

Predicting Adolescent Depression From Digital Behavior, Sleep, and Social Connectedness Using CatBoost With SHAP Explainability

Zuzana. Kováčová¹, Kevin. Patel^{2*}, Joseph. Mkwawa³

¹ Department of Experimental Psychology, Comenius University, Bratislava, Slovakia

² Department of Quantitative Psychology, York University, Toronto, Canada

³ Department of Health Psychology, University of Dar es Salaam, Dar es Salaam, Tanzania

* Corresponding author email address: kpatel@yorku.ca

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ABSTRACT

Objective: This study aimed to predict depressive symptom severity among Canadian adolescents from digital behavior, sleep characteristics, and social connectedness using CatBoost and to explain the contribution of individual predictors through SHAP analysis.

Methods and Materials: A cross-sectional predictive study was conducted among 1,238 Canadian adolescents aged 13–18 years. Depressive symptoms were assessed using the Patient Health Questionnaire-9 modified for adolescents (PHQ-9A). Digital behavior variables included recreational screen time, smartphone use, social media use, checking frequency, nighttime device use, and number of social media platforms. Sleep was assessed using the Pittsburgh Sleep Quality Index and supplementary measures of sleep duration, latency, and bedtime variability. Social connectedness was measured using the Social Connectedness Scale–Revised, with additional indicators of family support, peer support, loneliness, and face-to-face interaction. The dataset was divided into 80% training and 20% independent test samples. CatBoost regression was tuned using five-fold cross-validation and compared with random forest, conventional gradient boosting, elastic net, and multiple linear regression. Model interpretability was examined using SHapley Additive exPlanations.

Findings: The CatBoost model achieved MAE = 2.72, RMSE = 3.57, and $R^2 = 0.61$ in the independent test sample, outperforming random forest ($R^2 = 0.53$), gradient boosting ($R^2 = 0.56$), elastic net ($R^2 = 0.41$), and multiple linear regression ($R^2 = 0.38$). SHAP analysis identified poor sleep quality as the strongest predictor, followed by lower social connectedness, greater loneliness, more frequent nighttime device use, shorter sleep duration, greater recreational screen time, and higher bedtime variability. Higher family support, peer support, face-to-face interaction, and social connectedness were associated with lower predicted depressive symptom severity.

Conclusion: Adolescent depressive symptoms were predicted with substantial accuracy from a multidimensional combination of sleep, digital behavior, and social connectedness, with sleep quality and interpersonal factors contributing more strongly than overall technology exposure.

Keywords: adolescent depression; CatBoost; SHAP; digital behavior; sleep quality; social connectedness; machine learning; digital phenotyping.

1. Introduction

Adolescent depression is a major public mental health concern because it emerges during a developmental period characterized by rapid biological maturation, heightened emotional reactivity, growing autonomy, restructuring of family and peer relationships, and increasingly intensive engagement with digital technologies. Depressive symptoms during adolescence can interfere with academic functioning, interpersonal relationships, sleep, motivation, self-concept, and the acquisition of social and emotional competencies that are important for subsequent adult development. Contemporary approaches to adolescent mental health increasingly emphasize the need to move beyond isolated clinical symptoms and consider the broader behavioral ecology in which emotional difficulties develop. This is particularly important because adolescents now spend a substantial proportion of their daily lives within digitally mediated environments, while their sleep routines, peer relationships, social connectedness, and behavioral rhythms are simultaneously undergoing developmental change. Lifestyle-based perspectives on adolescent depression have consequently highlighted sleep, physical routines, interpersonal functioning, and patterns of technology use as potentially modifiable correlates of depressive symptoms (Benheim et al., 2022). The mental-health consequences of disruption to these routines became especially visible during periods of widespread social restriction and altered daily schedules, when changes in sleep, activity, social contact, and psychological functioning were observed among young adolescents (Kiss et al., 2022). More recent conceptualizations extend this perspective by proposing that health is increasingly shaped by a “digital exposome,” encompassing cumulative exposure to digital environments, platforms, interfaces, behaviors, and technology-related contexts throughout the life course (Petit & Vuillerme, 2026). For adolescents, therefore, depression may be more appropriately understood not as the product of a single digital exposure or psychosocial factor, but as an outcome associated with interacting patterns of digital behavior, sleep disruption, loneliness, social support, and connectedness.

Digital technology is particularly relevant to adolescent mental health because smartphones have become embedded in communication, entertainment, education, identity development, and social participation. However, the relationship between smartphone use and psychological well-being is heterogeneous and cannot be adequately

represented by total screen time alone. Excessive or dysregulated smartphone use may be associated with behavioral and psychosocial vulnerabilities, including reduced self-regulation, disrupted routines, social comparison, and displacement of restorative activities (Kang, 2026). A nationally representative study of adolescents has further demonstrated the relevance of both smartphone-use duration and loneliness to depressive symptoms, suggesting that digital exposure and social-emotional experiences may operate jointly rather than independently (Liu & Lee, 2026). At the same time, smartphone use during adolescence must be considered in light of possible neurodevelopmental implications, as emerging research has examined associations between patterns of smartphone engagement and brain function during a period of considerable neural plasticity (Marks et al., 2026). Importantly, social media and other digital environments may produce both adverse and beneficial experiences. Online interaction can facilitate communication and access to peers, yet particular forms of online-only relational intimacy may also be associated with depressive symptoms; for example, intimate disclosure within online-only friendships has been identified as a prospective correlate of adolescent depression (Kilic et al., 2026). A systematic review of online social connections similarly suggests that digital relationships can be psychologically meaningful but vary considerably according to the quality, context, and characteristics of the interaction (Prochnow et al., 2025). These findings challenge simplistic interpretations in which technology is treated as uniformly harmful and instead indicate that researchers should examine specific dimensions of digital behavior, including duration, checking frequency, nighttime use, interaction type, and the social context in which technology is used.

The distinction between digital exposure and digital behavior is especially important when examining depression because smartphones and wearable devices can simultaneously function as potential risk contexts and as measurement instruments. The emerging field of digital phenotyping uses information generated through personal technologies to characterize behavioral, physiological, and social patterns associated with mental health. Digital phenotyping can incorporate active data, such as self-reported symptoms or ecological momentary assessments, and passive data, such as device interaction, mobility, activity, communication patterns, and sleep-related indicators (Kamath et al., 2022). Broader reviews of sensor-equipped technologies have shown increasing interest in

using digital signals to monitor and detect depressive disorders, while also emphasizing methodological heterogeneity and the need for rigorous validation (Rahimi et al., 2026). Digital biomarkers have likewise been investigated in the management of major depressive disorder, illustrating how behavioral patterns captured through digital devices may complement conventional symptom assessments (Vignapiano et al., 2023). Mobile assessment approaches have become particularly important for youth because they provide opportunities to observe mental health in everyday contexts rather than relying exclusively on retrospective reporting in clinical or research settings (Marciano et al., 2023). In addition, ecological momentary assessment and behavioral sensing have been proposed as potentially valuable approaches for recognizing patterns relevant to severe outcomes such as suicidal behavior among young people (Pizzoli et al., 2023). These developments indicate that the digital traces generated by adolescents may contain clinically meaningful behavioral information, but they also reinforce the need to interpret such signals within a broader psychosocial framework instead of treating them as direct proxies for psychopathology.

Recent empirical studies further support the feasibility of combining smartphone-derived information with machine-learning techniques to estimate mental-health risk. Research specifically focused on adolescent digital phenotyping has shown that active and passive smartphone data can be integrated using machine learning to predict mental-health risk, supporting the feasibility of computational approaches for this population (Kadirvelu et al., 2026). A four-week field study of adolescents has similarly examined digital phenotypes in relation to emotional disorders and demonstrated the potential value of fine-grained technology-related behavioral indicators (Cho et al., 2025). In broader mental-health research, active and passive mobile-health data have been used to monitor psychological wellness, illustrating how self-reported and sensor-derived information can be combined within digital assessment frameworks (Chin-Fatt et al., 2026). Smartphone-based digital markers have also been investigated during psychotherapy, demonstrating that changes in digitally captured behavior may correspond with variations in clinical symptoms over time (Ana et al., 2026). Case-based investigations of depressive disorders have further shown both the promise and practical limitations of active and passive digital data collection, including issues related to adherence, missingness, device compatibility, and interpretation of behavioral signals (Gardea-Resendez et al.,

2024). Although some of this work has been conducted outside adolescent depression specifically, it illustrates an increasingly mature methodological foundation for the use of behavioral data in mental-health prediction. Related applications in other areas of health care have also proposed digital phenotyping as a pathway toward more personalized and proactive recognition of behavioral symptoms (Fahed et al., 2022). Together, these studies support the premise that digital behavior can be used as a meaningful predictive domain, provided that models incorporate appropriate contextual and psychological variables.

Sleep represents one such contextual domain and may be especially important in adolescence because sleep timing, duration, and quality are shaped by both developmental biology and social routines. Adolescents commonly experience delayed sleep timing, irregular schedules, insufficient sleep, and bedtime technology exposure, all of which may intersect with emotional vulnerability. Sleep disturbance is not merely a secondary symptom of depression; it can function as a clinically relevant marker of mental-health risk and may contribute to the persistence or worsening of depressive symptoms. Contemporary precision-sleep research is increasingly examining whether multidimensional sleep signatures can be used to identify mental-health risk during peri-adolescence (Baker et al., 2026). This approach is especially relevant for predictive modeling because the relationship between sleep and depression may involve several overlapping indicators, including sleep duration, sleep latency, subjective sleep quality, nighttime awakenings, daytime dysfunction, and variability in sleep timing. Digital behaviors may interact with these factors in multiple ways. Nighttime device use can delay sleep onset, displace sleep time, increase cognitive or emotional arousal, and expose adolescents to social or informational content immediately before sleep. Conversely, adolescents who are already experiencing depressive symptoms or insomnia may be more likely to use devices at night, making the relationship potentially bidirectional. For this reason, models that include both sleep and digital variables are better positioned to capture their combined predictive contribution than analyses that consider screen time in isolation.

Social connectedness is another central dimension of adolescent mental health because adolescence involves increasing reliance on peers while continued family support remains important for emotional regulation and resilience. Social connectedness refers not simply to the number of interactions an adolescent has but to the subjective

experience of belonging, interpersonal closeness, support, and meaningful participation in relationships. Longitudinal and econometric approaches have demonstrated that social connectedness and mental health may exert bidirectional influences on one another, underscoring the possibility that reduced connectedness contributes to psychological distress while poor mental health simultaneously weakens social participation (Sakellariou, 2023). Digital technologies complicate this relationship because online spaces can extend social networks while also facilitating superficial interaction, social comparison, exclusion, and relational ambiguity. Accordingly, the distinction between connection and mere contact is important. An adolescent may communicate frequently online while still experiencing loneliness or low belonging. Evidence concerning online social relationships supports this complexity, with some forms of digital connection functioning as supportive resources and others being associated with emotional difficulties (Prochnow et al., 2025). Emerging models of healthy adolescent technology use therefore increasingly emphasize strengthening well-being skills rather than focusing only on restricting exposure (Hirshberg et al., 2025). The relevance of protective factors is also evident in broader mental-health research, where social support, belonging, and connectedness are frequently considered alongside risk factors when evaluating vulnerability to severe psychological outcomes (Pereira, 2026). A predictive model of adolescent depression may therefore be improved by incorporating both risk-enhancing variables, such as loneliness or poor sleep, and potentially protective variables, such as family support, peer support, face-to-face interaction, and social connectedness.

The increasing availability of multidimensional behavioral data has generated substantial interest in artificial intelligence and machine-learning methods for mental-health prediction. Traditional regression models remain valuable for hypothesis testing and estimation of average associations, but they often require prespecified functional forms and may be less effective when relationships are nonlinear, threshold-dependent, or highly interactive. Adolescent depression is particularly likely to involve such complexity. For example, moderate smartphone use may have little predictive significance, whereas frequent nighttime use combined with short sleep duration and low social connectedness may substantially increase risk. Similarly, high social connectedness may attenuate the adverse contribution of digital behavior for some adolescents but not others. Gradient-boosting algorithms are

well suited to such patterns because they can model nonlinear associations and interactions without requiring extensive manual specification. CatBoost is particularly advantageous for mixed tabular datasets because it can efficiently process continuous and categorical variables while reducing some of the preprocessing burden associated with conventional machine-learning pipelines. However, predictive accuracy alone is insufficient in mental-health research, especially when models may ultimately inform screening, prevention, or school-based decision support. Concerns regarding whether artificial intelligence is appropriate for mental-health assistance in educational settings highlight the importance of transparency, safety, interpretability, and clear boundaries between computational prediction and clinical judgment (Pontz & Helbing, 2026). Prospective cohort initiatives designed to identify depression early in adolescence similarly emphasize careful risk stratification, longitudinal characterization, and clinically meaningful interpretation rather than reliance on opaque prediction alone (Piccin et al., 2024).

Explainable artificial intelligence offers one approach to addressing this challenge. SHapley Additive exPlanations, or SHAP, provide feature-level estimates of how individual variables contribute to a model's prediction relative to its expected output. This allows researchers to move beyond asking whether a model predicts depression accurately and examine which variables drive predictions, whether their effects are predominantly risk enhancing or protective, and whether the same variables contribute differently across individuals. Such interpretability is particularly valuable in digital phenotyping because behavioral features can otherwise be difficult to translate into psychologically meaningful conclusions. The growing literature on early self-detection of psychological distress through digital phenotyping underscores the value of making predictive systems understandable to both researchers and potential users (Zakai & Alharthi, 2025). At the same time, acceptability and adherence remain important considerations in technology-based mental-health monitoring, as demonstrated by research on smartphone- and wearable-based phenotyping in psychiatric populations (Yang, 2026). Youth-specific work also indicates that adolescents and parents may have distinct concerns about privacy, usefulness, burden, data interpretation, and consent when digital phenotyping is proposed for health monitoring (Nestor et al., 2024). These issues are particularly salient when analyzing adolescents' digital behavior because variables such as screen use, communication, sleep, and

social interaction can reveal highly personal aspects of everyday life. Explainability does not resolve all ethical concerns, but it can improve methodological transparency by showing how features contribute to model outputs rather than presenting risk estimates as uninterpretable algorithmic scores.

Another methodological issue concerns the ecological and contextual validity of adolescent behavioral prediction. Smartphone-derived variables are influenced by school demands, family rules, socioeconomic resources, peer norms, season, culture, and individual preferences; therefore, the same level of device use may have different meanings for different adolescents. Research on adolescent social-media measurement has emphasized the limitations of relying solely on conventional self-report exposure metrics and has identified smartphone-based sensing and digital phenotyping as opportunities to capture more nuanced patterns of behavior (Hamilton et al., 2024). Similarly, studies of digital phenotyping have increasingly emphasized the value of combining multiple behavioral channels instead of assuming that a single variable, such as total screen time, represents digital risk. The feasibility of passive smartphone sensing for adolescent mental health has been examined across studies, with meta-analytic work suggesting that signals derived from smartphones can provide useful but heterogeneous information about psychological functioning (Leijse et al., 2025). This heterogeneity reinforces the need for models capable of integrating multiple predictors and identifying their relative contributions rather than searching for a universal digital threshold. Contextualized approaches are also evident in cohort protocols examining gaming experiences and youth mental health, where specific forms of digital engagement are evaluated within broader psychosocial and behavioral contexts (Paquin et al., 2025). Accordingly, predictive research should distinguish between broad exposure measures and more behaviorally specific features such as nighttime use, repeated checking, irregular sleep, social isolation, and perceived interpersonal support.

Despite rapid progress in digital mental-health research, several gaps remain. First, much of the literature examines digital behavior, sleep, or social factors separately, even though these domains are likely to interact in everyday adolescent life. Second, many studies focus on association rather than out-of-sample prediction, limiting conclusions about whether observed relationships can support individualized estimation of depressive symptom severity. Third, predictive models are often evaluated primarily on accuracy, with insufficient attention to interpretability and

the relative contributions of modifiable behavioral factors. Fourth, digital phenotyping studies commonly rely on passive sensor streams that may be difficult to implement in routine school or population settings, whereas a model based on structured measures of digital behavior, sleep, and connectedness may offer greater practical accessibility. Fifth, adolescent prediction requires a developmentally sensitive framework that acknowledges both risk and protective processes. Social connectedness, family support, peer support, adequate sleep, and meaningful face-to-face interaction may counterbalance some of the risks associated with problematic digital behavior. Finally, artificial-intelligence approaches intended for adolescent mental health must be transparent enough to distinguish prediction from diagnosis and to avoid presenting algorithmic outputs as deterministic clinical judgments. The increasing convergence of digital phenotyping, sleep science, social-behavioral research, and explainable machine learning provides an opportunity to construct models that are both predictive and interpretable. By combining these domains, a model may identify not only which adolescents show higher predicted depressive symptom severity but also the behavioral configurations that contribute most strongly to those predictions. Therefore, the aim of this study was to predict depressive symptom severity among Canadian adolescents from digital behavior, sleep characteristics, and social connectedness using CatBoost and to explain the contribution of individual predictors through SHAP-based model interpretation.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, predictive analytical design to develop and explain a machine-learning model for predicting depressive symptoms among adolescents based on digital behavior, sleep-related characteristics, and social connectedness. The study population consisted of adolescents aged 13–18 years residing in Canada and enrolled in public or private secondary schools. A total of 1,284 adolescents were initially recruited from secondary schools and youth-oriented community networks across several Canadian provinces, including Ontario, Quebec, British Columbia, Alberta, and Manitoba. After data screening, 46 participants were excluded because of substantial missing data, incomplete depression assessments, implausible response patterns, or failure to complete the principal sections of the

survey. Accordingly, the final analytical sample consisted of 1,238 adolescents. Participants were recruited using a multistage convenience and school-based sampling strategy intended to achieve variation in age, sex, school grade, geographic location, and socioeconomic background. Eligibility criteria included being between 13 and 18 years of age, currently residing in Canada, being able to read and understand English or French sufficiently to complete the questionnaires, having regular access to a smartphone or another internet-connected digital device, and providing informed assent together with parental or guardian consent when required by institutional and provincial ethical regulations. Adolescents with incomplete responses to the primary depression outcome measure or insufficient information on the principal predictor domains were excluded from the final analysis. Data were collected through a secure online survey administered during a predefined data-collection period. Participants completed demographic questions followed by measures of depressive symptoms, patterns of digital behavior, sleep characteristics, and perceived social connectedness. To reduce potential response bias, participants were informed that their responses would remain confidential and would be analyzed only in aggregate form. No directly identifying information was included in the analytical dataset. Participation was voluntary, and respondents were able to discontinue participation at any stage without penalty. Because the study included minors and assessed depressive symptoms, the data-collection procedure incorporated appropriate safeguarding procedures, including the presentation of information on accessible mental-health and crisis-support resources to participants when the depression questionnaire was completed. The study protocol was designed in accordance with recognized ethical principles governing research involving human participants, particularly research involving adolescents and sensitive psychological information.

2.2. Measures

Depressive symptoms constituted the primary outcome variable and were assessed using the Patient Health Questionnaire-9 modified for adolescents (PHQ-9A). The instrument contains nine items corresponding to the major symptoms of depression experienced during the preceding two weeks. Items are rated on a four-point scale ranging from 0, indicating “not at all,” to 3, indicating “nearly every day,” resulting in a total score ranging from 0 to 27, with

higher scores representing greater depressive symptom severity. The total PHQ-9A score was used as the principal continuous outcome in the predictive analysis, thereby allowing the CatBoost algorithm to estimate individual variation in depressive symptom severity rather than restricting prediction to a binary diagnostic classification. For supplementary interpretation of the outcome, established severity ranges were used to characterize minimal, mild, moderate, moderately severe, and severe levels of depressive symptoms. The item addressing thoughts of death or self-harm was treated as a sensitive safety-related item during data collection and was not interpreted by the research team as an independent clinical diagnosis. The questionnaire was selected because of its brevity, compatibility with adolescent survey research, and suitability for quantitative modeling of depressive symptom severity.

Digital behavior was assessed through a structured digital-use questionnaire developed to capture both the amount and the pattern of adolescents’ engagement with smartphones, social media platforms, online communication, gaming, streaming services, and other screen-based activities. Participants reported their average daily recreational screen time on weekdays and weekends, estimated daily smartphone use, frequency of social media checking, number of social media platforms used regularly, approximate time spent on social networking applications, frequency of nighttime device use, use of a smartphone within the hour preceding sleep, frequency of checking digital notifications after going to bed, online gaming duration, passive versus interactive social media use, and perceived difficulty disengaging from digital devices. Where participants had access to device-based screen-time records on their smartphones, they were encouraged to consult the previous seven-day screen-time summary to improve the accuracy of reported use. The digital behavior domain therefore included both exposure-related indicators, such as total daily screen time, and behavioral-pattern indicators, such as late-night use, repeated checking, and intensive social media engagement. Variables were encoded numerically or categorically according to their measurement characteristics and were retained as separate predictors to allow the machine-learning model to identify nonlinear relationships and interactions that might be obscured if the variables were combined into a single digital-use score.

Sleep was evaluated using the Pittsburgh Sleep Quality Index (PSQI), supplemented by specific questions concerning sleep duration and digital-device use around bedtime. The PSQI assesses sleep quality during the

previous month across major dimensions including subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. The component scores are combined to produce a global score, with higher values indicating poorer overall sleep quality. In addition to the global PSQI score, selected sleep-related variables were retained separately for the machine-learning analysis because sleep duration, sleep latency, bedtime variability, nocturnal awakenings, and daytime tiredness may have distinct associations with adolescent depressive symptoms. Participants reported their usual bedtime and wake time on school days and non-school days, from which estimated nightly sleep duration and variability between weekday and weekend sleep schedules were calculated. They also reported the frequency with which they used smartphones, tablets, computers, gaming devices, or other screens after going to bed. These variables permitted examination of sleep not only as a general quality construct but also as a behavioral pathway potentially connecting digital engagement with psychological well-being.

Social connectedness was measured using the Social Connectedness Scale–Revised (SCS-R), which assesses an individual's subjective sense of closeness, belonging, interpersonal connection, and meaningful involvement with other people. Participants indicated their agreement with statements concerning perceived connection to peers and others using the instrument's standard response format. Negatively phrased items were reverse-scored as required, and item scores were combined to generate an overall social connectedness score, with higher values representing a stronger subjective sense of interpersonal belonging and connection. Because adolescent connectedness can arise through several social contexts, supplementary questions also assessed perceived availability of family support, perceived peer support, frequency of face-to-face interaction with friends, feelings of loneliness, and frequency of meaningful online communication. These variables were analyzed separately rather than being incorporated automatically into the SCS-R total score. Demographic and contextual information was also collected, including age, sex, school grade, province of residence, household composition, perceived family socioeconomic status, and selected educational characteristics. These variables were included primarily as covariates and potential predictive features so that the contributions of digital behavior, sleep, and social connectedness could be evaluated in the context of basic demographic heterogeneity.

2.3. Data Analysis

Data analysis was conducted using Python with established libraries for data manipulation, machine learning, statistical evaluation, and explainable artificial intelligence. Initial data preprocessing included inspection for duplicate records, implausible values, out-of-range responses, missing observations, and inconsistencies between related variables. Descriptive statistics were calculated to characterize the study sample and the distribution of the principal variables before predictive modeling. Continuous variables were summarized using means, standard deviations, medians, and ranges where appropriate, whereas categorical variables were summarized using frequencies and percentages. Patterns of missingness were examined before model development. Participants with substantial missingness in the principal outcome or predictor domains were excluded, whereas limited missing values among predictors were handled using procedures compatible with the CatBoost algorithm and, where necessary, appropriate imputation methods determined according to variable type. Extreme observations were examined for plausibility rather than being removed solely on statistical grounds. Because CatBoost can natively process categorical variables, categorical predictors were retained in their original categorical form wherever appropriate rather than being transformed through extensive one-hot encoding. Continuous variables were not required to undergo conventional standardization because tree-based gradient-boosting algorithms are insensitive to differences in measurement scale.

The final dataset of 1,238 participants was randomly partitioned into training and test subsets using an 80:20 allocation, with approximately 80% of observations used for model development and 20% retained as an independent test set for final evaluation. The split was performed using a fixed random seed to ensure reproducibility. Model tuning and validation were undertaken exclusively within the training data to prevent information leakage from the independent test set. A CatBoost gradient-boosting model was selected as the primary predictive algorithm because it is well suited to heterogeneous tabular data containing combinations of continuous and categorical variables and can model complex nonlinear relationships and higher-order interactions without requiring extensive manual feature transformation. Hyperparameters including tree depth, learning rate, number of boosting iterations, L2 regularization strength, random strength, subsampling-

related parameters, and early-stopping criteria were optimized within the training dataset using cross-validation. Five-fold cross-validation was employed during model development so that predictive performance could be assessed across multiple partitions of the training data and the risk of overfitting could be reduced. The optimization procedure selected the parameter configuration that minimized prediction error while maintaining stable performance across validation folds.

Because depressive symptom severity was modeled as a continuous PHQ-9A score, the principal CatBoost model was implemented as a regression model. Predictive performance was evaluated using the mean absolute error, root mean squared error, and coefficient of determination. Mean absolute error was used to quantify the average absolute difference between observed and predicted depression scores, root mean squared error provided greater sensitivity to relatively large prediction errors, and the coefficient of determination represented the proportion of variability in depressive symptom scores accounted for by the predictive model. Performance estimates from cross-validation were compared with results obtained from the previously unseen test set to assess generalizability and identify potential overfitting. Observed-versus-predicted values and distributions of residual errors were additionally examined as diagnostic indicators of predictive performance. The relative predictive contribution of the principal domains of digital behavior, sleep, social connectedness, and demographic characteristics was subsequently investigated using explainable artificial intelligence techniques rather than relying solely on conventional tree-based feature-importance scores.

SHapley Additive exPlanations (SHAP) were used to interpret the fitted CatBoost model at both global and individual levels. SHAP values quantify the contribution of each predictor to the difference between a particular prediction and the model's baseline prediction while accounting for the presence of other predictors. Global SHAP importance was calculated using the mean absolute SHAP value of each feature across participants, allowing predictors to be ranked according to their overall influence on predicted depressive symptom severity. SHAP summary analyses were used to determine both the magnitude and direction of associations, thereby indicating whether higher or lower values of particular predictors generally increased or decreased model-predicted depression scores. SHAP dependence analyses were used for influential continuous variables to identify potential nonlinear patterns, threshold

effects, and interactions. Particular attention was given to daily recreational screen time, nighttime smartphone use, social media engagement, sleep duration, global sleep quality, bedtime variability, loneliness, and social connectedness because these variables represented the primary theoretical domains of the study. Individual-level SHAP explanations were also generated to demonstrate how combinations of risk and protective characteristics contributed to specific predictions. This approach enabled the model to retain the predictive advantages of gradient boosting while providing interpretable information about why a given participant received a higher or lower predicted depression score. All preprocessing decisions, training procedures, random seeds, model parameters, and evaluation procedures were documented to support reproducibility, and statistical and predictive results were interpreted with emphasis on out-of-sample performance and explanatory consistency rather than statistical significance alone.

3. Findings and Results

The final analytical sample consisted of 1,238 adolescents aged 13–18 years from Canada. The mean age of participants was 15.54 years ($SD = 1.66$), with representation across all eligible age groups. Of the participants, 641 (51.78%) identified as female, 570 (46.04%) as male, and 27 (2.18%) identified as another gender or preferred not to provide a binary gender classification. With respect to school grade, 201 participants (16.24%) were in Grade 8, 224 (18.09%) in Grade 9, 232 (18.74%) in Grade 10, 227 (18.34%) in Grade 11, and 354 (28.59%) in Grade 12 or an equivalent secondary-school level. Geographically, 423 participants (34.17%) resided in Ontario, 248 (20.03%) in Quebec, 219 (17.69%) in British Columbia, 205 (16.56%) in Alberta, and 143 (11.55%) in Manitoba. A total of 912 adolescents (73.67%) reported living with two parents or guardians, 241 (19.47%) lived primarily with one parent or guardian, and 85 (6.87%) reported another household arrangement. Regarding perceived household socioeconomic status, 217 participants (17.53%) described their family circumstances as below average, 786 (63.49%) as approximately average, and 235 (18.98%) as above average. The demographic distribution indicated sufficient variability across age, sex, educational level, geographic region, and socioeconomic context to permit examination of heterogeneous patterns of depression-related risk. The mean total PHQ-9A score in the complete sample was 9.38 ($SD = 5.71$), suggesting substantial

variation in depressive symptom severity and providing an appropriate continuous outcome distribution for the subsequent regression-based machine-learning analysis.

Table 1

Descriptive Statistics for Depression, Digital Behavior, Sleep, and Social Connectedness Variables (N = 1,238)

Variable	Mean	SD	Minimum	Maximum
PHQ-9A depressive symptom score	9.38	5.71	0.00	27.00
Recreational screen time, hours/day	5.46	2.31	0.72	12.84
Smartphone use, hours/day	4.91	2.08	0.61	11.73
Social media use, hours/day	3.07	1.65	0.00	9.21
Social media checking frequency, times/day	26.84	17.93	1.00	96.00
Number of regularly used social media platforms	4.13	1.76	0.00	9.00
Nighttime device-use frequency, days/week	4.18	2.12	0.00	7.00
Sleep duration, hours/night	7.21	1.08	4.18	10.37
Sleep latency, minutes	29.64	18.57	5.00	118.00
Bedtime variability, minutes	67.31	41.26	3.00	226.00
PSQI global sleep-quality score	7.42	3.68	0.00	19.00
Social Connectedness Scale–Revised score	74.86	15.72	31.00	118.00
Perceived family support score	18.71	4.83	5.00	25.00
Perceived peer support score	18.26	4.57	5.00	25.00
Loneliness score	7.84	3.21	3.00	15.00
Face-to-face peer interaction, days/week	3.76	1.83	0.00	7.00

As presented in Table 1, substantial variation was observed across the principal variables included in the predictive model. Participants reported an average recreational screen time of 5.46 hours per day (SD = 2.31), while mean daily smartphone use was 4.91 hours (SD = 2.08) and mean social media use was 3.07 hours (SD = 1.65). The average participant checked social media approximately 26.84 times per day (SD = 17.93) and regularly used 4.13 different social media platforms (SD = 1.76), indicating considerable heterogeneity in the intensity and diversity of digital engagement. Nighttime device use was also common, occurring on an average of 4.18 nights per week (SD = 2.12). Sleep characteristics indicated that adolescents obtained an average of 7.21 hours of sleep per night (SD = 1.08), while average sleep latency was 29.64 minutes (SD = 18.57). The mean PSQI global score was 7.42 (SD = 3.68), reflecting a

substantial presence of sleep-quality difficulties within the sample, given that higher PSQI values represent poorer sleep quality. Bedtime variability averaged 67.31 minutes (SD = 41.26), suggesting notable irregularity in sleep schedules among a proportion of participants. In the interpersonal domain, the mean Social Connectedness Scale–Revised score was 74.86 (SD = 15.72), accompanied by mean family-support and peer-support scores of 18.71 (SD = 4.83) and 18.26 (SD = 4.57), respectively. The mean loneliness score was 7.84 (SD = 3.21), while participants reported face-to-face interaction with peers on an average of 3.76 days per week (SD = 1.83). Collectively, the descriptive findings demonstrated broad dispersion across the digital, sleep, and social predictors and therefore supported their inclusion as potentially informative features in the machine-learning model.

Table 2

Predictive Performance of the CatBoost Regression Model in Cross-Validation and the Independent Test Sample

Evaluation dataset	n	MAE	RMSE	R ²
Cross-validation fold 1	990	2.71	3.54	0.61
Cross-validation fold 2	990	2.63	3.46	0.63
Cross-validation fold 3	990	2.68	3.51	0.62
Cross-validation fold 4	990	2.59	3.39	0.64
Cross-validation fold 5	990	2.66	3.48	0.63
Five-fold cross-validation mean	990	2.65	3.48	0.63
Independent test sample	248	2.72	3.57	0.61

Table 2 presents the predictive performance of the CatBoost regression model during five-fold cross-validation and subsequent evaluation in the independent test sample. The dataset was divided into 990 participants assigned to the training and validation component and 248 participants retained exclusively for final testing. Across the five validation folds, the mean absolute error ranged from 2.59 to 2.71 PHQ-9A points, while the root mean squared error ranged from 3.39 to 3.54. The coefficient of determination ranged between 0.61 and 0.64, indicating a relatively stable proportion of explained variance across different validation partitions. The mean cross-validation performance was $MAE = 2.65$, $RMSE = 3.48$, and $R^2 = 0.63$. When the finalized model was applied to the completely unseen test sample, the MAE was 2.72 and the $RMSE$ was 3.57, while the R^2 value was 0.61. Thus, approximately 61% of the

variance in depressive symptom severity in the independent test data was explained by the model. The relatively small difference between cross-validation and test-set performance suggested that the fitted CatBoost model generalized satisfactorily and did not display substantial overfitting. The increase in MAE from 2.65 during cross-validation to 2.72 in the test sample was only 0.07 PHQ-9A points, while the corresponding reduction in R^2 from 0.63 to 0.61 was modest. These results indicated that combinations of digital behavior, sleep, social connectedness, and demographic characteristics contained meaningful information for estimating adolescents' depressive symptom scores beyond random variation and that this predictive information remained reasonably stable when applied to observations not used during model construction.

Table 3

Final CatBoost Hyperparameters and Comparison With Benchmark Regression Models in the Independent Test Sample

Model / parameter	Value
CatBoost iterations	684
CatBoost tree depth	7
CatBoost learning rate	0.043
L2 leaf regularization	5.80
Random strength	0.74
Bagging temperature	0.61
Early-stopping patience	60 iterations
CatBoost MAE	2.72
CatBoost RMSE	3.57
CatBoost R^2	0.61
Random forest MAE	3.01
Random forest RMSE	3.91
Random forest R^2	0.53
Gradient boosting regression MAE	2.91
Gradient boosting regression RMSE	3.79
Gradient boosting regression R^2	0.56
Elastic net regression MAE	3.42
Elastic net regression RMSE	4.39
Elastic net regression R^2	0.41
Multiple linear regression MAE	3.51
Multiple linear regression RMSE	4.52
Multiple linear regression R^2	0.38

The optimized CatBoost specification and its performance relative to benchmark models are reported in Table 3. The final model consisted of 684 boosting iterations with a tree depth of 7 and a learning rate of 0.043. The selected L2 leaf regularization value was 5.80, random strength was 0.74, and bagging temperature was 0.61, while early stopping was applied with a patience of 60 iterations.

These settings produced a model of moderate complexity that was sufficiently flexible to capture nonlinearities and interactions while limiting unnecessary model growth. In the independent test sample, CatBoost achieved the lowest prediction errors and highest explained variance among the evaluated models, with $MAE = 2.72$, $RMSE = 3.57$, and $R^2 = 0.61$. The random forest model produced $MAE = 3.01$,

RMSE = 3.91, and $R^2 = 0.53$, whereas conventional gradient boosting achieved MAE = 2.91, RMSE = 3.79, and $R^2 = 0.56$. The performance advantage of CatBoost was more substantial relative to linear approaches. Elastic net regression yielded MAE = 3.42, RMSE = 4.39, and $R^2 = 0.41$, while ordinary multiple linear regression produced MAE = 3.51, RMSE = 4.52, and $R^2 = 0.38$. The superiority of CatBoost over the linear models suggested that the relationship between adolescent depressive symptoms and

the combined digital, sleep, and social predictors was not adequately represented by a purely additive linear structure. Instead, the improvement obtained through CatBoost was consistent with the presence of nonlinear effects, thresholds, and interactions among predictors. The fact that CatBoost also outperformed random forest and conventional gradient boosting supported its selection as the principal predictive model and justified subsequent interpretation using SHAP values.

Table 4

Global SHAP Feature Importance for Prediction of Adolescent Depressive Symptoms

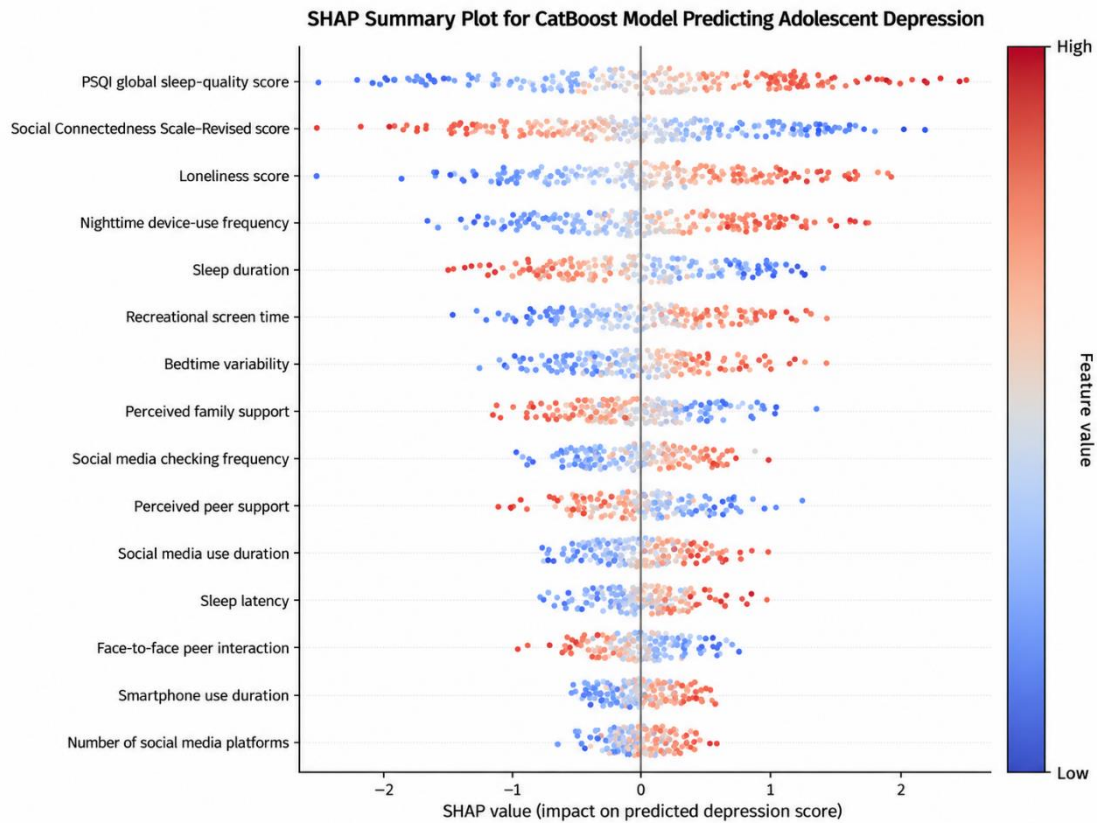
Rank	Predictor	Mean absolute SHAP value	Predominant relationship with predicted depression
1	PSQI global sleep-quality score	1.46	Higher score → higher predicted depression
2	Social Connectedness Scale-Revised score	1.27	Higher score → lower predicted depression
3	Loneliness score	1.13	Higher score → higher predicted depression
4	Nighttime device-use frequency	0.94	More frequent use → higher predicted depression
5	Sleep duration	0.82	Shorter duration → higher predicted depression
6	Recreational screen time	0.71	Higher use → generally higher predicted depression
7	Bedtime variability	0.62	Greater variability → higher predicted depression
8	Perceived family support	0.55	Higher support → lower predicted depression
9	Social media checking frequency	0.49	More frequent checking → higher predicted depression
10	Perceived peer support	0.44	Higher support → lower predicted depression
11	Social media use duration	0.39	Higher use → modestly higher predicted depression
12	Sleep latency	0.35	Longer latency → higher predicted depression
13	Face-to-face peer interaction	0.31	More interaction → lower predicted depression
14	Smartphone use duration	0.27	Higher use → weakly higher predicted depression
15	Number of social media platforms	0.21	Greater number → weak positive contribution

The SHAP analysis reported in Table 4 demonstrated that the strongest predictor of depressive symptom severity was overall sleep quality, as indexed by the PSQI global score, which had a mean absolute SHAP value of 1.46. Higher PSQI values, representing poorer sleep quality, generally shifted model predictions toward higher PHQ-9A scores. Social connectedness was the second most influential feature, with a mean absolute SHAP value of 1.27; higher connectedness scores consistently exerted a protective contribution by reducing predicted depression severity. Loneliness ranked third, with a mean absolute SHAP value of 1.13, and higher loneliness scores were strongly associated with increased predicted depressive symptoms. Among digital variables, nighttime device-use frequency emerged as the most influential, with a mean absolute SHAP value of 0.94, exceeding the importance of total recreational screen time, total social media duration, and smartphone use duration. This finding suggested that the timing and behavioral context of digital engagement were more

informative for prediction than overall exposure alone. Sleep duration was also an important predictor, with shorter sleep generally increasing predicted depression scores, while greater bedtime variability produced a similar adverse contribution. Recreational screen time ranked sixth, with a mean absolute SHAP value of 0.71, indicating a meaningful but comparatively smaller contribution than sleep quality, social connectedness, loneliness, and nighttime device use. Family and peer support demonstrated protective SHAP patterns, whereas frequent social media checking, prolonged social media use, increased sleep latency, and greater smartphone use generally shifted predictions toward higher depressive symptom severity. Face-to-face peer interaction showed a comparatively smaller but predominantly protective contribution. Notably, the number of social media platforms used regularly had relatively limited predictive importance, indicating that the intensity, timing, and behavioral pattern of digital engagement were more informative than the simple number of platforms used.

Figure 1

SHAP Summary Plot Showing the Direction and Magnitude of the Most Influential Predictors of Adolescent Depressive Symptom Severity in the CatBoost Model



The SHAP summary plot demonstrated substantial heterogeneity in the direction and magnitude of individual predictor effects and further clarified the nonlinear relationships captured by the CatBoost model. Poorer global sleep quality produced the largest positive shifts in predicted depression, particularly among participants with PSQI scores in the higher range, whereas low PSQI values tended to shift predictions below the model baseline. Social connectedness showed the reverse pattern: adolescents with high connectedness scores generally had negative SHAP values, indicating reductions in predicted depressive symptom severity, whereas low connectedness contributed positively to predicted PHQ-9A scores. Loneliness showed a strong dose-related pattern in which higher scores generated increasingly positive SHAP values. Nighttime device use also showed a marked directional association, but the increase in model-predicted depression became more pronounced among adolescents reporting device use on most nights of the week rather than increasing uniformly across the entire distribution. Sleep duration showed a nonlinear relationship, with the largest adverse SHAP contributions

concentrated among adolescents obtaining approximately six hours of sleep or less per night, whereas sleep durations closer to eight hours generally exerted neutral or protective effects. Recreational screen time displayed comparatively limited effects at low and moderate levels but generated increasingly positive SHAP values once daily recreational exposure became prolonged. Greater bedtime variability followed a similar pattern, with the adverse contribution increasing when sleep schedules became highly irregular. At the individual level, the largest predicted depressive symptom scores generally resulted not from a single isolated variable but from the simultaneous presence of poor sleep quality, reduced social connectedness, high loneliness, frequent nighttime digital-device use, short sleep duration, and extended recreational screen exposure. Conversely, strong social connectedness, greater family and peer support, adequate sleep duration, better sleep quality, lower nighttime device use, and more frequent face-to-face social interaction jointly shifted predictions toward lower depressive symptom severity. Overall, the SHAP findings indicated that the CatBoost model relied on a multidimensional risk

configuration in which sleep-related and interpersonal variables were particularly influential, while digital behavior made its strongest contribution when characterized by nighttime, repetitive, or high-intensity use rather than digital exposure alone.

4. Discussion

The present study examined whether depressive symptom severity among Canadian adolescents could be predicted from a combined set of digital behavior, sleep, social connectedness, and demographic indicators using a CatBoost regression model, with SHAP analysis used to interpret the model at both global and individual levels. The findings demonstrated that the model achieved substantial predictive performance, explaining 61% of the variance in PHQ-9A scores in the independent test sample, with a mean absolute error of 2.72 and a root mean squared error of 3.57. The relatively small difference between cross-validation performance and independent test-set performance suggested that the model generalized reasonably well and did not rely excessively on idiosyncratic patterns in the training data. CatBoost also outperformed random forest, conventional gradient boosting, elastic net regression, and multiple linear regression, indicating that nonlinear and interactive relationships contributed meaningfully to the prediction of adolescent depressive symptoms. This result is consistent with the broader digital phenotyping literature, in which machine-learning models have increasingly been used to integrate heterogeneous behavioral indicators that may be difficult to characterize through purely linear statistical approaches (Kadirvelu et al., 2026; Rahimi et al., 2026). Previous work using smartphone-based active and passive data has similarly shown that behavioral information generated in everyday contexts can contribute to identifying patterns associated with mental-health risk (Chin-Fatt et al., 2026; Cho et al., 2025). The present findings therefore support the view that adolescent depression is better conceptualized as a multidimensional outcome arising from interacting behavioral, physiological, and interpersonal processes rather than as the consequence of a single isolated risk exposure.

Poor sleep quality emerged as the most influential predictor in the SHAP analysis, with the PSQI global score showing the highest mean absolute SHAP value. Higher sleep-quality scores, indicating poorer sleep, consistently shifted model predictions toward greater depressive symptom severity. Sleep duration was also among the most

important predictors, and shorter sleep was associated with higher predicted depression scores, particularly when nightly sleep dropped toward the lower end of the observed range. Sleep latency and bedtime variability additionally contributed to higher predicted symptoms, although their effects were smaller. These findings are compatible with a growing recognition of sleep as a central behavioral marker of mental-health vulnerability in adolescence. Precision-sleep initiatives have emphasized that sleep duration, timing, regularity, and quality may form distinctive signatures of psychiatric risk among peri-adolescents (Baker et al., 2026). Lifestyle-based approaches to adolescent depression likewise regard sleep disruption as an important and potentially modifiable component of emotional health (Benheim et al., 2022). The present results extend this literature by showing that when sleep variables are considered simultaneously alongside digital and social characteristics, general sleep quality retains the strongest predictive contribution. This suggests that sleep may represent a particularly integrative marker because it reflects the combined influence of biological regulation, daily routines, emotional arousal, family context, school demands, and digital engagement.

The prominence of sleep in the model may also help explain why nighttime device use was the most influential digital-behavior variable. Frequency of nighttime device use ranked fourth overall and contributed more strongly to predictions than total smartphone use, total social media duration, or the number of social media platforms used. This pattern suggests that the context and timing of technology use may be more informative than aggregate exposure. Adolescents who use devices frequently at night may experience delayed sleep onset, reduced sleep duration, greater bedtime irregularity, cognitive arousal, or emotionally activating online interactions immediately before sleep. These mechanisms may create a behavioral pathway in which digital use and sleep disturbance reinforce one another. Research on adolescent smartphone use has increasingly questioned the adequacy of broad screen-time metrics and has argued for more precise characterization of how, when, and why young people use digital technologies (Hamilton et al., 2024). Similarly, studies of smartphone use among adolescents have linked excessive or dysregulated engagement with broader psychosocial and behavioral difficulties (Kang, 2026). The present results are consistent with this more nuanced perspective because total smartphone-use duration had only modest global SHAP importance, whereas nighttime use made a substantially

larger contribution. Thus, the findings do not support the interpretation that digital exposure is inherently harmful; rather, they indicate that particular patterns of use may carry greater predictive relevance.

Recreational screen time, social media checking frequency, and social media-use duration also contributed positively to predicted depression, although their effects were smaller than those of sleep quality, social connectedness, loneliness, and nighttime device use. The number of social media platforms used was among the least influential predictors. These findings are important because they suggest that the behavioral intensity and repetitiveness of online engagement may matter more than simple breadth of platform participation. Frequent checking may reflect habitual monitoring, sensitivity to social feedback, fear of missing out, heightened vigilance to peer evaluation, or difficulty disengaging from online environments. Associations between smartphone-use duration, loneliness, and depressive symptoms reported in adolescent populations provide support for the possibility that technology-related behavior and social-emotional vulnerability may cluster together rather than operate independently (Liu & Lee, 2026). Research examining smartphone use and adolescent brain function has also highlighted the importance of moving beyond simple exposure measures toward more detailed characterization of usage patterns and their developmental implications (Marks et al., 2026). At the same time, the comparatively modest predictive importance of total smartphone use and number of platforms cautions against interpreting high device use alone as a direct marker of psychopathology. Digital engagement may serve educational, recreational, relational, and identity-related functions, and its psychological meaning depends on the surrounding social and behavioral context.

Social connectedness emerged as the second strongest predictor of depressive symptoms and displayed a predominantly protective relationship. Adolescents with higher Social Connectedness Scale–Revised scores tended to receive lower predicted PHQ-9A scores, whereas low connectedness contributed to greater predicted depression. Loneliness ranked third in global SHAP importance and showed the opposite pattern, with higher loneliness strongly increasing predicted symptom severity. These findings reinforce the distinction between objective interaction frequency and the subjective quality of interpersonal belonging. An adolescent may communicate frequently with peers, including through digital platforms, while still experiencing low belonging or social isolation. Previous

research has demonstrated that social connectedness and mental health may influence one another bidirectionally in adolescence, such that poorer connectedness can contribute to psychological distress while depressive symptoms may simultaneously reduce social engagement and perceived belonging (Sakellariou, 2023). The strong contribution of loneliness in the present study is also consistent with findings showing that loneliness and smartphone use jointly relate to adolescent depressive symptoms (Liu & Lee, 2026). These results indicate that predictive models should not treat digital communication as equivalent to social connection; the emotional quality and subjective meaning of relationships may be considerably more important.

The protective contributions of perceived family support, peer support, and face-to-face peer interaction further support this interpretation. Although these variables were less influential than global social connectedness and loneliness, higher levels generally shifted predictions toward lower depressive symptom severity. This pattern suggests that interpersonal support may act as a resilience factor even when adolescents are exposed to potentially adverse digital or sleep-related patterns. Research on online social connections has shown that digital relationships can have both beneficial and harmful associations with mental health, depending on their quality and context (Prochnow et al., 2025). More specifically, intimate disclosure in online-only friendships has been associated with adolescent depressive symptoms, indicating that digital closeness is not necessarily equivalent to psychologically protective connectedness (Kilic et al., 2026). The present findings align with emerging frameworks that emphasize the cultivation of well-being skills and healthy relational practices rather than technology restriction alone (Hirshberg et al., 2025). They also suggest that face-to-face interaction continues to carry distinct protective value within an increasingly digital social environment.

The superiority of CatBoost over the linear benchmark models provides further evidence that the relationships among these variables are unlikely to be purely additive. The difference between the CatBoost R^2 of 0.61 and the multiple linear regression R^2 of 0.38 is substantial and suggests that nonlinear thresholds and interactions were important. SHAP patterns supported this conclusion. For example, shorter sleep appeared to exert a disproportionately adverse contribution at lower durations, while recreational screen time and nighttime device use became more problematic at higher levels rather than showing uniform linear effects across their full distributions. Such patterns are consistent

with the broader premise of digital phenotyping, which seeks to infer clinically meaningful states from combinations of behavioral signals rather than from single variables considered independently (Kamath et al., 2022; Vignapiano et al., 2023). Smartphone-based markers have been shown to fluctuate alongside clinical symptoms in other psychiatric contexts, further supporting the idea that behavioral indicators can provide meaningful but context-dependent information (Ana et al., 2026). Similarly, case-based studies of depressive disorders have demonstrated both the promise and complexity of interpreting active and passive digital data (Gardea-Resendez et al., 2024). The present study extends these principles to a structured adolescent dataset in which conventional behavioral and psychosocial measures were integrated within an explainable machine-learning framework.

The use of SHAP was especially important because strong predictive accuracy without interpretability would have limited the practical and theoretical value of the model. SHAP analysis revealed not only which predictors mattered most, but also the direction in which high and low feature values tended to influence predictions. This type of explanation is particularly relevant in youth mental health, where artificial intelligence may eventually be considered for screening or school-based support but where opaque algorithmic decisions would raise substantial ethical and clinical concerns. Discussions of artificial intelligence in school health have emphasized the need to distinguish supportive computational tools from inappropriate substitution for professional mental-health assessment (Pontz & Helbing, 2026). Similarly, research on digital phenotyping for early detection of distress highlights both the potential value and the need for interpretable and responsible implementation (Zakai & Alharthi, 2025). The present findings demonstrate how explainability can make machine-learning results more clinically comprehensible: rather than producing only a predicted depression score, the model can show whether the prediction was driven primarily by poor sleep, loneliness, low connectedness, nighttime device use, or another combination of factors.

These results also align with the broader movement toward ecologically valid monitoring of adolescent mental health. Mobile assessment and digital phenotyping research has emphasized the value of observing behavior in naturalistic contexts rather than relying solely on retrospective clinical reports (Marciano et al., 2023). Passive smartphone sensing studies have likewise suggested that everyday digital signals may contain information relevant to

adolescent psychological functioning, although the strength and consistency of associations vary across studies (Leijse et al., 2025). Prospective cohort designs focused on early identification of adolescent depression increasingly seek to integrate multiple domains of risk and functioning rather than rely on a single screening indicator (Piccin et al., 2024). Similar context-sensitive approaches are evident in studies of gaming and youth mental health, where digital activities are examined within broader behavioral and psychosocial systems (Paquin et al., 2025). The present study supports this direction by showing that digital behavior becomes more informative when analyzed alongside sleep and social connectedness rather than in isolation.

5. Conclusion

At the same time, the findings should be interpreted within the ethical context of digital mental-health research. Adolescents and families may have legitimate concerns regarding privacy, surveillance, consent, and the interpretation of behavioral data. Research involving young people and digital phenotyping has shown that acceptability depends on how data are collected, what information is inferred, and how clearly the purpose of monitoring is communicated (Nestor et al., 2024). Adherence and acceptability issues have also been identified in smartphone- and wearable-based psychiatric monitoring more broadly (Yang, 2026). These considerations are especially important because behavioral signals such as nighttime device use, social interaction, or sleep irregularity are probabilistic rather than diagnostic. They may help identify patterns of vulnerability but cannot establish that an adolescent has a depressive disorder. The present model should therefore be understood as a predictive research tool that illustrates how multidimensional behavioral information can be combined, not as a replacement for clinical assessment or diagnostic interviewing. This interpretation is consistent with the broader digital-exposome perspective, which conceptualizes digital environments as one component of cumulative health exposure rather than as deterministic causes of psychological outcomes (Petit & Vuillerme, 2026). It is also compatible with prevention frameworks that emphasize balancing risk indicators with protective factors, particularly social support and connectedness (Pereira, 2026).

6. Limitations & Suggestions

Several limitations should be considered when interpreting the findings. First, the cross-sectional design

prevents determination of temporal or causal relationships. Poor sleep, loneliness, and intensive nighttime device use may contribute to depressive symptoms, but depression itself may also lead adolescents to sleep irregularly, withdraw socially, or use smartphones more frequently. Second, although the sample included adolescents from several Canadian provinces, the recruitment strategy was not fully population based and therefore cannot guarantee national representativeness. Third, several behavioral variables were based on self-report, which may be affected by recall error, social desirability, or imprecise estimation of screen time and checking frequency. Fourth, the model was internally evaluated using a held-out test set but was not externally validated in an independent cohort, and its predictive performance may therefore decline in populations that differ in age distribution, cultural background, socioeconomic context, school environment, or technology use. Fifth, the study focused on depressive symptom severity rather than a clinician-established depressive disorder, meaning that the model predicts questionnaire scores rather than diagnosis. Sixth, potentially important variables such as physical activity, family psychiatric history, bullying, academic stress, substance use, chronic illness, personality characteristics, and adverse life events were not included. Finally, SHAP values explain the behavior of the fitted prediction model and should not be interpreted as estimates of causal effects.

Future studies should replicate the model in larger and independently recruited adolescent samples and should prioritize external validation across provinces, countries, cultural groups, and socioeconomic strata. Longitudinal designs would be particularly valuable for determining whether changes in sleep, connectedness, loneliness, and digital behavior precede changes in depressive symptoms or primarily reflect existing emotional difficulties. Future research should also combine validated questionnaires with objective smartphone and wearable measures, including screen-on time, app-use patterns, bedtime phone activity, physical activity, and sleep timing, while maintaining strict privacy protections. Repeated-measures and time-series approaches could determine whether within-person changes are more informative than between-person differences. Comparative studies should evaluate CatBoost against additional algorithms and assess calibration, fairness, subgroup performance, and transportability in addition to conventional accuracy metrics. Future models should also investigate interactions among sleep, digital behavior, and social connectedness more explicitly and examine whether

protective factors moderate the effects of potentially harmful digital patterns. Prospective studies could further test whether explainable prediction improves early identification when added to conventional screening tools and whether risk estimates remain stable over time.

The findings suggest that adolescent mental-health assessment should focus on behavioral patterns rather than relying on screen time alone. Schools, primary-care services, counselors, and youth mental-health programs could incorporate brief questions about sleep quality, sleep duration, bedtime regularity, nighttime device use, loneliness, perceived connectedness, and family and peer support when evaluating emotional well-being. Prevention programs should avoid framing technology as uniformly harmful and instead emphasize healthy timing, boundaries around nighttime use, regular sleep schedules, meaningful social relationships, and opportunities for face-to-face interaction. Explainable machine-learning tools may eventually assist screening by identifying combinations of risk and protective factors that warrant further assessment, but such systems should function only as decision-support instruments and not as autonomous diagnostic mechanisms. Any implementation involving adolescents should include transparent communication about what data are collected, strong confidentiality safeguards, explicit consent procedures, clear pathways for professional follow-up, and routine evaluation for unintended bias. In practice, the most useful implication of the present findings is that potentially modifiable sleep, digital, and social behaviors should be considered together when designing adolescent depression prevention and early-intervention strategies.

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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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