns of smartphone and internet use with a broad range of psychological and social outcomes, including anxiety, mood disturbance, behavioral problems, sleep difficulties, and impaired psychosocial functioning (Gupta et al., 2023; Nagata et al., 2026; Patel et al., 2025). At the same time, emerging research increasingly cautions against reducing digital exposure to a single measure of “screen time,” because different forms, timings, contexts, and patterns of smartphone behavior may have markedly different implications for psychological well-being (Fortunato et al., 2023; Xu et al., 2025). This shift from total exposure toward behavioral patterning is especially important for the study of emotional distress, which is intrinsically dynamic and may fluctuate from day to day rather than remaining stable over long periods.

The relationship between digital media use and adolescent mental health is complex because smartphone behavior reflects both potential causes and consequences of emotional difficulty. An adolescent experiencing anxiety, sadness, irritability, or social stress may increase smartphone use to seek distraction, reassurance, social contact, or emotional escape, whereas heavy or fragmented smartphone engagement may itself contribute to attentional disruption, reduced sleep, social withdrawal, and heightened emotional reactivity. Longitudinal work on problematic mobile phone

use suggests that such behaviors can develop along heterogeneous trajectories and interact with psychological characteristics such as intolerance of uncertainty and distress tolerance (Xie et al., 2025). Person-centered research has similarly demonstrated that adolescents cannot be adequately characterized simply as “high” or “low” smartphone users, because distinctive profiles of application use, communication, entertainment, and habitual engagement can emerge within the same population (Fortunato et al., 2023; Haag et al., 2024). Research on adolescent phubbing further indicates that technology-related behaviors themselves may follow meaningful developmental trajectories rather than representing static individual traits (Zhao & Li, 2026). These findings underscore the importance of studying how digital behaviors evolve over time and how temporal changes may correspond with psychological states. A single cross-sectional estimate of average screen exposure may therefore obscure the behavioral instability that is most informative for identifying short-term emotional vulnerability.

One of the most consistent pathways linking smartphone use and psychological functioning involves sleep and nighttime device behavior. Late-night screen use can delay bedtime, shorten sleep duration, increase cognitive and emotional arousal, and interfere with daily routines that are important for adolescent self-regulation. Evidence among adolescents has linked late-night screen activity and problematic screen use with poor sleep and related health outcomes (Gale et al., 2024), while research among high school students has shown that the relationship between technology use and sleep can vary across social and historical contexts (Sheehan et al., 2025). Classroom-based evidence has also associated nocturnal social media use with poorer sleep quality and anxiety among middle adolescents (Ntumi et al., 2025). Studies focusing on digital media use have further documented associations with digital eye strain and reduced sleep quality, emphasizing that the timing as well as the amount of exposure may matter (Aykutlu et al., 2024). At the same time, recent findings suggest that emotional symptoms may themselves be stronger predictors of poor sleep than pre-sleep screen use in some populations, reminding researchers that behavioral and emotional processes are likely bidirectional (Zhang, 2026). Consequently, late-night device activity should not be interpreted only as an exposure variable; it may also operate as a behavioral marker of existing emotional dysregulation. For digital phenotyping, this distinction is important because the predictive objective is not necessarily to establish

causality but to identify behavioral configurations that reliably accompany periods of elevated emotional distress.

Beyond sleep-related behavior, the structure and content of mobile engagement may provide additional signals of psychological state. Fragmented smartphone use, characterized by frequent checking and short, repeated interactions, has been associated with distraction, procrastination, and anxiety-related processes (Yi et al., 2025). Problematic use may also involve nomophobia, compulsive dependence, or social withdrawal, with recent evidence indicating associations between nomophobia and adolescent social isolation in rapidly changing cultural contexts (Ayhan, 2026). From another perspective, trait mindfulness appears inversely related to problematic internet use, excessive screen exposure, and nomophobia, suggesting that patterns of digital engagement may partially reflect broader differences in attentional control and self-regulation (Fendel et al., 2025). Social anxiety and risk perception have also been linked with problematic mobile phone and video-game use, with potentially different patterns across genders (Ruiz-Olivares et al., 2025). Research on problematic internet and mobile phone use in adults likewise shows that digital dysregulation can co-occur with psychological distress and individual neurobehavioral traits (Floris & Gentili, 2026). Although these studies span different age groups and settings, they collectively support the hypothesis that smartphone-derived behavioral features may capture psychologically meaningful information beyond simple duration of use.

The social environment surrounding digital media also plays a substantial role in adolescent psychological functioning. Family processes can influence both the quantity and quality of media use, and systematic evidence indicates that parental behavior, family relationships, household rules, and communication practices are associated with adolescent screen media use and mental health outcomes (Liu et al., 2024). Family-level media behaviors may cluster into distinctive patterns rather than operating independently, as shown in latent-profile research on family media use (Hamp et al., 2024, 2025). Parental phubbing has also been linked with child problem behaviors through pathways involving parent-child conflict and screen time, suggesting that smartphone behavior can be embedded within broader relational systems (Gu & Zhao, 2025). Research conducted during the COVID-19 period further demonstrated how disruptions in social routines and increased reliance on digital communication could alter children's and adolescents' media habits, sometimes

intensifying concerns about excessive screen exposure and developmental consequences (Islam, 2023). Similar evidence from systematic reviews has associated elevated screen time during the pandemic with behavioral disorders and related psychological concerns in children and adolescents (Abdoli et al., 2024), while a subsequent review identified links between cyberspace exposure and attention-deficit/hyperactivity-related symptoms (Abdoli et al., 2025). Clinical evidence likewise suggests that screen exposure may relate to symptom presentation and severity among children diagnosed with attention-deficit/hyperactivity disorder (Gamli & Gürbüz, 2025). These findings emphasize that digital behaviors should be interpreted as part of a broader behavioral ecology rather than as isolated technological habits.

Social media specifically represents another important dimension of adolescent emotional experience. Platforms can support connection, identity exploration, peer interaction, and access to social support, but they can also intensify social comparison, interpersonal pressure, fear of exclusion, and continuous exposure to emotionally charged content. Research among young people has linked social media use, loneliness, and emotional distress, highlighting the potential role of online engagement in both social connectedness and psychological vulnerability (Martínez et al., 2025). Broader reviews of social media use have identified a diverse set of determinants, including psychological motives, peer influences, habitual patterns, and environmental factors, reinforcing the need to move beyond simple measures of exposure (Fatima et al., 2025). In adolescent boys and young men, digital media use has also been associated with multiple domains of psychosocial health, again suggesting that its effects cannot be understood without considering the type and context of use (Nagata et al., 2026). The developmental significance of smartphone engagement may even extend to brain function, as recent scoping evidence has examined associations between smartphone use and neurocognitive processes during adolescence (Marks et al., 2026). Phenomenological research on so-called "brain rot" has additionally highlighted how young people themselves describe cognitive fatigue, overstimulation, reduced concentration, and perceived mental saturation in relation to intensive digital consumption (Özbay, 2026). Although such constructs require careful empirical definition, they reflect growing concern that behavioral patterns associated with constant digital engagement may correspond with meaningful changes in attention and subjective well-being.

These concerns have motivated a transition from conventional questionnaire-based assessment toward digital phenotyping, in which passive or minimally intrusive data from personal devices are used to characterize behavioral states. Smartphones can continuously record behavioral metadata related to device interaction, app use, communication frequency, mobility, activity, and temporal routines. Importantly, these data can be collected without accessing the semantic content of messages, calls, or social media interactions, making it possible to study behavioral rhythms while preserving a greater degree of privacy. Recent adolescent research has shown that digital phenotypes may be associated with emotional disorders and that smartphone-based behavioral information can complement self-report assessment (Cho et al., 2025). Artificial intelligence and machine-learning approaches have also been applied to adolescent smartphone overdependence, demonstrating that conceptually informed computational models can identify complex risk patterns that may vary across contextual settings (Kim et al., 2025). These developments are important because emotional distress frequently fluctuates more rapidly than traditional clinical assessments can capture. Standardized questionnaires administered monthly or only at baseline and follow-up may identify overall symptom burden, but they are less suited to detecting the short-term behavioral transitions that occur immediately before or during periods of increased distress. Passive smartphone sensing offers a way to observe such transitions at a much finer temporal resolution.

The predictive value of digital phenotyping, however, depends on the analytical methods used to represent time. Many conventional statistical and machine-learning approaches treat each observation as independent, even when data are collected repeatedly from the same person over consecutive days. Such approaches may identify associations between average screen time and distress, yet fail to model whether changes accumulate, persist, reverse, or interact over time. This limitation is particularly relevant when psychological states emerge from combinations of behavior rather than isolated features. For example, one day of reduced mobility may be unremarkable, whereas several consecutive days of reduced movement combined with increased nighttime use and altered communication frequency may represent a meaningful deviation from an adolescent's typical behavioral routine. Similarly, a short-lived increase in entertainment-app use may reflect ordinary leisure, while persistent escalation occurring alongside sleep disruption and reduced routine regularity may provide a

stronger signal of emotional strain. Research emphasizing developmental trajectories of problematic mobile phone behavior (Xie et al., 2025; Zhao & Li, 2026) and person-centered profiles of smartphone activities (Fortunato et al., 2023; Haag et al., 2024) provides conceptual support for models capable of representing sequential structure rather than static exposure.

Long Short-Term Memory networks are particularly well suited to this problem because they are designed to learn dependencies within sequential data. Unlike conventional feed-forward neural networks, LSTM architectures use recurrent memory mechanisms that regulate the retention and forgetting of information across time steps. This enables the model to distinguish transient fluctuations from behavior that persists across multiple days and to learn interactions among contemporaneous and lagged behavioral features. In the context of adolescent emotional distress, an LSTM model can integrate several days of screen duration, device-unlock frequency, nighttime engagement, mobility, communication, and application use into a temporally structured representation of behavioral change. This is theoretically preferable to treating each day as an isolated unit because emotional distress is often cumulative and may be preceded by subtle changes in sleep-related routines, movement, social interaction, or digital engagement. It also aligns with emerging evidence that problematic screen use has networked effects across several developmental domains rather than operating through a single pathway (Xu et al., 2025). Furthermore, digital behaviors associated with distress may differ substantially across individuals, making nonlinear modeling advantageous when the relationship between smartphone behavior and emotional state is not expected to follow a simple linear form.

Despite growing interest in smartphone-based mental health prediction, several methodological gaps remain. Much of the existing literature focuses on total screen time, problematic-use questionnaires, or cross-sectional associations rather than continuous behavioral sensing. Studies often examine one domain at a time, such as social media use, sleep, or addiction-like smartphone behavior, even though emotional distress may be reflected in the interaction among several daily domains. Existing evidence linking screen behavior with attention problems (Abdoli et al., 2025; Gamli & Gürbüz, 2025), sleep disturbance (Aykutlu et al., 2024; Gale et al., 2024), anxiety (Ntumi et al., 2025; Ruiz-Olivares et al., 2025), social isolation (Ayhan, 2026), and broader psychosocial health (Gupta et al., 2023; Patel et al., 2025) suggests that no single

behavioral indicator is likely to provide sufficient predictive information. Moreover, findings based on highly specific populations or pandemic-era behavior may not generalize across settings. The role of cultural, educational, socioeconomic, and family context is likely to be substantial, as digital norms and patterns of access differ across societies. Even studies using advanced computational methods may be limited if training and testing observations from the same participant are mixed, because this can inflate apparent predictive performance by allowing models to learn person-specific behavioral baselines rather than generalizable distress-related patterns.

These limitations are especially relevant in Latin American contexts, where empirical work on passive smartphone sensing and adolescent emotional distress remains comparatively limited. Colombia provides an important setting for investigating digital behavioral markers because adolescents increasingly participate in smartphone-mediated educational, recreational, and social activities while simultaneously experiencing heterogeneous family, school, and urban environments. A model developed in this context must therefore distinguish between ordinary variations in digital lifestyle and behavioral changes associated with emotional difficulty. This requires participant-level validation, longitudinal data, multiple behavioral feature domains, and explicit evaluation against simpler predictive approaches. It is equally important to avoid interpreting behavioral correlations deterministically. High screen time, late-night use, reduced mobility, or communication changes do not inherently constitute psychopathology, and the same pattern may carry different meanings across individuals. Evidence that digital behavior is shaped by family context (Hamp et al., 2025; Liu et al., 2024), psychological resilience (Wu et al., 2024), social circumstances (Martínez et al., 2025), and broader patterns of technology engagement (Sheehan et al., 2025) reinforces the need for probabilistic rather than diagnostic interpretation. Digital sensing should therefore be viewed as a potential complement to psychological assessment, not a substitute for direct evaluation by qualified professionals.

Another important issue concerns the distinction between risk detection and causal explanation. Smartphone sensing models are designed primarily to recognize patterns associated with a psychological state; they do not establish that those behaviors caused the state. This distinction is critical because emotional distress may precede changes in smartphone behavior, follow them, or interact reciprocally with them. For instance, problematic use may worsen sleep

and emotional regulation, but an adolescent already experiencing distress may also engage more intensively with a device as a coping strategy. Similarly, lower mobility may reflect withdrawal and low mood, but it may also result from school schedules, weather, illness, or household circumstances. The same reasoning applies to social media use, where increased interaction may represent either social support or heightened exposure to interpersonal stress. Studies examining psychosocial risk profiles (Haag et al., 2024), digital phenotypes (Cho et al., 2025), resilience and mobile phone addiction (Wu et al., 2024), and problematic-use trajectories (Xie et al., 2025) collectively reinforce the value of interpreting smartphone signals as context-dependent probabilistic markers. A scientifically useful detection model must therefore demonstrate not only discrimination but also robustness across behavioral domains, sequence lengths, and alternative outcome thresholds.

Recent research also points toward the importance of integrating several dimensions of digital behavior rather than privileging any single metric. Excessive screen exposure may have different implications depending on whether the time is spent in communication, education, entertainment, or fragmented checking. Likewise, application-use duration can be interpreted differently depending on whether it occurs during the day or late at night, and communication frequency may have different psychological meanings depending on whether it rises, falls, or becomes more erratic relative to an individual's typical pattern. The literature on adolescent digital media use increasingly reflects this multidimensional perspective, whether through latent behavioral profiles (Fortunato et al., 2023), family media-use configurations (Hamp et al., 2024), AI-based risk modeling (Kim et al., 2025), or network-oriented analyses of problematic screen use (Xu et al., 2025). Such findings suggest that emotionally salient information may be distributed across several weak signals that become informative only when modeled jointly. LSTM networks are particularly compatible with this framework because they can incorporate multivariate daily sequences and learn combinations that are difficult to specify a priori using conventional statistical models.

The present study was therefore designed to address these gaps by combining passive smartphone sensing, repeated daily emotional assessments, participant-level model separation, and sequential deep learning in a Colombian adolescent sample. Rather than relying on a single measure of total screen exposure, the study incorporated multiple behavioral domains, including smartphone interaction

intensity, application use, communication metadata, mobility, and temporal routines. The analytical strategy further compared the LSTM model with conventional machine-learning and non-recurrent neural approaches in order to determine whether explicitly modeling temporal dependence improved the detection of emotional distress. This design was informed by evidence showing that emotional, cognitive, social, and sleep-related aspects of digital engagement are interdependent rather than isolated (Fatima et al., 2025; Fendel et al., 2025; Marks et al., 2026), and by findings indicating that problematic technology use can manifest through heterogeneous behavioral profiles and developmental pathways (Ruiz-Olivares et al., 2025; Zhao & Li, 2026). Accordingly, the aim of this study was to determine whether daily smartphone-derived behavioral patterns could accurately detect high emotional distress among Colombian adolescents using Long Short-Term Memory networks and to evaluate whether sequential deep learning outperformed alternative non-sequential predictive models.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a prospective longitudinal observational design to investigate whether patterns of everyday smartphone use could be used to detect emotional distress among adolescents through Long Short-Term Memory (LSTM) neural networks. The study was conducted in Colombia and included 312 adolescents recruited from public and private secondary schools in Bogotá, Medellín, and Cali. Participants were between 13 and 18 years of age, with a mean age of 15.62 years ($SD = 1.47$). Recruitment was conducted through collaborating schools after obtaining authorization from school administrators and relevant educational authorities. Information sessions were organized for students and their parents or legal guardians to explain the study objectives, passive smartphone sensing procedures, psychological assessments, confidentiality measures, and participants' right to discontinue participation at any time. Adolescents were eligible for inclusion if they were between 13 and 18 years of age, were currently enrolled in secondary education, regularly used an Android smartphone compatible with the study application, had used their personal smartphone for at least six months before enrollment, and were able to complete questionnaires and ecological momentary assessments in Spanish. Participants were excluded if they had a cognitive or developmental

condition that substantially interfered with their ability to understand the study procedures or independently complete the assessments, did not have regular access to their smartphone during the observation period, or provided fewer than 70% of the minimum required daily behavioral records. Data were collected over eight consecutive weeks for each participant, allowing the study to capture both relatively stable individual patterns and short-term fluctuations in smartphone behavior and emotional state. Because smartphone behavioral indicators vary considerably between individuals, the longitudinal design was selected to provide repeated observations within participants and enable the LSTM architecture to model temporal dependencies rather than treating each day as an independent observation. Written informed consent was obtained from a parent or legal guardian, and written assent was obtained from each adolescent before data collection. Participants were informed that the application did not record the content of telephone conversations, text messages, photographs, passwords, web pages, or social media communications. Instead, only behavioral metadata necessary for constructing daily digital behavioral features were collected. Each participant was assigned a randomly generated research identifier, and identifying information was maintained separately from behavioral and psychological data. All study procedures followed established ethical principles for research involving minors and digital behavioral data, with particular attention to privacy, data minimization, confidentiality, and secure storage of smartphone-derived information.

2.2. Measures

Data were collected using a custom smartphone sensing application installed on participants' personal Android smartphones together with brief daily ecological momentary assessments and standardized psychological questionnaires. The smartphone application operated passively in the background and recorded non-content behavioral information that could characterize participants' daily patterns of device interaction, mobility, communication activity, and temporal routines. Screen-related indicators included total daily screen-on duration, number of screen activation events, mean duration of smartphone-use sessions, frequency of device unlocking, duration of nighttime smartphone activity, and the timing of the first and last daily smartphone interaction. Application-use variables included total application-use duration, frequency of

application launches, number of application transitions, and the distribution of use across broad categories such as social communication, entertainment, education, productivity, and gaming. To protect privacy, the semantic content entered or viewed within applications was not recorded. Communication-related metadata included the daily number of incoming and outgoing calls, total call duration, frequency of missed calls, and counts of incoming and outgoing text-message events when such metadata were accessible to the application; telephone numbers, message contents, and contact identities were never stored. Mobility and activity indicators were generated from privacy-preserving location and motion data and included daily distance traveled, estimated radius of gyration, number of distinct location clusters visited, time spent at the most frequently visited location, mobility entropy, and periods of prolonged physical inactivity. Temporal and behavioral regularity variables were also derived to represent consistency in sleep-related smartphone inactivity, nighttime device use, daily mobility, communication frequency, and overall smartphone engagement. Raw sensing observations were aggregated into daily feature vectors using a 24-hour interval beginning at 00:00 and ending at 23:59 local time. To reduce privacy risks, precise geographical coordinates were transformed into mobility features before analysis and were not retained in the final analytical dataset.

Emotional distress was assessed through a combination of daily self-reports and standardized symptom measures. Participants received a brief ecological momentary assessment notification each evening between 7:00 p.m. and 10:00 p.m. and were asked to rate their emotional state during that day. Daily emotional distress was measured using items assessing sadness, anxiety or worry, irritability, perceived stress, emotional exhaustion, and difficulty coping with daily demands. Each item was rated on a five-point response scale ranging from 0 (not at all) to 4 (extremely). A daily emotional distress score was calculated as the mean of the completed items, with higher values indicating greater distress. For the primary classification analysis, each daily observation was categorized as high emotional distress when the daily mean score was 2.00 or higher and as low-to-moderate emotional distress when the score was below 2.00. This threshold was defined before model development to identify days characterized by at least moderate distress across the assessed emotional domains. Daily ecological assessments served as the primary ground-truth outcome because their temporal correspondence with smartphone-derived data allowed the model to associate behavioral

sequences with emotional states occurring during the same observation period. To obtain broader information on participants' psychological status, depressive symptoms were additionally assessed at baseline and at the end of the eight-week observation period using the Patient Health Questionnaire for Adolescents, whereas anxiety symptoms were assessed using the Generalized Anxiety Disorder seven-item scale. These standardized measures were used for descriptive characterization of the sample and for supplementary validity analyses rather than as the primary outcome labels for the LSTM model. Demographic information, including age, sex, school grade, type of school, household composition, and average daily smartphone use before participation, was collected using a baseline questionnaire. Technical logs generated by the sensing application were used to identify periods in which data were unavailable because of device shutdown, application removal, operating-system restrictions, disabled permissions, or loss of connectivity. All data transmitted from participants' smartphones were encrypted during transmission and stored on a secure research server. Personally identifying information was stored separately from behavioral data, and linkage was possible only through encrypted study identifiers.

2.3. Data Analysis

Data preprocessing and statistical analyses were conducted before development of the predictive models. Smartphone sensing records were first synchronized by participant identifier and timestamp and then aggregated into daily observations. Variables with impossible values or values produced by confirmed technical errors were removed. Features with more than 30% missing observations across the study sample were excluded from model development. For the remaining variables, short periods of missing sensor data were imputed within the training data using the median value of the corresponding participant when sufficient individual observations were available; otherwise, the median calculated from the training sample was used. Missing-value indicators were retained for selected behavioral variables so that the predictive algorithm could distinguish true low activity from technically missing observations. Continuous features were standardized using z scores based exclusively on the mean and standard deviation of the training data in each validation cycle, thereby preventing information leakage from validation or test observations. Highly skewed count and duration variables

were transformed using logarithmic transformation when appropriate. Pairwise correlations and variance patterns were examined during preprocessing, and features demonstrating near-zero variance or essentially redundant information were removed. Daily observations were organized into sequential windows of seven consecutive days, with the smartphone behavioral features from these days constituting the input sequence to the LSTM network and emotional-distress status on the final day of each sequence serving as the primary prediction target. Sequences containing insufficient sensing coverage were excluded according to predefined data-completeness criteria. Importantly, data splitting was performed at the participant level rather than the daily-observation level, ensuring that data from the same adolescent could not appear simultaneously in the training and test sets. This procedure was adopted to obtain a more conservative estimate of the ability of the model to generalize to adolescents whose behavioral data had not previously been observed.

The primary predictive model was constructed using an LSTM neural network because smartphone behavior represents sequential data in which current psychological states may be associated not only with behavior observed on the same day but also with behavioral changes occurring across several preceding days. The input layer received the standardized multivariate behavioral sequence, which was passed to an LSTM layer designed to retain temporally informative behavioral signals while reducing the influence of irrelevant information through its input, output, and forget gates. Dropout regularization was incorporated to reduce overfitting, followed by a fully connected dense layer and a sigmoid output unit producing the estimated probability of high emotional distress. The binary cross-entropy loss function was used for optimization. Model weights were estimated using the Adam optimizer, and early stopping was applied according to validation loss so that training terminated when additional epochs no longer improved performance. Hyperparameters, including the number of LSTM units, dropout rate, learning rate, batch size, sequence length, and number of dense-layer units, were optimized using only the training and validation data. Class imbalance was addressed by applying class weights derived from the frequency of high-distress and low-to-moderate-distress observations within the training dataset rather than artificially duplicating observations across participants. The final dataset was divided at the participant level into a training set comprising 70% of participants, a validation set comprising 15%, and an independent test set comprising the

remaining 15%. Stratification was used where feasible to maintain comparable distributions of participants with relatively higher and lower levels of emotional distress across the three subsets. All preprocessing parameters, feature transformations, and model-selection decisions were estimated without access to the independent test set, which was used only once for final performance evaluation.

Predictive performance was evaluated using the area under the receiver operating characteristic curve, area under the precision-recall curve, accuracy, sensitivity, specificity, precision, F1 score, and balanced accuracy. Because the principal purpose of the system was to identify adolescents experiencing elevated emotional distress, sensitivity and the area under the precision-recall curve were considered particularly informative when interpreting model performance. Ninety-five percent confidence intervals for primary test-set performance measures were estimated using participant-level bootstrap resampling to account for clustering of repeated daily observations within individuals. Calibration was additionally examined by comparing predicted probabilities with observed distress frequencies and by calculating the Brier score. The discriminatory performance of the LSTM model was compared with conventional machine-learning approaches trained on the same smartphone-derived variables, including logistic regression, random forest, and gradient-boosting classifiers, as well as a feed-forward neural network that did not explicitly model temporal dependence. These comparisons were conducted to determine whether explicitly incorporating sequential behavioral information improved emotional-distress detection beyond models relying on aggregated or non-sequential predictors. Supplementary analyses examined the predictive contribution of major feature domains by training reduced models based separately on smartphone interaction, application use, mobility, communication, and temporal-routine indicators. Feature importance and model interpretability were examined using model-appropriate post hoc explanation procedures to identify behavioral characteristics that contributed most strongly to predictions while avoiding causal interpretation of predictive associations. Sensitivity analyses were performed using alternative emotional-distress thresholds and different sequence lengths to assess the robustness of model performance. Descriptive statistics were calculated for demographic, psychological, and smartphone-use variables, with means and standard deviations reported for approximately normally distributed continuous variables, medians and interquartile ranges for substantially skewed

variables, and frequencies and percentages for categorical variables. Statistical tests were two-tailed, and a significance level of $p < .05$ was adopted for supplementary inferential analyses. The principal criterion for the machine-learning analysis, however, was out-of-sample predictive performance rather than statistical significance. All conventional statistical analyses and data-quality procedures were conducted using Python-based analytical libraries, and the LSTM architecture was implemented using a deep-learning framework suitable for sequential neural-network modeling.

3. Findings and Results

The final analytical sample consisted of 312 adolescents who completed the baseline assessment and provided sufficient smartphone sensing and ecological momentary assessment data for inclusion in the longitudinal analyses. Participants ranged in age from 13 to 18 years, with a mean age of 15.62 years ($SD = 1.47$). Of the total sample, 164 participants (52.56%) were female and 148 (47.44%) were male. With respect to school location, 128 adolescents (41.03%) were recruited in Bogotá, 101 (32.37%) in Medellín, and 83 (26.60%) in Cali. A total of 181 participants (58.01%) attended public schools and 131 (41.99%) attended private schools. The distribution across school grades was relatively balanced, although the largest proportion of participants were enrolled in grades 9 and 10.

Most participants reported living with at least one parent or legal guardian, and 226 adolescents (72.44%) lived in households with four or more members. During the eight-week monitoring period, 17,472 participant-days were theoretically available. After exclusion of days affected by insufficient sensing coverage, incomplete ecological momentary assessments, or technical interruptions that did not meet the predefined data-completeness criteria, 15,884 valid daily observations remained, corresponding to an overall usable-data rate of 90.91%. Of these daily observations, 4,731 days (29.78%) were classified as high emotional distress and 11,153 days (70.22%) as low-to-moderate emotional distress according to the predefined ecological momentary assessment threshold. After constructing consecutive seven-day sequences and removing windows with incomplete temporal coverage, 13,912 sequences were available for predictive modeling. Participant-level data partitioning resulted in 218 adolescents in the training set, 47 in the validation set, and 47 in the independent test set. No statistically meaningful differences were detected among these three subsets with respect to age, sex distribution, baseline depressive symptoms, baseline anxiety symptoms, or proportion of high-distress days, indicating that the participant-level allocation produced broadly comparable groups while preserving strict separation between training, validation, and test observations.

Table 1

Descriptive Statistics for Daily Emotional Distress and Smartphone-Derived Behavioral Features

Variable	Mean	SD	Median	IQR
Daily emotional distress score	1.46	0.87	1.33	1.25
Total daily screen-on duration, min	287.64	96.82	276.41	128.73
Daily smartphone unlocks, n	74.36	28.51	70.00	36.00
Mean smartphone session duration, min	4.21	1.73	3.96	2.11
Nighttime smartphone use, min	47.83	31.26	41.18	39.72
Social/communication application use, min	103.52	46.91	96.73	61.48
Entertainment application use, min	76.29	42.37	68.14	52.65
Educational/productivity application use, min	34.18	21.46	29.77	26.34
Daily distance traveled, km	12.73	8.64	10.46	9.82
Radius of gyration, km	4.18	2.91	3.37	3.46
Distinct daily location clusters, n	4.63	1.82	4.00	2.00
Time at most frequently visited location, min	892.47	186.35	918.36	231.44
Incoming and outgoing calls, n	5.74	3.68	5.00	4.00
Total call duration, min	18.39	14.77	14.61	18.08
Daily messaging events, n	42.85	27.53	36.00	33.00
First smartphone interaction, hour	7.18	1.21	7.07	1.46
Last smartphone interaction, hour	23.41	1.06	23.37	1.28

Table 1 summarizes the daily emotional and smartphone-derived behavioral characteristics across all valid participant-days. The mean daily emotional distress score was 1.46 (SD = 0.87), although the difference between the mean and median and the relatively wide interquartile range indicated substantial within- and between-person variability over the eight-week observation period. Smartphone engagement was pronounced, with adolescents recording an average of 287.64 minutes of screen-on time per day and 74.36 daily device unlocks. Nighttime smartphone activity averaged 47.83 minutes, demonstrating that a substantial proportion of device interaction occurred during periods typically associated with preparation for sleep or sleep itself. Social and communication applications accounted for the largest category of daily application use, averaging 103.52 minutes, followed by entertainment applications at 76.29 minutes. Educational and productivity applications represented a comparatively smaller proportion of smartphone activity, averaging 34.18 minutes per day.

Mobility indicators demonstrated considerable heterogeneity across daily observations. Participants traveled a mean of 12.73 km per day and visited an average of 4.63 distinct location clusters, whereas the mean duration spent at the most frequently visited location was 892.47 minutes, or approximately 14.87 hours. Communication behavior was also variable, with a mean of 5.74 calls, 18.39 minutes of total call duration, and 42.85 messaging events per day. The temporal indicators showed that the average first smartphone interaction occurred shortly after 7:00 a.m., whereas the final interaction occurred at approximately 11:25 p.m. Collectively, these descriptive results demonstrate substantial daily variability across screen engagement, social communication, mobility, and temporal-routine indicators, supporting the use of a sequential modeling approach capable of learning dynamic behavioral patterns rather than relying solely on static individual averages.

Table 2

Predictive Performance of the Final LSTM Model in the Independent Test Set

Performance indicator	Estimate	95% CI
ROC-AUC	0.886	0.864–0.907
PR-AUC	0.774	0.741–0.806
Accuracy	0.823	0.804–0.842
Sensitivity	0.811	0.782–0.839
Specificity	0.828	0.806–0.849
Precision	0.676	0.646–0.706
F1 score	0.737	0.711–0.762
Balanced accuracy	0.819	0.799–0.838
Brier score	0.132	0.124–0.141

The final LSTM model demonstrated good discriminatory performance in the independent test sample comprising participants who had not contributed any observations to model development. The area under the receiver operating characteristic curve was 0.886 (95% CI = 0.864–0.907), indicating that the model had a high probability of assigning a greater predicted distress probability to a randomly selected high-distress observation than to a randomly selected low-to-moderate-distress observation. The precision-recall area under the curve was 0.774 (95% CI = 0.741–0.806), which was particularly informative because high-distress days represented less than one-third of the total daily observations. Overall classification accuracy reached 82.3%, while balanced accuracy was 81.9%, demonstrating that the model performed consistently across both outcome categories

despite the unequal frequency of high-distress and low-to-moderate-distress days. Sensitivity was 81.1%, indicating that approximately four out of five high-distress days were correctly identified by the model, whereas specificity was 82.8%, showing a similarly strong ability to recognize days on which adolescents reported lower levels of emotional distress. Precision was 67.6%, reflecting the proportion of model-generated high-distress classifications that corresponded to actual high-distress observations, while the F1 score of 0.737 indicated an acceptable balance between precision and sensitivity. The Brier score of 0.132 further suggested that the model-generated probabilities were reasonably well calibrated rather than merely producing strong categorical discrimination. Inspection of calibration across probability intervals showed that predicted risk corresponded relatively closely with observed distress

frequency throughout most of the probability distribution, although modest overprediction occurred among observations assigned probabilities above approximately 0.80. These findings indicate that the sequential smartphone behavioral patterns captured by the LSTM contained

meaningful information regarding short-term emotional distress and that the model maintained its predictive capacity when evaluated exclusively among previously unseen adolescents.

Table 3

Comparison of the LSTM Model With Alternative Machine-Learning Models

Model	ROC-AUC	PR-AUC	Accuracy	Sensitivity	Specificity	F1 score
Logistic regression	0.724	0.548	0.704	0.676	0.716	0.596
Random forest	0.801	0.649	0.756	0.728	0.768	0.652
Gradient boosting	0.827	0.691	0.778	0.751	0.790	0.681
Feed-forward neural network	0.842	0.711	0.791	0.766	0.802	0.698
LSTM network	0.886	0.774	0.823	0.811	0.828	0.737

As shown in Table 3, the LSTM network consistently outperformed all comparison models across the principal predictive-performance metrics. Logistic regression produced the weakest overall discrimination, with a ROC-AUC of 0.724 and a PR-AUC of 0.548, indicating that a conventional linear combination of smartphone features captured only a limited proportion of the predictive structure associated with adolescents' daily emotional distress. Random forest classification improved performance, achieving a ROC-AUC of 0.801 and an F1 score of 0.652, while gradient boosting further increased the ROC-AUC to 0.827 and the PR-AUC to 0.691. The feed-forward neural network achieved stronger performance than the conventional machine-learning algorithms, with a ROC-AUC of 0.842, PR-AUC of 0.711, and overall accuracy of 79.1%; however, it remained inferior to the LSTM model on every reported metric. Relative to the feed-forward neural network, the LSTM increased ROC-AUC by 0.044, PR-

AUC by 0.063, sensitivity by 4.5 percentage points, and F1 score by 0.039. The superiority of the LSTM over models trained on the same general behavioral feature set suggests that the predictive gain was not attributable merely to the use of nonlinear modeling but was associated with the explicit representation of temporal dependencies across consecutive days. This pattern supports the central analytical premise of the study that adolescent emotional distress may be reflected not only in absolute levels of smartphone use but also in changes, persistence, and temporal organization of behavior. For example, several consecutive days characterized by increasingly late device use, decreasing mobility, and altered communication activity may be more informative than the same measurements considered independently on a single day. The comparative results therefore provide empirical support for the selection of LSTM modeling for temporally structured smartphone behavioral data.

Table 4

LSTM Performance Across Behavioral Feature Domains and Alternative Sequence Lengths

Model specification	ROC-AUC	PR-AUC	Sensitivity	Specificity	F1 score
Full feature model, 7-day sequence	0.886	0.774	0.811	0.828	0.737
Smartphone interaction features only	0.793	0.641	0.721	0.751	0.646
Application-use features only	0.778	0.619	0.704	0.742	0.628
Mobility features only	0.812	0.666	0.739	0.769	0.661
Communication features only	0.748	0.574	0.681	0.713	0.596
Temporal-routine features only	0.817	0.681	0.744	0.777	0.669
Full feature model, 3-day sequence	0.842	0.707	0.763	0.795	0.697
Full feature model, 5-day sequence	0.869	0.746	0.794	0.814	0.722
Full feature model, 10-day sequence	0.879	0.761	0.803	0.823	0.731

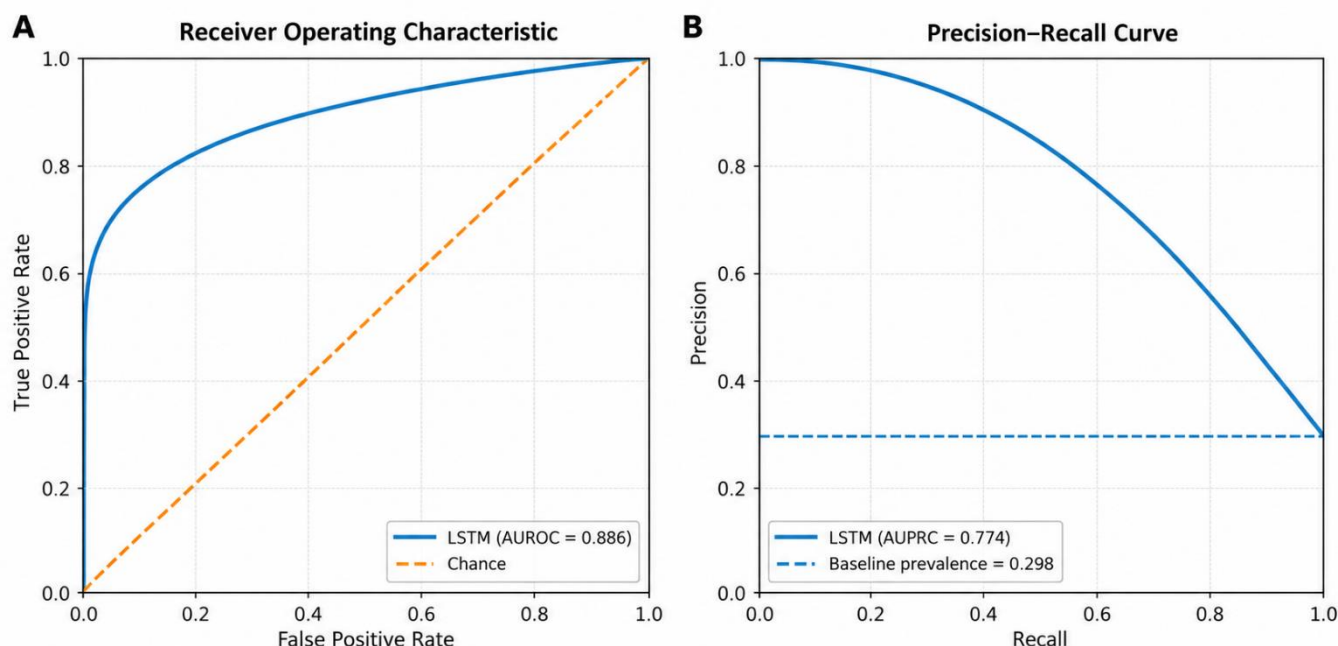
The analyses presented in Table 4 indicate that predictive performance depended both on the combination of multiple behavioral domains and on the temporal duration represented in the input sequence. None of the single-domain models achieved the performance of the complete seven-day LSTM model. Among the isolated domains, temporal-routine features produced the highest ROC-AUC at 0.817, closely followed by mobility features at 0.812. Smartphone interaction features also demonstrated meaningful predictive value, producing a ROC-AUC of 0.793, whereas application-use features alone produced a ROC-AUC of 0.778. Communication metadata showed the weakest independent performance, with a ROC-AUC of 0.748 and a PR-AUC of 0.574. These findings indicate that emotional distress was not represented by a single smartphone behavior but rather by multivariate behavioral configurations spanning different dimensions of daily life. In post hoc feature-importance analyses, increased nighttime smartphone use, later final device interaction, reduced daily mobility, greater time spent at the primary location, elevated overall screen duration, increased variability in daily unlock frequency, and reduced regularity of daily routines were among the features most consistently associated with a higher model-predicted probability of emotional distress. However, the contribution of individual variables differed across participants and across temporal sequences, and none of these associations should be interpreted as independently causal. Sequence-length analyses further demonstrated that temporal context materially affected classification performance. Reducing the observation window to three days lowered ROC-AUC to 0.842 and PR-AUC to 0.707, suggesting that very short behavioral histories did not fully capture the gradual changes associated with elevated distress. Performance improved with a five-day sequence, reaching a ROC-AUC of 0.869, and was highest for the predefined seven-day sequence, which yielded a ROC-AUC of 0.886. Extending the window to 10 days did not provide additional improvement and instead produced a small decline in discrimination, with a ROC-AUC of 0.879. This pattern suggests that approximately one week of preceding behavioral information represented an appropriate temporal

interval for capturing meaningful short-term changes while avoiding dilution of recent distress signals by older behavioral observations.

Additional sensitivity analyses supported the stability of the primary findings. When the threshold used to define high emotional distress was increased so that only more severe daily distress observations were categorized as positive cases, overall sensitivity decreased modestly, but ROC-AUC remained above 0.86, indicating that the model retained substantial discriminatory ability under a stricter outcome definition. Conversely, use of a more permissive distress threshold increased the prevalence of positive observations and improved precision while producing only a small reduction in specificity. The model also remained stable when days with moderate amounts of missing sensing data were excluded rather than imputed, with changes in ROC-AUC of less than 0.02 compared with the primary analysis. Participant-level bootstrap estimates demonstrated relatively narrow confidence intervals for the principal performance indicators, suggesting that results were not driven by a small number of highly predictable participants. Exploratory error analysis showed that false-negative classifications occurred disproportionately on high-distress days when smartphone behavior remained similar to the participant's usual routine, whereas false-positive classifications were more common following pronounced deviations in nighttime use, mobility, or communication that were not accompanied by a high self-reported emotional-distress score. This pattern is consistent with the proposition that behavioral sensing is most informative when distress coincides with observable disruption of routine behavior and less informative when psychological distress is internally experienced without corresponding changes in smartphone activity. Overall, the findings demonstrate that daily smartphone-derived behavioral patterns contain a substantial and temporally structured signal associated with adolescent emotional distress and that an LSTM network integrating multiple behavioral domains across a seven-day period provided the strongest and most stable predictive performance among the models examined.

Figure 1

Receiver Operating Characteristic and Precision-Recall Curves of the LSTM Model for Detecting High Daily Emotional Distress in the Independent Test Set



The receiver operating characteristic and precision-recall patterns illustrated in Figure 1 were consistent with the quantitative performance estimates reported in Table 2. The receiver operating characteristic curve remained substantially above the diagonal line representing chance-level classification across a broad range of classification thresholds, indicating stable discrimination rather than performance that depended narrowly on a single probability cutoff. The corresponding precision-recall curve also remained clearly above the expected baseline determined by the prevalence of high emotional distress in the test data. This result is particularly relevant because precision-recall performance is sensitive to class imbalance and therefore provides a more stringent assessment when the positive outcome is less frequent than the negative outcome. The shapes of the two curves indicated that reductions in the classification threshold could increase sensitivity without producing a disproportionate deterioration in specificity, whereas more conservative thresholds substantially increased precision at the cost of missing a larger proportion of true high-distress observations. The selected operating threshold represented the value identified in the validation set as providing the most appropriate balance between sensitivity and specificity. Because the intended analytical objective was early identification of elevated emotional distress rather than definitive clinical diagnosis, the

relatively high sensitivity achieved at this threshold was considered advantageous. Nevertheless, the observed trade-off between precision and sensitivity confirms that the model should be interpreted as a probabilistic screening and risk-detection system rather than as a substitute for direct psychological or clinical assessment.

4. Discussion

The present study demonstrated that daily smartphone-derived behavioral patterns can provide a meaningful signal for detecting elevated emotional distress among adolescents and that a sequential deep-learning framework can exploit this signal with substantial predictive accuracy. The final LSTM model achieved a ROC-AUC of 0.886, a PR-AUC of 0.774, an accuracy of 82.3%, a sensitivity of 81.1%, a specificity of 82.8%, and an F1 score of 0.737 in an independent test set composed entirely of adolescents who had not contributed data to model development. These findings indicate that the model was able to discriminate high-distress days from low-to-moderate-distress days with a favorable balance between identifying true cases and avoiding excessive false-positive classifications. The importance of this result lies not only in the absolute level of prediction but also in the fact that the model relied on passive behavioral features rather than the semantic content of adolescents' communications. This supports the growing

view that digital phenotyping can extend conventional psychological assessment by capturing fluctuations in everyday behavior that occur between formal evaluations. Previous work has similarly shown that digital phenotypes can be associated with emotional disorders among adolescents and that behavioral characteristics observed through smartphones may provide clinically relevant information beyond conventional self-report measures (Cho et al., 2025). Research on adolescent smartphone overdependence has also demonstrated that machine-learning approaches can identify complex behavioral patterns that are difficult to capture through simple linear models (Kim et al., 2025). More broadly, the current findings are consistent with evidence linking smartphone and digital-media behaviors with psychosocial health, anxiety, behavioral disturbance, sleep problems, and emotional functioning across adolescent and youth populations (Gupta et al., 2023; Nagata et al., 2026; Patel et al., 2025). At the same time, the results reinforce the argument that digital behavior should not be reduced to total screen exposure, because the strongest predictive performance emerged from the combination and temporal organization of several behavioral domains rather than from any single metric (Fortunato et al., 2023; Xu et al., 2025).

The superiority of the LSTM model over logistic regression, random forest, gradient boosting, and a feed-forward neural network provides particularly strong evidence that temporal dependencies contributed materially to emotional-distress detection. The LSTM achieved a ROC-AUC of 0.886 compared with 0.842 for the feed-forward neural network, 0.827 for gradient boosting, 0.801 for random forest, and 0.724 for logistic regression. Because these models were trained on the same general behavioral feature set, the performance gain associated with the LSTM is most plausibly interpreted as reflecting its ability to learn sequential dependencies across consecutive days. Emotional distress is rarely expressed as a single isolated behavioral event; instead, it may emerge through changes that accumulate over time, such as progressively later device use, increasing fragmentation of smartphone interactions, reduced mobility, disrupted routine, or shifts in communication behavior. This interpretation aligns with longitudinal research showing that problematic mobile phone use develops through heterogeneous trajectories and interacts with psychological factors such as distress tolerance and intolerance of uncertainty (Xie et al., 2025). It is also compatible with developmental work showing that phubbing behaviors can follow distinct trajectories across

adolescence rather than remaining static (Zhao & Li, 2026). Person-centered studies have likewise identified heterogeneous smartphone-use profiles and psychosocial risk configurations, suggesting that temporal and multivariate patterns may be more informative than cross-sectional exposure levels (Fortunato et al., 2023; Haag et al., 2024). The present findings therefore extend this literature by showing that sequence-based modeling can translate these conceptual insights into improved predictive performance. The comparison with the feed-forward network is especially important because it suggests that the advantage did not arise merely from greater model complexity or nonlinearity, but from representing the ordering and persistence of behavior across time.

The feature-domain analyses also showed that emotional distress was distributed across multiple aspects of everyday smartphone behavior. Temporal-routine features produced the strongest single-domain performance, followed closely by mobility, while smartphone interaction intensity, application use, and communication features each contributed additional predictive information. Increased nighttime smartphone use, later final device interaction, reduced mobility, greater time spent at the primary location, elevated overall screen duration, irregular unlock patterns, and reduced routine regularity were among the most influential behavioral characteristics. This pattern is consistent with a substantial literature linking nighttime digital engagement and sleep-related disruption with poorer psychological and physical outcomes in adolescents. Late-night screen use has been associated with poor sleep and related health outcomes (Gale et al., 2024), while nocturnal social media use has been linked with reduced sleep quality and anxiety among middle adolescents (Ntumi et al., 2025). Digital-media use has similarly been associated with sleep quality and digital eye strain (Aykutlu et al., 2024), and high-school research suggests that the association between technology use and sleep may vary across broader social contexts (Sheehan et al., 2025). At the same time, evidence that emotional symptoms may themselves predict poor sleep more strongly than pre-sleep screen exposure cautions against treating late-night smartphone activity as a simple causal risk factor (Zhang, 2026). In the present study, nighttime use and temporal irregularity are therefore better interpreted as behavioral correlates or markers of distress rather than definitive causal mechanisms. This distinction is important because emotionally distressed adolescents may turn to their smartphones during late hours for distraction, social connection, reassurance, or avoidance, while late-

night use may simultaneously contribute to sleep loss and impaired emotional regulation.

The observed role of mobility and routine is also theoretically meaningful. Reduced distance traveled, greater time spent in a dominant location, and lower behavioral regularity may reflect social withdrawal, reduced engagement with school or extracurricular activities, low motivation, or disruption of established daily routines. Such patterns are compatible with the broader literature showing that psychological distress is intertwined with social isolation, reduced resilience, and maladaptive digital engagement. Evidence linking nomophobia with adolescent social isolation suggests that intensive smartphone dependence may coexist with reduced offline participation or social connectedness (Ayhan, 2026). Similarly, research on psychological resilience and mobile phone addiction indicates that adolescents differ in the extent to which digital behavior becomes embedded within broader patterns of vulnerability or adaptation (Wu et al., 2024). The association between problematic mobile phone use and social anxiety further supports the interpretation that behavioral restriction and digital engagement can occur together as part of a broader emotional profile (Ruiz-Olivares et al., 2025). Social media research has also connected digital engagement with loneliness and emotional distress among young people (Martínez et al., 2025). Importantly, these associations are likely bidirectional. Reduced mobility may indicate distress-related withdrawal, but constrained activity can also arise from contextual factors such as household routines, academic demands, transportation limitations, or temporary illness. Likewise, increased time spent in social or entertainment applications may represent maladaptive avoidance in one adolescent but adaptive social support or leisure in another. The strong performance of the full multivariate model therefore suggests that emotional meaning emerges more reliably from combinations of behavioral indicators than from any single behavior considered in isolation.

The comparatively weaker performance of communication metadata when used alone is also notable. Communication behavior may be highly heterogeneous because both increased and decreased social interaction can occur during periods of emotional distress. Some adolescents may withdraw from calls and messaging when distressed, whereas others may increase communication in response to loneliness, anxiety, conflict, or a need for reassurance. This may explain why communication counts alone produced lower predictive discrimination than

temporal-routine or mobility variables. Evidence from research on social media use, loneliness, and emotional distress supports the idea that digital communication can function simultaneously as a source of connection and a context for psychological vulnerability (Martínez et al., 2025). Similarly, broader reviews indicate that social-media behavior is shaped by multiple determinants, including individual motives, peer influences, environmental context, and habitual use patterns (Fatima et al., 2025). The family context may further alter the meaning of communication and screen exposure. Systematic review evidence shows that parental behavior, household relationships, and family media practices influence both adolescent screen use and mental-health outcomes (Liu et al., 2024). Family media-use profiles are themselves heterogeneous and may shape the degree to which device use becomes problematic or disruptive (Hamp et al., 2024, 2025). Parent-child conflict and parental phubbing have also been linked with children's problematic behaviors through screen-related pathways (Gu & Zhao, 2025). These findings help explain why communication metadata may be less interpretable when detached from interpersonal context and why a multivariate model integrating communication with mobility, timing, and device interaction performs more effectively.

The sequence-length analyses further demonstrated that seven days provided the most informative temporal window. A three-day sequence yielded weaker performance, a five-day sequence improved discrimination, and a 10-day sequence did not outperform the seven-day configuration. This pattern suggests that emotional distress may be reflected most clearly in behavioral changes occurring over approximately one week, whereas shorter windows may fail to capture sufficient accumulation and longer windows may dilute recent signals with older behavior. The result is consistent with the conceptualization of adolescent digital behavior as dynamic and trajectory-based rather than static. Research on developmental trajectories of problematic mobile phone use (Xie et al., 2025) and phubbing (Zhao & Li, 2026) similarly emphasizes temporal progression, while latent-class and profile-based work demonstrates that smartphone behaviors cluster into distinctive patterns (Fortunato et al., 2023; Haag et al., 2024). The current results extend this perspective by suggesting that the temporal horizon itself is an important modeling parameter. From a clinical and preventive perspective, the identification of a meaningful seven-day window is potentially useful because it balances responsiveness to recent behavioral change with enough longitudinal context to avoid overreacting to isolated

daily fluctuations. The finding may also reflect weekly rhythms in school attendance, sleep, social interaction, and leisure behavior, although this interpretation should be examined directly in future studies.

The results also support a broader conceptual shift from “screen time” toward pattern-based interpretations of digital behavior. Systematic and empirical studies have repeatedly shown that total duration alone provides an incomplete representation of digital exposure. Problematic screen behavior may involve fragmentation, compulsion, loss of control, timing, social context, and displacement of other activities rather than simply high duration (Fendel et al., 2025; Xu et al., 2025). Research on problematic digital behavior has linked intensive or dysregulated use with a range of mental-health and developmental concerns, including attention-related symptoms (Abdoli et al., 2025; Gamli & Gürbüz, 2025), behavioral disorders (Abdoli et al., 2024), and broader psychosocial impairment (Islam, 2023). Recent work has also examined cognitive and neurofunctional implications of smartphone use during adolescence (Marks et al., 2026), while qualitative research has described experiences of cognitive overload and perceived mental fatigue associated with intensive digital consumption (Özbay, 2026). The present study is consistent with this multidimensional view because the strongest predictions were obtained when the model combined timing, mobility, application use, communication, and interaction patterns across multiple days. The findings therefore argue against interpreting elevated screen duration as a sufficient marker of emotional distress. Instead, potentially concerning behavior appears more likely to involve changes in routine, timing, fragmentation, and cross-domain coordination.

The model’s sensitivity analyses further strengthen confidence in the robustness of the main findings. Performance remained strong when stricter or more permissive emotional-distress thresholds were used, and excluding observations with moderate missingness produced only small changes in ROC-AUC. The participant-level bootstrap confidence intervals were relatively narrow, suggesting that model performance was not driven by a small subgroup of unusually predictable adolescents. Error analysis nevertheless revealed an important limitation of behavioral detection: false negatives were more common when adolescents experienced distress without noticeable deviation from their usual smartphone routines, whereas false positives tended to occur when substantial behavioral disruption was present without a corresponding high self-reported distress score. This pattern illustrates an inherent

feature of digital phenotyping. Behavioral sensors can detect deviations in observable activity, but not all internal emotional states produce measurable behavioral change, and not all behavioral change is caused by emotional distress. The result is compatible with evidence showing that individual psychological characteristics, family factors, social context, and resilience modify the relationship between digital behavior and well-being (Liu et al., 2024; Wu et al., 2024). It also reinforces the need to view LSTM-based detection as probabilistic rather than diagnostic. The model may be useful for identifying periods in which further assessment is warranted, but it cannot determine why a behavioral change occurred or whether it represents a psychiatric condition.

5. Conclusion

An implication concerns the ethical and practical role of smartphone-based prediction in adolescent mental health. The model achieved a relatively high sensitivity while using non-content behavioral metadata, suggesting that useful monitoring may be possible without collecting message text, call content, browsing histories, or other highly sensitive personal information. This is important because privacy concerns are particularly pronounced when digital phenotyping involves minors. The findings suggest that data-minimization principles can be compatible with meaningful prediction when models rely on behavioral structure rather than semantic content. Nevertheless, the literature on digital addiction and smartphone overdependence indicates that technological behavior is deeply embedded within developmental and social contexts (Kim et al., 2025; Patel et al., 2025). Consequently, algorithmic predictions should not be used to label adolescents or infer pathology in isolation. The most appropriate role for such systems is likely to be as an adjunct to existing school-based, family-based, or clinical support systems in which elevated digital risk triggers a proportionate and privacy-preserving opportunity for further assessment rather than an automated conclusion.

6. Limitations & Suggestions

Several limitations should be considered when interpreting the findings. First, the study was observational, and the predictive associations identified by the LSTM model cannot establish causal relationships between smartphone behavior and emotional distress. Second, although the sample included adolescents from Bogotá,

Medellín, and Cali and incorporated both public and private schools, it cannot be assumed to represent all Colombian adolescents, particularly those living in rural areas, adolescents without regular smartphone access, or those using incompatible devices. Third, emotional distress was operationalized primarily through daily self-report ratings, which remain vulnerable to response bias, mood-congruent recall, and variation in interpretation despite their temporal proximity to the behavioral data. Fourth, the study focused on Android-compatible sensing and therefore did not capture adolescents whose primary devices operated on other systems. Fifth, passive sensing can be affected by operating-system restrictions, battery management, disabled permissions, and temporary connectivity problems, and imputation cannot fully reconstruct missing behavioral information. Sixth, although participant-level data separation reduced leakage and provided a conservative estimate of generalization to unseen individuals, external validation in an independent cohort was not conducted. Finally, behavioral indicators such as reduced mobility or late-night phone use are nonspecific and may reflect academic demands, physical illness, family routines, travel restrictions, or ordinary lifestyle variation rather than emotional difficulty.

Future studies should prioritize external validation across larger and more diverse adolescent populations, including rural communities, different socioeconomic groups, and countries with distinct cultural and technological environments. Longer observation periods would help determine whether the seven-day window identified in this study remains optimal across seasons, school terms, examinations, holidays, and major life events. Future models could incorporate individualized baselines so that deviations are evaluated relative to each adolescent's usual behavioral pattern rather than only against population-level distributions. Multimodal studies could also combine smartphone sensing with wearable-derived sleep and activity measures, ecological assessments of social stress, and repeated validated measures of depression and anxiety to improve construct specificity. Further research should compare LSTM networks with newer sequence-modeling architectures and examine whether attention mechanisms or personalized temporal models improve interpretability without sacrificing performance. Prospective studies should also investigate whether changes in predicted risk precede increases in self-reported distress, which would be necessary to establish utility for early warning rather than contemporaneous detection. Finally, fairness analyses

should assess whether prediction accuracy differs by age, sex, socioeconomic status, school type, device characteristics, or geographic setting, and future studies should explicitly evaluate how adolescents and caregivers perceive the acceptability, privacy implications, and psychological consequences of passive monitoring.

In practical settings, smartphone-based emotional-distress detection should be implemented as a supportive screening layer rather than a diagnostic system. Schools, adolescent health services, and counseling programs could use privacy-preserving monitoring frameworks to identify periods in which an adolescent may benefit from a brief check-in, while ensuring that any response is proportionate and does not stigmatize the individual. Systems should prioritize behavioral metadata over message content and should clearly communicate what information is collected, how long it is retained, and who can access it. Adolescents and caregivers should retain meaningful control over participation, withdrawal, and notification preferences. Risk alerts should be reviewed within an established human decision-making process rather than triggering automated disciplinary or clinical actions. Practitioners should interpret elevated digital risk alongside contextual information such as sleep, school workload, recent interpersonal stress, physical health, and changes in routine. The strongest practical use of the present model is therefore likely to be early identification of behavioral change that prompts timely, low-intensity, and supportive assessment before distress becomes more severe.

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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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