

Forecasting Daily Stress in Adolescents from Mood Variability, Sleep Quality, Social Interaction, and Smartphone Use Using Long Short-Term Memory Networks

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ABSTRACT

Objective: This study aimed to forecast next-day stress among Canadian adolescents using seven-day temporal sequences of mood variability, sleep quality, social interaction, and smartphone use through a long short-term memory network.

Methods and Materials: A prospective intensive longitudinal study was conducted with 312 adolescents aged 13–18 years recruited from Ontario, British Columbia, Alberta, and Quebec, Canada. Participants completed baseline assessments followed by 30 consecutive days of ecological momentary assessment and passive smartphone monitoring. Daily perceived stress was assessed each evening, mood was recorded four times daily, sleep quality was measured through morning sleep diaries, and social interaction was evaluated using daily self-reports and communication metadata. Passive smartphone indicators included total screen time, device unlocks, session duration, application-category use, and nighttime smartphone activity. Seven-day sliding windows were used to predict the following day's stress. Data were divided at the participant level into training, validation, and independent test sets. The LSTM model was compared with persistence, multiple linear regression, random forest, and feedforward neural-network models.

Findings: The LSTM model demonstrated the best predictive performance in the independent test set, with a mean absolute error of 1.42, root mean square error of 1.89, coefficient of determination of .62, and correlation of .79 between observed and predicted stress. It reduced mean absolute error by 27.6% compared with the persistence model, 20.2% compared with linear regression, 11.8% compared with random forest, and 7.8% compared with the feedforward neural network. Ablation analyses showed that removing mood, sleep, social-interaction, and smartphone-use variables increased prediction error, with mood variability producing the greatest decline in performance. Negative-mood variability, subjective sleep quality, nighttime smartphone use, loneliness, and previous-day stress were the most influential predictors.

Conclusion: Sequential patterns of mood, sleep, social experiences, and smartphone behavior can meaningfully forecast adolescents' next-day stress, and LSTM networks offer greater predictive accuracy than conventional and nonsequential models.

Keywords: Adolescent stress; long short-term memory; ecological momentary assessment; mood variability; sleep quality; social interaction; smartphone use.

1. Introduction

Adolescence is a developmental period characterized by rapid biological maturation, expanding cognitive capacities, increasing academic demands, changing family relationships, and heightened sensitivity to peer evaluation and social belonging. These concurrent transitions can make stress a frequent and highly variable feature of everyday life. Unlike chronic stress, which reflects relatively enduring exposure to adverse conditions, daily stress may rise and fall in response to immediate experiences such as examinations, interpersonal conflict, sleep disruption, social exclusion, family expectations, and online interactions. These short-term fluctuations are clinically and developmentally important because repeated elevations in stress can accumulate over time, interfere with emotional regulation, disrupt sleep, impair concentration, and increase vulnerability to anxiety, depressive symptoms, and maladaptive coping behaviors (Liu et al., 2025). Consequently, understanding adolescent stress requires more than estimating an average level across weeks or months; it requires attention to how stress changes from one day to the next and how those changes are preceded by patterns in mood, behavior, social experience, and digital activity.

The contemporary digital environment has introduced an additional layer of complexity into adolescent stress processes. Smartphones are now embedded in communication, education, recreation, identity development, and peer relationships, making them neither uniformly harmful nor uniformly beneficial. Their effects depend on how, when, and why they are used, as well as on the psychological and social context of the user. Systematic reviews have generally shown associations between extensive screen exposure and poorer mental health outcomes in adolescents, including depressive symptoms, anxiety, reduced psychological wellbeing, and behavioral difficulties, although effect sizes and causal interpretations vary across studies (Santos et al., 2023; Serrano et al., 2022). Reviews focusing specifically on children and adolescents have similarly noted that increasing media use may affect sleep, emotional regulation, attention, and social functioning, while emphasizing the need to distinguish between types of media use and patterns of engagement (Bhatia, 2023). Excessive smartphone use has also been associated with a range of psychological morbidities among adolescents and young adults, including stress, anxiety, low mood, impaired self-control, and sleep-related problems

(Rathod et al., 2022). These findings indicate that smartphone behavior may serve not only as a potential source of stress but also as a behavioral marker of emerging psychological strain.

The relationship between smartphones and adolescent mental health is likely to be bidirectional. Adolescents experiencing stress, anxiety, loneliness, or negative mood may increase their smartphone use in search of distraction, reassurance, social connection, or emotional escape. At the same time, fragmented use, repeated checking, nighttime engagement, exposure to social comparison, and interruption of offline activities may intensify stress or undermine recovery. Research on smartphone attachment has suggested that emotional dependence on the device may be associated with poorer mental health, making the psychological meaning of smartphone access as important as the total duration of use (Liu et al., 2025). Longitudinal evidence reviewed in relation to smartphone addiction further indicates that emotional symptoms, social difficulties, impulsivity, poor self-regulation, and existing patterns of problematic use can increase the likelihood of subsequent smartphone-related impairment (Crowhurst & Hosseinzadeh, 2024). Broader reviews have raised concern that sustained high-intensity digital engagement may influence memory, attention, executive functioning, and cognitive efficiency, particularly when device use repeatedly displaces focused activity or restorative sleep (Ali et al., 2024). Accordingly, total screen time alone may be too crude to represent the psychological significance of smartphone use; temporal indicators such as nighttime use, session fragmentation, frequency of unlocking, and deviation from habitual use may provide more meaningful information.

Sleep represents one of the most plausible pathways linking digital behavior, mood, and daily stress. Adolescents experience developmental changes in circadian timing that often favor later sleep onset, while school schedules continue to require early awakening. This biological-social mismatch makes adolescent sleep vulnerable to behavioral and environmental disruption. Psychosocial influences on adolescent sleep include academic pressure, family routines, emotional arousal, social relationships, technology use, and beliefs about sleep, and adolescents themselves often describe difficulty disengaging from evening activities despite awareness of the consequences of insufficient rest (Vandendriessche et al., 2022). Smartphone use before bedtime may delay sleep onset, increase cognitive or emotional activation, expose users to light that interferes with circadian processes, and encourage continued

engagement beyond intended sleep times. These mechanisms are particularly relevant when social communication, gaming, or rapidly changing media content continues into the night.

Prospective research examining electronic-device use, sleep, and mental health has shown that disrupted or shortened sleep may operate as an important mechanism through which digital activity contributes to poorer emotional outcomes (Dibben et al., 2023). Excessive social media use has likewise been associated with both reduced sleep quality and poorer mental health among students, suggesting that sleep and psychological wellbeing are closely intertwined within patterns of digital engagement (Bezerra et al., 2023). Evidence from university and young-adult populations has shown that smartphone addiction, sleep disturbance, and depressive symptoms frequently co-occur, with sleep potentially functioning as both a consequence of problematic use and a contributor to psychological distress (Gao et al., 2023). Among middle adolescents, nocturnal social media engagement has been linked to lower sleep quality and greater anxiety, reinforcing the importance of when smartphone use occurs rather than only how much use is recorded across the day (Ntumi et al., 2025). Passive digital monitoring in diverse adolescent samples has further demonstrated the value of objectively capturing sleep–smartphone relationships in naturalistic settings, where self-reported estimates may not fully represent actual patterns of device engagement (Shahnovsky et al., 2026).

Nevertheless, the relationship between social media use and next-day wellbeing is not necessarily uniformly negative. Experience-sampling research has shown that social media use may have weak, heterogeneous, or person-specific associations with sleep and subsequent school wellbeing, and that average group-level effects can obscure substantial individual variation (Maksniemi et al., 2023). Similarly, daily social media use may coincide with both positive and negative mood states, depending on the adolescent's motives, the nature of the interaction, and the broader social circumstances in which use occurs (Dreier et al., 2023). These findings challenge deterministic interpretations of smartphone use and suggest that forecasting stress requires models capable of detecting nonlinear, cumulative, and context-dependent relationships. For one adolescent, increased digital communication may reflect supportive peer connection and predict lower stress; for another, the same increase may signal social conflict,

compulsive checking, or sleep displacement and predict higher stress.

Mood variability is another central component of daily stress. Adolescents often experience more pronounced emotional fluctuations than adults because of neurodevelopmental changes, sensitivity to reward and rejection, emerging identity concerns, and limited experience regulating complex emotions. Mean mood scores provide information about whether an adolescent is generally feeling positive or negative, but they do not indicate how rapidly or intensely affect changes within a day. Mood variability may therefore capture a dimension of emotional instability that is particularly relevant to forecasting stress. Rapid shifts between calmness, irritability, anxiety, sadness, and positive affect may indicate difficulties in emotional regulation or exposure to changing interpersonal and academic conditions. Such variability may precede stress by weakening perceived control and increasing reactivity, while stress may also contribute to subsequent emotional instability. Because these processes unfold over time, repeated daily or within-day assessments are more suitable than retrospective questionnaires for capturing their temporal order.

Ecological momentary assessment offers an important methodological advantage in this context. By collecting reports close to the time experiences occur, it reduces retrospective bias and allows researchers to distinguish within-person fluctuations from stable differences between participants. Smartphone-based ecological momentary assessment can be combined with passive sensing to integrate subjective experiences with behavioral indicators. Protocols designed to identify person-specific drivers of adolescent depression have demonstrated how repeated smartphone assessments and passive data can capture dynamic relationships among mood, behavior, sleep, and environmental exposure (Ng et al., 2023). This approach is directly relevant to stress forecasting because it produces temporally ordered observations rather than isolated questionnaire scores. Prospective cohort research has also documented physical, psychological, and social effects of mobile phone use in children, reinforcing the need to examine multiple domains simultaneously rather than treating smartphone exposure as an isolated predictor (Gupta et al., 2023). Research on screen time and children's behavior has similarly indicated that intensive digital exposure may be related to irritability, attention problems, reduced activity, and altered behavioral routines, although

developmental context and family practices remain important moderators (Naima, 2023).

Social interaction is especially important during adolescence because peer relationships become increasingly central to emotional security, identity, and belonging. High-quality interaction and perceived support can buffer stress by providing validation, advice, companionship, and practical assistance. In contrast, loneliness, exclusion, conflict, or uncertainty in peer relationships may heighten vigilance and increase daily stress. Smartphone-mediated communication complicates this association because it can extend supportive relationships across time and distance while also creating continuous availability, social comparison, pressure to respond, and exposure to interpersonal ambiguity. Risk-profile research has shown that combinations of smartphone activities and psychosocial characteristics are more informative than any single indicator in identifying adolescents vulnerable to poor adjustment (Haag et al., 2024). This supports an integrative perspective in which social-interaction quality, loneliness, mood, sleep, and smartphone behavior are modeled together.

The heterogeneity of adolescent digital experiences also has implications for prevention. Clinical and public health recommendations increasingly emphasize establishing healthy cell phone routines rather than relying solely on rigid screen-time limits. Suggested strategies include reducing use before bedtime, limiting notifications, creating device-free family periods, discouraging overnight phone access, and promoting intentional rather than automatic use (Alkureishi et al., 2024). Digital wellbeing interventions have also used active nudging to reduce excessive mobile-phone exposure and improve sleep-related behaviors, indicating that small changes in device routines may be feasible and potentially beneficial (Thiêm & Tagliabue, 2025). Broader eHealth approaches to optimizing adolescent internet use recommend combining digital literacy, self-monitoring, family guidance, and behavioral supports rather than framing technology as inherently harmful (Singhal et al., 2022). Mixed-method evaluations of mobile healthy-lifestyle interventions similarly suggest that adolescents may engage with technology-based mental health promotion when interventions are accessible, relevant, and sensitive to their everyday routines (Peuters et al., 2024). These approaches would benefit from tools capable of detecting when an adolescent's behavioral pattern begins to indicate elevated stress, because interventions could then be delivered selectively and at an appropriate time.

Traditional statistical models may be limited in their ability to provide such forecasts. Daily stress is influenced by repeated observations that are temporally dependent, meaning that values from adjacent days are not independent. The effect of a given predictor may also depend on its sequence. For example, one night of poor sleep may have little impact, whereas several nights of worsening sleep combined with rising mood instability and nighttime smartphone use may substantially increase next-day stress. Linear models can estimate average associations but may fail to represent threshold effects, delayed effects, interactions, and nonlinear temporal dependencies. Machine-learning methods can address some of these limitations, but models that collapse a seven-day period into means or summary scores still lose information about the order in which changes occurred.

Long short-term memory networks are a form of recurrent neural network designed to process sequential data. Their internal gating mechanisms allow them to retain relevant information across multiple time steps while discarding less useful information. In adolescent stress forecasting, this capability makes it possible to model whether a sequence of worsening sleep, increasing negative-mood variability, declining social interaction, and more fragmented smartphone use predicts stress differently from the same values occurring in another order. LSTM models can also learn complex interactions among predictors without requiring researchers to specify every possible relationship in advance. Such models are therefore well suited to intensive longitudinal data collected through ecological momentary assessment and passive sensing.

Despite growing evidence connecting adolescent mental health with smartphone use, sleep, and social behavior, several gaps remain. Much of the existing literature is cross-sectional, limiting inference about temporal sequence. Many studies rely on retrospective screen-time estimates, which may be imprecise, or use broad measures that do not distinguish nighttime use, session frequency, or category of engagement. Other studies examine only one predictor domain, such as smartphone addiction or sleep quality, despite evidence that these factors operate together. Reviews of nomophobia have shown substantial associations with anxiety, smartphone addiction, and insomnia, illustrating the interdependence of digital attachment, emotional symptoms, and sleep disturbance (Daraj et al., 2023). At the same time, evidence of person-specific and occasionally neutral effects of social media use shows that simple assumptions of uniform harm are insufficient. A forecasting framework

must therefore account for multiple daily processes, their temporal ordering, and their potentially nonlinear interactions.

A further limitation of prior research is its emphasis on explaining average associations rather than predicting future states in unseen individuals. Explanation and prediction are related but distinct goals. A statistically significant association may not provide accurate individual forecasts, while a predictive model must demonstrate performance in participants whose data were not used during training. This distinction is essential for any future application in preventive mental health, because an early-warning system must generalize beyond the sample used to develop it. Comparing an LSTM model with persistence, linear, tree-based, and nonsequential neural-network benchmarks can determine whether temporal modeling adds meaningful value. Domain-ablation analysis can further show whether mood, sleep, social interaction, and smartphone behavior each contribute unique predictive information. Such analyses are necessary to move beyond broad claims about digital exposure and toward a more precise understanding of which patterns matter most for daily stress.

The Canadian adolescent context also warrants direct investigation. Canada is geographically, culturally, and socioeconomically diverse, and adolescents' digital routines, school demands, family structures, and access to mental health services may differ across regions and communities. A multisite Canadian sample can therefore provide a more heterogeneous test of model generalizability than a single-school or single-city design. Moreover, combining self-reported experiences with privacy-preserving passive smartphone indicators allows daily stress to be studied without collecting message content, contact identities, or other highly sensitive information. This balance between predictive usefulness and data minimization is especially important in research involving minors.

Taken together, the literature suggests that daily adolescent stress emerges from an interacting system of emotional variability, sleep-related restoration, social connection or isolation, and smartphone behavior. Existing studies support the relevance of each domain, but they also reveal inconsistent average effects, bidirectional relationships, and substantial variation across individuals and days. Intensive longitudinal assessment can capture these fluctuations, while LSTM networks can evaluate their temporal structure and forecast subsequent stress. A model that accurately identifies emerging stress from naturally occurring behavioral and experiential data could contribute

to more timely, personalized, and minimally intrusive forms of adolescent mental health monitoring.

The aim of this study was to forecast next-day stress among Canadian adolescents from seven-day sequences of mood variability, sleep quality, social interaction, and smartphone use using a long short-term memory network and to compare its predictive performance with conventional and nonsequential benchmark models.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a prospective intensive longitudinal design to forecast daily perceived stress among Canadian adolescents based on temporal patterns of mood variability, sleep quality, social interaction, and smartphone use. The study included exactly 312 adolescents between 13 and 18 years of age who were recruited from public and private secondary schools, community youth centers, and adolescent health services in Ontario, British Columbia, Alberta, and Quebec, Canada. A multistage recruitment procedure was used to increase the demographic and socioeconomic diversity of the sample. Schools and youth-serving organizations were first invited to distribute study information to potentially eligible adolescents and their parents or legal guardians. Interested families contacted the research team through a secure online registration system and completed an initial eligibility screening. Adolescents were eligible to participate when they were between 13 and 18 years of age, were currently residing in Canada, were enrolled in secondary education, had sufficient English-language proficiency to understand the study questionnaires, owned an Android or iOS smartphone compatible with the study application, and were willing to complete repeated assessments and permit the collection of non-content smartphone-use data. Adolescents were excluded when they had a severe cognitive, developmental, neurological, or communication difficulty that prevented independent completion of the assessments, did not have regular access to their smartphone, or anticipated being unable to participate throughout the data-collection period. The presence of a psychological disorder or previous use of mental health services was not considered an exclusion criterion because the study sought to capture the natural variability of stress experiences within a heterogeneous adolescent population.

Each participant completed a baseline assessment followed by 30 consecutive days of smartphone-based

ecological momentary assessment and passive digital-behavior monitoring. The 312 participants therefore contributed a maximum of 9,360 person-days of observation. The intensive longitudinal design was selected because adolescent stress, mood, social behavior, sleep, and smartphone engagement fluctuate considerably from day to day and may exhibit delayed, cumulative, and nonlinear relationships that cannot be adequately represented by a single cross-sectional measurement. Repeated daily observations also made it possible to model within-person temporal dependencies and to use sequences of preceding daily experiences to forecast stress on the following day. Participants received automated reminders through the study application when an assessment became available. Assessments remained accessible for a limited period to reduce retrospective reporting and improve the temporal accuracy of the data. Technical support was available throughout the study, and participants were contacted when data synchronization problems or extended periods of nonresponse were detected.

Before participation, written informed consent was obtained from adolescents who were 18 years of age. For participants younger than 18 years, written informed consent was obtained from a parent or legal guardian, and written informed assent was obtained from the adolescent. Participants and their guardians were informed that the smartphone-monitoring component recorded behavioral indicators such as screen time, device-unlock frequency, application-category use, and communication frequency but did not collect message content, photographs, audio recordings, passwords, search terms, or the content of telephone conversations. Participants could pause passive monitoring or withdraw from the study without penalty. All data were encrypted during transmission and storage, and identifying information was stored separately from assessment and smartphone-use data. Each participant was assigned a randomly generated study code that was used throughout the analytical dataset.

2.2. Measures

Baseline information was collected through a secure online questionnaire administered before the beginning of the 30-day monitoring period. The questionnaire assessed age, gender, school grade, province of residence, family structure, parental education, perceived family socioeconomic status, current psychological treatment, history of mental health service use, and typical patterns of

smartphone access. Baseline stress was assessed to characterize participants' general stress levels before the intensive monitoring phase. Participants also completed a brief orientation session in which they were instructed in the use of the study application, the meaning of each rating scale, the assessment schedule, and the privacy protections applied to passive smartphone data. A one-day practice period was completed before formal data collection to identify technical difficulties and ensure that participants understood the ecological momentary assessment procedure. Practice-day observations were not included in the final analysis.

Daily perceived stress was the primary outcome variable. It was measured every evening using a brief four-item daily perceived stress measure designed to assess the extent to which participants experienced the events and demands of that day as unpredictable, difficult to control, overwhelming, or emotionally taxing. Each item was rated on a five-point scale ranging from 0, indicating not at all, to 4, indicating extremely. Item scores were summed to produce a daily stress score ranging from 0 to 16, with higher scores representing greater perceived stress. The evening assessment instructed participants to answer specifically in relation to their experiences since waking that morning rather than their general psychological condition. To support the temporal forecasting design, the daily stress score recorded on a given day was treated as the outcome to be predicted from the participant's measurements during the preceding seven days. The internal consistency of the daily stress items was evaluated across measurement occasions using multilevel reliability procedures that distinguished within-person from between-person consistency.

Mood was assessed four times per day through brief ecological momentary assessments delivered in the morning, around midday, in the late afternoon, and during the evening. At each assessment, participants rated the current intensity of six affective states: happy, calm, energetic, sad, anxious, and irritable. Ratings were made on a five-point scale ranging from 1, indicating not at all, to 5, indicating extremely. The items represented both positive and negative dimensions of adolescent mood while keeping each assessment brief enough to minimize participant burden. Daily mood variability was calculated from the four assessments rather than relying only on the participant's average mood. For each day, the within-day standard deviation of the mood ratings was calculated to represent the overall dispersion of affective states. The root mean square of successive differences was also computed to capture the

magnitude of changes between consecutive mood assessments. Separate indices were calculated for positive affect, negative affect, and overall affective instability. Daily mean levels of positive and negative mood were retained as supplementary predictors so that the predictive contribution of mood variability could be distinguished from the contribution of generally positive or negative mood states.

Sleep quality was measured each morning using a smartphone-adapted daily sleep diary. Participants reported their approximate bedtime, the time at which they attempted to sleep, estimated sleep-onset latency, number of nighttime awakenings, total time awake during the night, final awakening time, time of getting out of bed, and estimated total sleep duration. They also rated their overall sleep quality on a five-point scale ranging from 1, indicating very poor, to 5, indicating very good, and reported the degree to which they felt rested after waking. Sleep efficiency was calculated as the estimated amount of time asleep divided by the total time spent in bed and multiplied by 100. The principal sleep-related predictors were subjective sleep quality, total sleep duration, sleep-onset latency, nighttime awakening frequency, sleep efficiency, and deviation from the participant's typical bedtime. At baseline, general sleep quality during the previous month was assessed using the Pittsburgh Sleep Quality Index to provide a broader characterization of habitual sleep patterns. The baseline measure was used as a static participant-level covariate, whereas the daily sleep-diary indicators were used as time-varying predictors in the forecasting model.

Social interaction was assessed through a combination of daily self-report and privacy-preserving smartphone metadata. In the evening assessment, participants reported the approximate amount of time they had spent in face-to-face interaction with family members, friends, classmates, teachers, and other people during that day. They separately reported the amount of time spent communicating with others through telephone calls, text-based messaging, video calls, social networking platforms, and online gaming. Participants rated the perceived quality of their social interactions, the degree of emotional support they had received, their sense of social connectedness, and their loneliness during the day. These variables were rated on five-point scales, with higher scores indicating a greater level of the construct being measured. The passive component recorded the number and duration of incoming and outgoing calls, the frequency of messaging activity when technically available, and the number of communication-related application sessions. No names,

telephone numbers, contact identities, message content, or communication content were collected. Daily social-interaction features included face-to-face interaction duration, digital interaction duration, communication frequency, perceived interaction quality, perceived support, connectedness, and loneliness.

Smartphone use was measured continuously through a custom passive-sensing application installed on each participant's device. The application recorded total daily screen time, number of device unlocks, number and duration of smartphone-use sessions, average session length, longest uninterrupted session, and the amount of use occurring during the two hours before the participant's reported bedtime. Application activity was classified into broad functional categories, including social networking, communication, entertainment, gaming, education, productivity, and general browsing. Only the duration and frequency of category-level use were retained. The names of individual accounts, viewed content, typed text, photographs, videos, website content, and precise geographic location were not collected. Nighttime smartphone use was operationalized as the total duration of active screen use between the participant's reported bedtime and final morning awakening. Smartphone-use regularity was calculated from day-to-day variation in the timing and duration of use. To distinguish heavy use from fragmented use, total screen time and device-unlock frequency were entered as separate predictors. Data were synchronized with the secure research server at least once every 24 hours when an internet connection was available.

Compliance was monitored automatically. A daily observation was considered complete when the participant had provided the evening stress assessment, at least three of the four scheduled mood assessments, the morning sleep diary, and a minimum of 18 hours of passive smartphone data. Days with partial information were retained when sufficient values were available for the variables required by a specific analytical model. Participants were included in the primary analysis when they completed at least 21 of the 30 monitoring days. Time stamps were examined to identify assessments completed outside the permitted response windows, implausibly rapid responses, duplicate records, or technical synchronization errors. The research team did not manually alter valid participant responses. Observations identified as technical duplicates were removed according to predefined data-cleaning rules.

2.3. Data Analysis

Data analysis was conducted using Python and established machine-learning libraries for data processing, neural-network development, and model evaluation. Initial analyses included examination of response completeness, distributions, means, standard deviations, ranges, and within-person and between-person variation for all study variables. Daily observations were ordered chronologically within each participant. Continuous predictors were inspected for extreme values, impossible values, and sensor-related artifacts. Implausible sleep durations, negative usage times, and records exceeding the number of hours available in a day were treated as invalid. Highly skewed smartphone-use variables were transformed using a natural logarithmic transformation when necessary. Extreme but plausible values were winsorized at the first and ninety-ninth percentiles based only on the training data. Continuous variables were standardized to a mean of zero and a standard deviation of one using parameters estimated exclusively from the training dataset. The same training-set parameters were subsequently applied to the validation and test datasets to prevent information leakage.

Missing values were handled in a manner that preserved the temporal organization of the data. Short gaps in time-varying continuous predictors were imputed using participant-specific interpolation when values were available immediately before and after the missing observation. When interpolation was not possible, the participant's rolling seven-day median was used. Remaining missing values were imputed using medians calculated from the training dataset. Binary indicators were added to identify imputed observations so that the model could learn whether missingness itself contained predictive information. Daily outcome values were not imputed. Days without a valid daily stress score were excluded as prediction targets but could contribute predictor information to later sequences when their feature values were sufficiently complete.

To ensure an unbiased evaluation of generalization to previously unseen adolescents, data were divided at the participant level rather than at the daily-observation level. Of the 312 participants, 218 were assigned to the training set, 47 to the validation set, and 47 to the independent test set. Consequently, no daily observations from a participant in the validation or test sets were included in model training. Allocation was stratified by age group, gender, province, and baseline stress level to maintain comparable participant characteristics across the three datasets. The training set was

used to estimate model parameters, the validation set was used for hyperparameter selection and early stopping, and the test set was accessed only after the final model configuration had been selected.

A sliding-window procedure was used to transform the daily observations into sequences suitable for long short-term memory network analysis. For each participant, predictor values from the previous seven consecutive days were used to forecast the daily stress score on the following day. Each sequence therefore contained seven temporally ordered feature vectors representing mood variability, sleep quality, social interaction, and smartphone use. Static variables, including age, gender, province, socioeconomic status, and baseline stress, were repeated across the seven time steps and entered as contextual covariates. Sequences were created only when the target-day stress score was available. The seven-day window was chosen to capture short-term accumulation, persistence, and delayed effects across an entire week while retaining an adequate number of training sequences for each participant.

The primary forecasting model consisted of a masking layer followed by a long short-term memory layer with 64 hidden units, a dropout layer with a dropout rate of 0.20, a second long short-term memory layer with 32 hidden units, and a fully connected layer with 16 rectified linear units. The final output layer contained one neuron with a linear activation function representing the predicted daily stress score. The long short-term memory architecture was selected because it can retain and selectively update information across sequential observations and can model nonlinear dependencies between earlier behavioral patterns and subsequent stress. The model was trained using the Adam optimization algorithm with an initial learning rate of 0.001, a batch size of 32, and mean squared error as the loss function. Training was permitted to continue for a maximum of 200 epochs. Early stopping was applied when the validation loss failed to improve for 15 consecutive epochs, and the parameter values from the epoch with the lowest validation loss were restored. The learning rate was reduced when the validation loss reached a plateau.

The number of hidden units, dropout rate, learning rate, batch size, and sequence length were examined during model development using the validation dataset. Candidate sequence lengths of three, seven, and fourteen days were compared, and the seven-day sequence was retained when it provided the best balance between prediction accuracy, model stability, and availability of complete sequences. Hyperparameter selection was based primarily on

validation-set root mean square error. Model development was repeated with five random initializations, and the configuration with the lowest average validation error was selected to reduce the influence of random parameter initialization.

Forecasting accuracy was evaluated in the independent test set using mean absolute error, root mean square error, mean squared error, the coefficient of determination, and the Pearson correlation between observed and predicted daily stress scores. Mean absolute error was treated as the principal performance metric because it provides a readily interpretable estimate of the average difference between predicted and observed stress scores. Ninety-five percent confidence intervals for performance statistics were calculated through participant-level bootstrap resampling so that the clustering of repeated observations within individuals was preserved. Prediction errors were also examined across age groups, gender categories, baseline stress levels, and levels of data completeness to identify potential differences in model performance across participant subgroups.

The performance of the long short-term memory network was compared with several benchmark models. These included a persistence model that used the previous day's stress score as the forecast for the following day, a multiple linear regression model, a random forest regression model, and a feedforward neural network that did not explicitly represent temporal order. All benchmark models were trained and evaluated using the same participant-level data partitions. Where necessary, the seven-day predictors were summarized using means, standard deviations, minima, maxima, and most recent values for entry into nonsequential models. A superior performance of the long short-term memory model relative to these benchmarks was interpreted as evidence that modeling the temporal ordering and dependency of daily observations contributed additional predictive value.

To examine the contribution of the four predictor domains, ablation analyses were conducted by retraining the final model after removing mood variability, sleep quality, social interaction, or smartphone-use variables one domain at a time. The increase in test-set prediction error following removal of each domain was used to estimate its incremental predictive importance. Feature contributions were further examined using model-compatible explanation procedures that estimated the direction and magnitude of each predictor's influence on individual forecasts. Interpretation focused on aggregated patterns across participants rather

than isolated predictions. Sensitivity analyses were conducted using alternative sequence lengths, complete-case observations, different missing-data procedures, and models excluding the previous day's stress score. Statistical tests were two-tailed, and a significance level of .05 was applied where inferential analyses were performed.

3. Findings and Results

A total of 327 adolescents initially completed the eligibility screening and consent procedures. Fifteen participants were excluded from the final analysis because they completed fewer than 21 monitoring days, experienced persistent technical incompatibility between their smartphones and the passive-sensing application, or withdrew before sufficient longitudinal data had been obtained. The final analytical sample therefore consisted of 312 Canadian adolescents. Participants ranged in age from 13 to 18 years, with a mean age of 15.54 years and a standard deviation of 1.61 years. The sample included 165 girls (52.9%), 140 boys (44.9%), and seven adolescents who identified as nonbinary or used another gender description (2.2%). Forty-five participants were enrolled in Grade 8 (14.4%), 59 in Grade 9 (18.9%), 69 in Grade 10 (22.1%), 72 in Grade 11 (23.1%), and 67 in Grade 12 (21.5%). Regarding province of residence, 122 participants were recruited from Ontario (39.1%), 74 from British Columbia (23.7%), 63 from Alberta (20.2%), and 53 from Quebec (17.0%).

The sample reflected considerable ethnocultural diversity. A total of 146 participants identified as White or European Canadian (46.8%), 52 as East or Southeast Asian Canadian (16.7%), 39 as South Asian Canadian (12.5%), 29 as Black Canadian (9.3%), 18 as Middle Eastern or North African Canadian (5.8%), 15 as Indigenous, First Nations, Métis, or Inuit (4.8%), and 13 as having mixed or another ethnocultural background (4.2%). Based on adolescents' reports of household financial circumstances, 57 participants described their family socioeconomic status as below average or financially constrained (18.3%), 193 described it as average or middle income (61.9%), and 62 described it as above average or financially comfortable (19.9%). Eighty-one adolescents reported previous contact with a mental health professional or service (26.0%), and 39 were receiving psychological, psychiatric, or counseling services at the time of enrollment (12.5%). Regarding smartphone operating systems, 182 participants used an iOS device (58.3%), and 130 used an Android device (41.7%).

Across the 30-day monitoring period, the 312 participants could have provided a maximum of 9,360 daily observations. A total of 8,824 valid evening stress assessments were obtained, representing 94.3% of all possible participant-days. Participants completed an average of 28.28 valid daily stress assessments out of 30, with a standard deviation of 2.14 and a range from 21 to 30 days. Of the 37,440 scheduled mood prompts, 34,972 were completed within the designated response windows, corresponding to a mood-assessment completion rate of 93.4%. Valid morning sleep diaries were available for 8,690 participant-days, representing 92.8% of the maximum possible number, while at least 18 hours of usable passive smartphone data were obtained for 8,735 participant-days, representing 93.3%. The percentage of missing observations was therefore relatively low and was distributed across participants rather than being concentrated within a small subgroup.

Application of the seven-day sliding-window procedure produced 6,642 valid sequences for next-day stress forecasting. Of these sequences, 4,632 were obtained from the 218 participants assigned to the training dataset, 1,006 were obtained from the 47 participants assigned to the

validation dataset, and 1,004 were obtained from the 47 participants assigned to the independent test dataset. Comparisons conducted after participant-level allocation showed no statistically significant differences among the training, validation, and test groups in age, gender distribution, province, family socioeconomic status, baseline stress, average daily stress, or the proportion of completed observations. All corresponding probability values were greater than .10, indicating that the three datasets were sufficiently comparable and that the test dataset did not contain a systematically higher- or lower-risk subgroup.

Table 1 presents the descriptive statistics, intraclass correlation coefficients, and within-person correlations for the principal daily variables. The intraclass correlation coefficients quantify the proportion of total variability attributable to stable differences between adolescents, whereas the within-person correlations describe whether day-to-day changes in one variable were associated with changes in another variable within the same adolescent. The correlations were estimated using repeated-measures procedures that accounted for the clustering of daily observations within participants.

Table 1

Descriptive Statistics, Intraclass Correlations, and Within-Person Correlations among the Principal Daily Variables

Variable	Mean	SD	Observed range	ICC	1	2	3	4	5	6	7	8	9
1. Daily perceived stress	6.91	3.08	0–16	.48	—								
2. Mood variability	0.91	0.33	0.13–2.07	.27	.46***	—							
3. Subjective sleep quality	3.29	0.89	1–5	.36	-.39***	-.28***	—						
4. Social-interaction quality	3.58	0.87	1–5	.41	-.26***	-.16***	.19***	—					
5. Perceived social support	3.47	0.94	1–5	.44	-.29***	-.18***	.21***	.53***	—				
6. Daily loneliness	2.11	0.96	1–5	.46	.37***	.27***	-.24***	-.41***	-.47***	—			
7. Total screen time, hours	5.71	2.28	0.42–13.88	.55	.21***	.19***	-.22***	-.08**	-.07**	.13***	—		
8. Nighttime smartphone use, hours	0.76	0.61	0–4.12	.33	.32***	.25***	-.35***	-.10***	-.09***	.16***	.44***	—	
9. Daily device unlocks	84.60	39.70	8–252	.52	.18***	.14***	-.18***	.03	.02	.10***	.58***	.31***	—

As shown in Table 1, the mean daily perceived stress score was 6.91 out of a possible 16, although the standard deviation of 3.08 and the full observed range from 0 to 16 demonstrated substantial variability in adolescents' daily stress experiences. The intraclass correlation coefficient for stress was .48, indicating that approximately 48% of the

variability in daily stress was attributable to relatively stable differences between adolescents, while the remaining 52% reflected within-person day-to-day fluctuations. This finding supported the use of an intensive longitudinal forecasting approach because more than half of the observed stress variability occurred within individuals over time. Mood

variability had a comparatively low intraclass correlation coefficient of .27, suggesting that affective instability was primarily a time-varying phenomenon rather than a stable characteristic of particular participants. In contrast, total screen time and device-unlock frequency had intraclass correlation coefficients of .55 and .52, respectively, indicating that adolescents differed consistently in their general levels of smartphone engagement, although meaningful day-to-day changes were also present.

Daily increases in mood variability were moderately associated with higher stress on the same day, with a within-person correlation of .46, which was the strongest bivariate association with stress among the principal time-varying predictors. Better subjective sleep quality was associated with lower daily stress, with a correlation of $-.39$, while higher loneliness was associated with higher stress, with a correlation of .37. Nighttime smartphone use showed a stronger relationship with daily stress than total screen time or device-unlock frequency. Specifically, nighttime use was correlated with stress at .32, compared with .21 for total screen time and .18 for unlock frequency. These patterns suggested that the timing and context of smartphone engagement were more relevant to adolescents' stress than the total quantity of smartphone use alone. Better social-interaction quality and greater perceived social support were associated with lower stress, with correlations of $-.26$ and $-.29$, respectively. Social-interaction quality and perceived

support were strongly positively related to one another, while both were inversely associated with loneliness. Sleep quality was also negatively related to nighttime smartphone use, indicating that adolescents tended to report poorer sleep on nights characterized by more extensive smartphone engagement after their reported bedtime. Although most correlations were statistically significant because of the large number of repeated observations, none approached a level indicating problematic redundancy among predictors. The observed pattern therefore supported retaining mood, sleep, social, and smartphone variables as conceptually distinct domains in the forecasting model.

Training of the long short-term memory network was terminated through the early-stopping procedure after 78 epochs. The lowest validation loss was observed at epoch 63, and the parameter estimates from this epoch were restored for final testing. Training and validation loss declined in parallel during the early and middle stages of optimization, and no substantial divergence was observed before early stopping. This pattern indicated that the use of dropout, participant-level data separation, and early stopping effectively limited overfitting. Table 2 compares the forecasting performance of the final LSTM network with the persistence, multiple linear regression, random forest, and feedforward neural-network benchmarks in the independent test dataset.

Table 2

Comparative Performance of the Daily Stress Forecasting Models in the Independent Test Dataset

Model	MAE	95% CI for MAE	RMSE	95% CI for RMSE	MSE	R ²	Correlation between observed and predicted stress
Previous-day persistence model	1.96	1.84–2.08	2.55	2.38–2.72	6.50	.31	.59
Multiple linear regression	1.78	1.67–1.90	2.34	2.18–2.50	5.48	.42	.66
Random forest regression	1.61	1.51–1.72	2.14	2.00–2.28	4.58	.52	.72
Feedforward neural network	1.54	1.44–1.64	2.05	1.92–2.18	4.20	.56	.75
Long short-term memory network	1.42	1.33–1.52	1.89	1.77–2.02	3.57	.62	.79

The LSTM network demonstrated the strongest forecasting performance across all evaluation metrics. Its mean absolute error of 1.42 indicated that the predicted next-day stress score differed from the observed score by an average of approximately 1.4 points on the 0-to-16 stress scale. The root mean square error was 1.89, and the mean squared error was 3.57. The model explained 62% of the variance in daily stress scores in adolescents who had not contributed any observations to model training, and the

correlation between observed and predicted stress was .79. The lower root mean square error relative to the competing models also indicated that the LSTM produced fewer large prediction errors. The mean prediction bias was -0.06 points, suggesting that the model had no meaningful overall tendency to overestimate or underestimate daily stress. The estimated calibration intercept was 0.18, and the calibration slope was .97, further indicating close agreement between

the magnitude of the predicted scores and the magnitude of the observed scores.

Compared with the persistence model, the LSTM reduced mean absolute error by 27.6% and root mean square error by 25.9%. This result indicated that forecasting stress from the preceding day's stress score alone did not adequately represent the changing behavioral and psychological conditions associated with next-day stress. The LSTM also reduced mean absolute error by 20.2% relative to multiple linear regression, 11.8% relative to random forest regression, and 7.8% relative to the feedforward neural network. The improvement over the feedforward network was particularly important because both models were capable of representing nonlinear relationships, but only the LSTM explicitly preserved the temporal order of the seven daily observations. Participant-level bootstrap comparisons showed that the confidence intervals for the differences in mean absolute error between the LSTM and each benchmark model did not include zero. The smallest difference was observed between the LSTM and feedforward network, but this difference remained statistically reliable.

Subgroup analyses indicated that model performance was generally stable across demographic groups. Mean absolute error was 1.40 among girls and 1.43 among boys. The corresponding values were 1.45 among participants aged 13

to 15 years and 1.39 among those aged 16 to 18 years. Mean absolute error was 1.47 among adolescents who had previously received mental health services and 1.40 among those without a history of service use. Provincial estimates ranged from 1.38 to 1.48. The seven gender-diverse participants had a mean absolute error of 1.51; however, this estimate was considered exploratory because of the small subgroup size. Overall, the differences between major demographic subgroups were small and did not indicate systematic deterioration in forecasting accuracy for a particular age, gender, provincial, or mental health-service group.

To determine whether all four predictor domains contributed meaningfully to forecasting, the LSTM was retrained after removing mood, sleep, social-interaction, or smartphone-use variables. Feature-level contributions were then examined using mean absolute SHAP values calculated across the independent test dataset. Higher mean absolute SHAP values indicated a greater average contribution to model predictions. Sensitivity analyses were also conducted to determine whether performance depended heavily on the seven-day window, the missing-data procedure, or inclusion of the preceding day's stress score. The results are presented in Table 3.

Table 3

Predictor-Domain Ablation, Feature Importance, and Sensitivity Analyses for the LSTM Model

Panel A: Predictor-domain ablation	MAE	RMSE	R ²	Increase in MAE relative to full model
Full LSTM model	1.42	1.89	.62	—
Model without mood variables	1.69	2.21	.48	0.27
Model without sleep variables	1.60	2.08	.54	0.18
Model without social-interaction variables	1.55	2.03	.56	0.13
Model without smartphone-use variables	1.51	1.98	.58	0.09
Panel B: Highest-ranking individual predictors	Mean absolute SHAP value		Predominant association with predicted next-day stress	
Previous-day stress score	0.842		Higher values predicted higher next-day stress	
Negative-mood variability	0.571		Greater variability predicted higher next-day stress	
Subjective sleep quality	0.492		Better quality predicted lower next-day stress	
Nighttime smartphone use	0.418		Greater use predicted higher next-day stress	
Daily loneliness	0.386		Greater loneliness predicted higher next-day stress	
Mean positive affect	0.344		Higher positive affect predicted lower next-day stress	
Deviation from usual sleep duration	0.311		Larger deviations predicted higher next-day stress	
Social-interaction quality	0.287		Better interaction quality predicted lower next-day stress	
Total daily screen time	0.241		Greater screen time generally predicted higher next-day stress	
Perceived social support	0.221		Greater support predicted lower next-day stress	
Device-unlock frequency	0.198		More frequent unlocking predicted higher next-day stress	
Panel C: Sensitivity analysis	MAE	RMSE	R ²	
Primary seven-day sequence model	1.42	1.89	.62	
Three-day sequence model	1.50	2.01	.57	
Fourteen-day sequence model	1.46	1.94	.60	
Complete-case observations only	1.40	1.87	.63	

Alternative median-based missing-data procedure	1.44	1.92	.61
Model excluding previous-day stress	1.59	2.10	.53

Removal of each predictor domain reduced forecasting accuracy, demonstrating that mood variability, sleep quality, social interaction, and smartphone use each provided information that was not fully represented by the other domains. Mood variables made the largest incremental contribution. When mood indicators were excluded, mean absolute error increased from 1.42 to 1.69, root mean square error increased from 1.89 to 2.21, and explained variance declined from .62 to .48. This reduction was consistent with the relatively strong within-person association between mood variability and stress shown in Table 1. Removing sleep variables produced the second-largest decline in performance, increasing mean absolute error by 0.18 points and reducing the explained variance to .54. Exclusion of social-interaction variables increased mean absolute error by 0.13 points, whereas exclusion of smartphone variables increased it by 0.09 points. Although the smartphone domain had the smallest domain-level effect, its removal still produced a measurable deterioration in independent test performance, showing that passive smartphone behavior added predictive information beyond adolescents' self-reported mood, sleep, and social experiences.

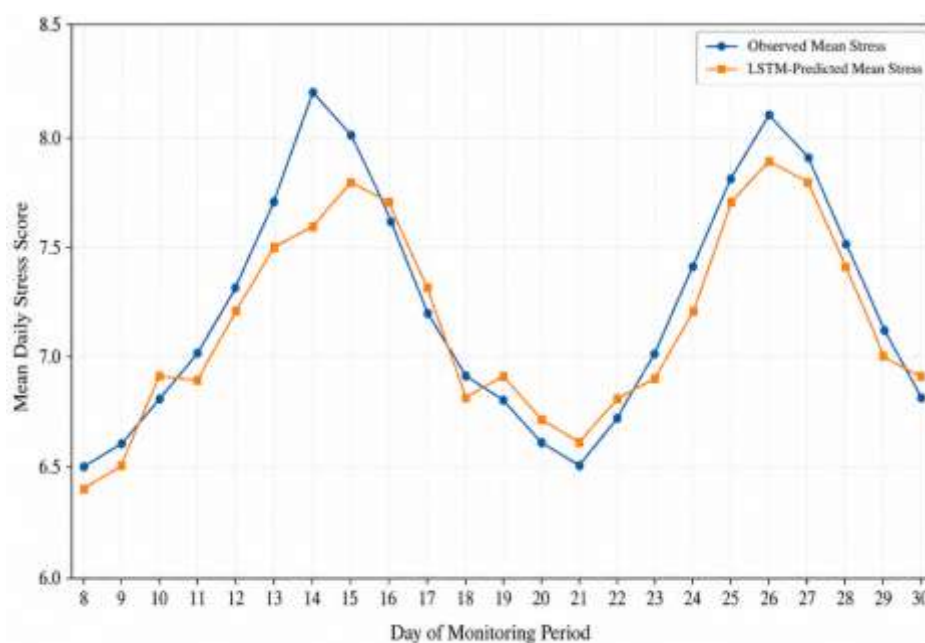
At the individual-feature level, the previous day's stress score was the strongest single predictor, but the model's performance was not determined by prior stress alone. Negative-mood variability was the highest-ranking non-stress predictor, indicating that rapid or substantial changes in anxiety, irritability, sadness, and related negative emotional states contributed more strongly to next-day forecasts than stable daily mood averages. Better subjective sleep quality consistently reduced predicted stress, whereas nighttime smartphone use increased predicted stress. The

importance of nighttime smartphone use was greater than that of total screen time and device-unlock frequency, reinforcing the finding that temporally disruptive use was more informative than overall device exposure. Loneliness increased predicted stress, while positive affect, high-quality social interaction, and perceived social support reduced it. Deviation from usual sleep duration showed a nonlinear association: both unusually short and unusually long sleep periods were associated with higher predicted next-day stress, whereas sleep durations close to each adolescent's personal average were associated with lower predicted stress.

Sensitivity analyses supported the robustness of the main findings. The seven-day sequence produced lower error than either the three-day or fourteen-day alternatives. The three-day model appeared to omit relevant cumulative information, while the fourteen-day model added sequence length without producing a corresponding increase in predictive accuracy. Restricting the analysis to complete cases resulted in a mean absolute error of 1.40 and an explained variance of .63, values that were nearly identical to those of the primary model. The alternative median-based missing-data procedure also produced performance estimates close to the primary analysis. Excluding the previous day's stress score reduced the explained variance from .62 to .53 and increased mean absolute error from 1.42 to 1.59. Nevertheless, this model continued to outperform the multiple linear regression benchmark and remained comparable to the random forest model. Therefore, mood, sleep, social, and smartphone indicators retained substantial forecasting value even when the most recent stress score was unavailable.

Figure 1

Observed and LSTM-Predicted Mean Daily Stress across the Forecastable Days of the 30-Day Monitoring Period



The observed and predicted trajectories displayed in Figure 1 were closely aligned across the 23 days for which seven preceding days of predictor information were available. The LSTM reproduced both gradual changes and shorter stress elevations observed across the monitoring period. The correlation between the observed and predicted aggregate daily means was .94, which was higher than the individual-observation correlation because aggregation reduced person-specific random variation. On 19 of the 23 forecastable days, the absolute difference between the observed mean and predicted mean was less than 0.30 stress points. The largest daily discrepancy was 0.63 points and occurred during a brief elevation in observed stress, during which the model underestimated the magnitude of the peak while correctly identifying its timing and subsequent decline. The model was especially accurate during periods of relatively stable or moderately changing stress. During the highest observed stress periods, predictions tended to be slightly closer to the overall sample mean, indicating a modest regression-to-the-mean pattern at the upper extreme. Conversely, days characterized by very low stress were occasionally predicted slightly above their observed values. Despite this attenuation at the extreme ends of the distribution, the predicted trajectory closely followed the direction, timing, and relative magnitude of the observed changes.

Additional examination of prediction errors showed that 71.4% of test predictions were within two points of the observed daily stress score, and 89.6% were within three points. Only 3.7% of predictions differed from the observed score by more than four points. Large errors were

disproportionately concentrated on days characterized by unusually abrupt stress changes that were not preceded by corresponding changes in mood, sleep, social interaction, or smartphone behavior. These cases suggested that some acute stressors, such as unexpected interpersonal conflicts, academic events, family difficulties, or other unmeasured experiences, could not be anticipated from the variables included in the model. Nevertheless, the overall correspondence between observed and predicted stress, the superiority of the LSTM over all benchmark models, and the consistency of the findings across ablation and sensitivity analyses demonstrated that sequential patterns of mood variability, sleep quality, social experience, and smartphone behavior provided substantial information for forecasting adolescents' daily stress.

4. Discussion

The present study examined whether daily stress among Canadian adolescents could be forecast from temporally ordered patterns of mood variability, sleep quality, social interaction, and smartphone use using a long short-term memory network. The findings demonstrated that adolescent stress was not only meaningfully variable across individuals but also fluctuated substantially within the same individual from day to day. Approximately half of the variability in daily stress reflected within-person changes, supporting the use of an intensive longitudinal design rather than relying solely on cross-sectional or trait-based assessments. The LSTM model achieved the strongest predictive performance among all evaluated models, with a mean absolute error of

1.42 points, a root mean square error of 1.89, and an explained variance of 62% in an independent test sample of adolescents who had not contributed data to model training. The model also demonstrated a strong correlation between observed and predicted stress scores and reproduced the general temporal trajectory of stress across the monitoring period. These results indicate that sequential patterns across psychological, behavioral, social, and digital domains contain substantial information about adolescents' next-day stress.

The superiority of the LSTM model over the persistence model, linear regression, random forest, and feedforward neural network suggests that the temporal organization of adolescents' daily experiences contributed meaningfully to forecasting. The persistence model assumed that tomorrow's stress would resemble today's stress, but its substantially larger error showed that recent stress alone did not adequately capture changes in adolescents' daily functioning. The linear regression model also performed less effectively, likely because the relationships among mood, sleep, social experiences, smartphone behavior, and stress were not entirely additive or linear. Although the random forest and feedforward neural network could represent nonlinear associations, neither explicitly preserved the order of the observations across the seven-day forecasting window. The better performance of the LSTM therefore suggests that a sequence of worsening sleep, increasing affective instability, reduced social support, or intensifying nighttime smartphone use may be more informative than simple weekly averages of those variables.

This finding is consistent with the broader literature emphasizing the dynamic and interdependent nature of adolescent mental health. Smartphone-based ecological momentary assessment and passive sensing have been proposed as useful methods for identifying person-specific drivers of adolescent psychological symptoms because they preserve temporal variation and reduce reliance on retrospective reporting (Ng et al., 2023). Similarly, passive digital monitoring has been shown to provide detailed information about the relationship between smartphone activity and sleep in diverse adolescent groups, supporting the use of naturally occurring digital behavior as a component of longitudinal mental health assessment (Shahnovsky et al., 2026). The present results extend this work by showing that multimodal daily data can be integrated through a sequential neural network to forecast stress prospectively rather than merely describe concurrent associations.

Mood variability emerged as the most important predictor domain after previous-day stress. Removing mood-related variables from the model produced the largest deterioration in predictive accuracy, and negative-mood variability ranked as the strongest non-stress feature. This result indicates that fluctuations in sadness, anxiety, irritability, and related negative emotional states provided more predictive information than stable mood levels alone. Adolescents whose negative affect changed substantially across the day may have been experiencing unstable environmental demands, difficulty regulating emotion, interpersonal sensitivity, or growing anticipatory tension. Such variability may increase the perceived unpredictability and uncontrollability of subsequent events, thereby contributing to higher next-day stress.

The importance of mood variability is compatible with daily research showing that adolescents' social media use and mood are closely linked, although the direction and strength of the association differ across individuals and contexts (Dreier et al., 2023). The present study suggests that the relevant psychological signal may not be simply whether mood is positive or negative, but whether it is unstable across short periods. This distinction helps explain why average associations between digital behavior and mental health are often modest. An adolescent may report an average mood score within the normal range while still experiencing repeated transitions between calmness, irritability, anxiety, and sadness. A sequential model can retain this information, whereas conventional analyses that rely on daily means may conceal it.

Sleep variables made the second-largest domain-level contribution to prediction. Better subjective sleep quality was associated with lower daily stress, while deviations from usual sleep duration and greater nighttime smartphone use predicted higher next-day stress. These findings are consistent with evidence that adolescent sleep is shaped by academic pressures, emotional arousal, family routines, social expectations, and technology-related habits (Vandendriessche et al., 2022). Poor sleep may reduce emotional regulation, impair attention, increase physiological reactivity, and make ordinary demands feel more difficult to manage. Conversely, stress may delay sleep onset or increase nighttime waking, creating a reciprocal cycle in which stress and sleep disturbance reinforce one another.

The present findings align with prospective evidence that interactive electronic-device use is related to adolescent sleep and mental health, with sleep acting as a plausible

pathway between digital engagement and psychological difficulty (Dibben et al., 2023). They are also consistent with reports that excessive social media use is associated with poorer sleep quality and adverse mental health outcomes among students (Bezerra et al., 2023). Research examining depression, smartphone addiction, and sleep has similarly demonstrated that these factors are closely interconnected rather than independent problems (Gao et al., 2023). The stronger predictive importance of nighttime use compared with total daily screen time is especially noteworthy. It suggests that the timing of use may be more consequential than overall duration because use after bedtime can directly interfere with sleep opportunity and recovery.

This interpretation is also supported by research linking nocturnal social media activity with poor sleep quality and anxiety among middle adolescents (Ntumi et al., 2025). However, the present findings should not be interpreted as evidence that all evening or nighttime smartphone use has an identical effect. Experience-sampling evidence has shown that social media use may not consistently impair sleep or next-day school wellbeing among all late adolescents (Maksniemi et al., 2023). The LSTM framework may have performed well partly because it allowed the significance of nighttime use to depend on prior mood, sleep, and social conditions. For example, an isolated episode of late smartphone use may have little effect, whereas repeated nighttime engagement during a period of worsening mood and declining sleep quality may carry a stronger risk signal.

Social-interaction variables also contributed unique predictive value. Greater loneliness predicted higher stress, while better interaction quality, perceived support, and positive social connection predicted lower stress. Adolescents' social worlds are central to emotional regulation and identity development, and daily experiences of acceptance, rejection, conflict, or support can strongly shape stress responses. The present findings indicate that the quality of interaction was more informative than communication frequency alone. This distinction is important because high levels of digital communication may reflect either meaningful social support or interpersonal pressure, compulsive checking, and social comparison.

Risk-profile research has similarly shown that adolescent adjustment is better understood through combinations of smartphone activities and psychosocial characteristics than through any single indicator of device use (Haag et al., 2024). The inverse associations of social support and interaction quality with stress are also consistent with the idea that digital communication can be beneficial when it

strengthens connection rather than replacing restorative or meaningful offline interaction. The present model did not treat smartphone use as inherently harmful; instead, it learned from the joint pattern of use, mood, sleep, loneliness, and support. This may explain why smartphone variables contributed less than mood and sleep at the domain level but still improved overall forecasting accuracy.

Among smartphone indicators, nighttime use was more influential than total screen time or device-unlock frequency. Total screen time was positively associated with stress, but its contribution was comparatively modest. This result is consistent with systematic reviews showing associations between screen exposure and adolescent mental health while also noting substantial heterogeneity and limited evidence for simple dose-response interpretations (Santos et al., 2023; Serrano et al., 2022). Reviews of increasing media use have likewise emphasized that the psychological implications of digital exposure depend on activity type, developmental context, displacement of sleep or physical activity, and the adolescent's pre-existing vulnerabilities (Bhatia, 2023). Therefore, the present findings support moving beyond broad screen-time totals toward more behaviorally specific indicators.

The association of frequent unlocking and fragmented use with higher predicted stress may reflect habitual checking, attentional interruption, perceived social obligation, or attempts to regulate discomfort through repeated device engagement. Smartphone attachment has been associated with poorer adolescent mental health, suggesting that the emotional dependence represented by repeated checking may be more important than device ownership itself (Liu et al., 2025). Longitudinal evidence concerning smartphone addiction also indicates that emotional symptoms, poor self-regulation, and psychosocial difficulties can precede and maintain problematic patterns of smartphone behavior (Crowhurst & Hosseinzadeh, 2024). This supports a bidirectional interpretation: adolescents may use their phones more frequently because they are stressed, while fragmented and poorly regulated use may further intensify stress.

The findings also correspond with evidence linking nomophobia to anxiety, smartphone addiction, and insomnia symptoms (Daraj et al., 2023). Fear of being disconnected or unavailable may produce repeated checking and make it difficult for adolescents to disengage from their devices, particularly at night. Excessive smartphone use has been associated with psychological morbidities including anxiety, low mood, stress, and sleep disruption among adolescents

and young adults (Rathod et al., 2022). At the same time, concerns about cognitive consequences such as reduced attention, memory inefficiency, and impaired sustained concentration have been raised in relation to intensive digital engagement (Ali et al., 2024). Although the present study did not directly assess cognition, attentional fragmentation may represent one pathway through which frequent device engagement increases perceived daily demands.

The model's subgroup performance was relatively stable across age, gender, province, and previous mental health-service use. This suggests that the learned patterns generalized across major demographic groups within the Canadian sample. However, this should not be interpreted as proof of equal performance in all populations, particularly because some subgroups were small. Nevertheless, the results provide preliminary evidence that privacy-preserving passive data and brief self-reports can be combined without requiring access to message content, contact identities, or personal media. This is important because adolescent digital mental health research must balance predictive utility with privacy, autonomy, and proportionality.

The ablation analyses further demonstrated that no single predictor domain was sufficient. Mood variables produced the largest performance decline when removed, followed by sleep, social interaction, and smartphone use. This ordering suggests that smartphone behavior may be most useful as a contextual and complementary signal rather than a stand-alone diagnostic indicator. Prospective cohort research has documented physical, psychological, and social correlates of mobile-phone use among children, indicating that digital behavior is embedded in broader patterns of functioning (Gupta et al., 2023). Research on screen time and child behavior has similarly linked digital exposure with irritability, attentional problems, and altered routines while emphasizing the role of environmental context (Naima, 2023). The present study reinforces the value of multimodal assessment by showing that smartphone data became more informative when combined with mood, sleep, and social variables.

The practical significance of the LSTM's performance should also be considered. An average error of approximately 1.4 points on a 16-point stress scale indicates useful but imperfect forecasting. Most predictions were within two or three points of observed stress, but larger errors occurred when stress changed abruptly without corresponding changes in the measured predictors. Such episodes may have reflected unexpected examinations, family conflict, peer incidents, health concerns, or other

acute events that were not captured. The tendency to underestimate extreme stress also indicates that the model was more effective at tracking general fluctuations than anticipating sudden peaks. Therefore, the model should be regarded as a probabilistic early-warning tool rather than a substitute for direct assessment or professional judgment.

5. Conclusion

The findings have relevance for preventive digital interventions. Guidance for healthy adolescent cell phone routines commonly emphasizes bedtime limits, reduced notifications, device-free periods, and intentional use (Alkureishi et al., 2024). Active nudging approaches have also shown potential for reducing excessive screen time and improving sleep-related behavior (Thiêm & Tagliabue, 2025). eHealth recommendations increasingly favor self-monitoring, family involvement, digital literacy, and adaptive regulation rather than complete avoidance of technology (Singhal et al., 2022). Mobile healthy-lifestyle interventions may be especially acceptable to adolescents when they are practical, personalized, and integrated into everyday routines (Peuters et al., 2024). A forecasting model could eventually support such interventions by identifying periods when worsening sleep, mood instability, loneliness, and nighttime use jointly indicate elevated stress risk.

6. Limitations & Suggestions

Several limitations should be considered when interpreting the findings. The study covered only 30 days, and this period may not capture seasonal changes, examination cycles, holidays, or longer-term developmental transitions. Although the sample included adolescents from four Canadian provinces, recruitment through schools, youth centers, and health services may have favored families willing to participate in intensive digital monitoring. Self-reported mood, stress, sleep, and social experiences remained vulnerable to reporting bias despite the use of repeated assessments. Passive smartphone data also differed in availability and technical precision across operating systems. The model did not include physiological indicators, academic events, family conflict, physical activity, substance use, or the content and emotional tone of online interactions. Some demographic subgroups were too small for definitive fairness analyses. Finally, the findings were generated from a predictive observational design and cannot establish that changing any individual predictor would necessarily cause a reduction in stress.

Future studies should examine longer monitoring periods and replicate the model across different countries, cultures, school systems, age groups, and clinical populations. Research should incorporate academic calendars, daily life events, physical activity, wearable-derived sleep indicators, heart-rate variability, and other physiological measures to improve the detection of sudden stress elevations. Larger samples are needed to evaluate algorithmic performance across gender-diverse adolescents, Indigenous communities, rural populations, socioeconomic groups, and adolescents with diagnosed mental health conditions. Future analyses should also compare LSTM models with transformers, temporal convolutional networks, personalized Bayesian models, and hybrid models combining population-level learning with individual calibration. Experimental studies could then test whether predictions can safely trigger low-burden interventions and whether such interventions improve stress, sleep, and functioning without increasing surveillance concerns or dependence on digital monitoring.

Schools, families, and adolescent health professionals should avoid interpreting total screen time as the sole indicator of digital risk. Greater attention should be given to nighttime use, repeated checking, sleep disruption, loneliness, and abrupt mood fluctuations. Brief daily monitoring may help identify adolescents whose stress is increasing before difficulties become severe, but any monitoring system should be transparent, voluntary, privacy-preserving, and accompanied by clear procedures for human review. Practical support should focus on establishing consistent sleep routines, reducing overnight phone access, strengthening supportive social interaction, teaching emotion-regulation skills, and helping adolescents recognize when smartphone use functions as avoidance rather than meaningful connection. Predictive systems should supplement, not replace, direct communication with adolescents and professional assessment.

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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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