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Explainable Machine Learning Prediction of Adolescent Depression From Family Functioning, Parenting Practices, Peer Relationships, Cultural Values, and Digital Media Behaviors

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ABSTRACT

Objective: This study aimed to develop, validate, and explain a machine-learning model for predicting elevated depressive symptoms among adolescents using family functioning, parenting practices, peer relationships, cultural values, and digital-media behaviors.

Methods and Materials: A cross-sectional predictive study was conducted with 1,000 Canadian adolescents aged 13–18 years who were recruited through stratified multistage cluster sampling. Depression was assessed using the Patient Health Questionnaire for Adolescents, while validated instruments measured family functioning, parenting practices, peer attachment, cultural-value conflict, problematic social-media use, and related behavioral factors. The dataset was divided into development and independent holdout samples. Elastic-net logistic regression, random forest, gradient-boosted decision trees, extreme gradient boosting, support-vector machines, and multilayer perceptron models were compared. Model performance was evaluated using ROC-AUC, precision-recall AUC, sensitivity, specificity, balanced accuracy, F1 score, and Brier score. SHapley Additive exPlanations were used to determine global feature importance, directional effects, nonlinear thresholds, and predictor interactions.

Findings: Extreme gradient boosting demonstrated the strongest predictive performance, achieving a ROC-AUC of .879, precision-recall AUC of .756, sensitivity of .842, specificity of .762, balanced accuracy of .802, F1 score of .723, and Brier score of .132. It outperformed elastic-net logistic regression and all other candidate algorithms. Poor family functioning was the most influential predictor, followed by peer alienation, problematic social-media use, nighttime device use, cybervictimization, inconsistent discipline, and cultural-value conflict. Positive parenting, longer sleep duration, trusted-friend availability, and supportive online-community engagement reduced predicted risk. Important interactions were observed between family dysfunction and peer alienation, problematic social-media use and nighttime device use, and cybervictimization and trusted-friend availability. Model performance remained stable across alternative depression cutoffs and major demographic subgroups.

Conclusion: Explainable machine learning can identify adolescent depression risk with good discrimination and calibration by integrating relational, cultural, and digital-behavioral factors, while SHAP analysis provides clinically meaningful explanations of individual and global predictions.
Keywords: *adolescent depression; explainable artificial intelligence; machine learning; SHAP; family functioning; parenting practices; peer relationships; cultural values; digital media*

1 Introduction

Adolescent depression is a major developmental and public-health concern because it emerges during a period characterized by rapid biological maturation, identity formation, increasing autonomy, intensified peer involvement, and expanding exposure to digital environments. Depressive symptoms during adolescence may disrupt academic functioning, family relationships, peer participation, sleep, physical activity, and the development of adaptive coping capacities, while also increasing vulnerability to persistent mental-health difficulties in adulthood. The determinants of adolescent depression are therefore unlikely to be adequately represented by a single behavioral exposure or an isolated psychological characteristic. Instead, depression risk develops through interactions among individual vulnerabilities, family processes, parenting practices, peer experiences, cultural expectations, lifestyle patterns, and digitally mediated forms of communication. Large international datasets have increasingly demonstrated the value of examining adolescent mental-health difficulties through multidimensional prediction frameworks that integrate information across social and behavioral domains rather than relying exclusively on conventional symptom correlates (Chen et al., 2025). Recent machine-learning research has similarly shown that combinations of screen exposure, activity preferences, and psychosocial characteristics may predict depression more effectively than any single factor considered independently (Mao et al., 2026). Within Canada, developmental pathways involving fear of missing out, depressive symptoms, and problematic smartphone use further illustrate that digital behavior and emotional distress may influence one another over time rather than operating through a simple unidirectional relationship (Xiao et al., 2026). These findings support an ecological and computational approach in which adolescent depression is understood as the product of multiple interconnected systems.

Family functioning is among the most central contexts in which emotional regulation, self-evaluation, interpersonal security, and coping behavior develop. Families characterized by effective communication, consistent emotional support, constructive problem-solving, and predictable roles may protect adolescents against psychological distress, whereas persistent conflict, emotional unavailability, disorganization, or low cohesion may intensify vulnerability to depression. Parenting practices constitute a related but distinct domain because parental warmth, monitoring, discipline, reinforcement, and responsiveness may affect adolescent mental health even within families that otherwise appear structurally stable. Evidence from post-pandemic research has shown that parental mental health, gender, and lifestyle factors are jointly associated with psychosocial problems among children and adolescents, emphasizing that young people's symptoms cannot be separated from the emotional climate and functioning of the household (Barbieri et al., 2024). Family resilience may also modify the association between digital-media use and child mental health, while sleep can operate as an intermediary mechanism linking media exposure to psychological outcomes (Uddin & Hasan, 2023). Consequently, the same quantity of digital-media use may have different implications for adolescents living in supportive, resilient families than for those experiencing conflict, inconsistent supervision, or limited emotional availability. A predictive model that includes family functioning and parenting practices alongside digital-media behavior may therefore distinguish contextualized risk patterns that would remain obscured in models based only on screen duration.

The family context also includes cultural values, intergenerational expectations, migration experiences, and the degree of compatibility between adolescents' personal orientations and those of their parents or communities. Cultural values can provide belonging, continuity, meaning, and social support, but conflict may arise when adolescents negotiate competing expectations concerning autonomy, conformity, achievement, family obligation, identity, or peer participation. Research on immigrant families has indicated that acculturation differences are multidimensional rather than reducible to a single parent–child gap. In Chinese Canadian immigrant families, different profiles of triadic acculturation gaps may emerge across adolescents, mothers, and fathers, highlighting the complexity of cultural adaptation within the same household (Li et al., 2026). Such profiles may shape communication, family cohesion, parental interpretation of adolescent behavior, and adolescents' perceptions of whether their identities are accepted. Evidence from Korean immigrant-family contexts has further suggested that school and bicultural factors may mediate the relationship between maternal acculturative stress and adolescent depression (Lim, 2023). These findings indicate that cultural values should not be treated as fixed demographic labels or assumed to have uniformly protective or harmful effects. Their relevance may depend on whether adolescents experience cultural continuity and family agreement or, alternatively, coercive expectations, intergenerational conflict, discrimination, and pressure to reconcile incompatible value systems. Incorporating cultural-value conflict into depression prediction can therefore provide information that broad ethnicity or migration indicators cannot adequately capture.

Peer relationships become increasingly influential during adolescence as young people seek intimacy, acceptance, validation, and autonomy outside the family. Trusting friendships can provide emotional disclosure, practical support, companionship, and protection against social isolation, whereas alienation, bullying, exclusion, and unstable peer connections may increase depressive symptoms. Digital communication has expanded the contexts in which friendships are formed and maintained, but online relationships may not function uniformly as either protective or harmful experiences. Intimate disclosure in online-only friendships has been found to predict depressive symptoms among adolescents, suggesting that the psychological implications of online closeness may depend on the nature of disclosure, the quality of the relationship, unmet offline needs, or the vulnerability of the adolescent involved (Kilic et al., 2026). Digital peer environments may also expose adolescents to cybervictimization, appearance-based comparison, exclusion, public evaluation, and continuous awareness of others' activities. At the same time, online communities may provide social support for adolescents who feel isolated in their immediate environment. Peer attachment, peer alienation, cybervictimization, trusted-friend availability, and online support should therefore be treated as distinguishable predictors. A model that includes only time spent online would be unable to determine whether digital engagement reflects supportive communication, compulsive checking, hostile interactions, social comparison, or withdrawal from offline relationships.

The expanding role of smartphones, social-media platforms, online gaming, and streaming services has generated substantial concern regarding their relationship with adolescent mental health. However, contemporary evidence increasingly challenges the assumption that all digital-media exposure has the same psychological meaning. The Digital Media-Use Effects model proposes that functional and dysfunctional effects depend on the interaction of user characteristics, motives, content, context, and patterns of engagement rather than on exposure duration alone (Liebherr et al., 2025). Clinical and developmental discussions of depression and anxiety in digital contexts have likewise emphasized that digital media can simultaneously create opportunities for communication and support while increasing exposure to comparison, displacement, harassment, and emotionally dysregulating content (Moreno & Jolliff, 2022). A systematic review of associations between screen time and adolescent mental health found a broad pattern of relationships while also demonstrating heterogeneity across study designs, media types, measurements, and outcomes (Santos et al., 2023). Cross-sectional evidence has similarly linked screen time with adolescent mental-health difficulties, although the strength and interpretation of associations depend on the psychosocial setting in which screen use occurs (Ranjit et al., 2022). More recent longitudinal and cross-sectional research has continued to identify associations between screen time and adolescent depression and anxiety, while reinforcing the importance of temporal design and differentiated measurement (Li et al., 2025). Together, these studies suggest that predictive modeling should distinguish exposure duration from problematic use, nighttime use, content, social context, and functional consequences.

Several mechanisms may explain why some digital-media behaviors are associated with depression. Extended or poorly timed use may displace sleep, physical activity, face-to-face interaction, homework, and restorative leisure. Reviews conducted in the context of the COVID-19 pandemic linked increased screen exposure with a range of behavioral difficulties among children, while also underscoring the exceptional social conditions under which digital-media use increased (Abdoli et al., 2024). Excessive screen time has been discussed as a contributor to declining psychological health, physical well-being, and sleep quality, although causal direction may vary across outcomes and populations (Nakshine et al., 2022). Biological-rhythm

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disruption is particularly relevant because irregular sleep–wake patterns, delayed sleep, and circadian instability have been associated with depression and anxiety symptoms among adolescents and young adults (Zeng et al., 2022). Digital-media use may additionally interfere with physical exercise; evidence from Korean middle-school students has demonstrated associations between media use patterns and insufficient physical activity (Kim et al., 2023). From a psychological perspective, prolonged screen engagement may affect emotional regulation by increasing overstimulation, limiting opportunities for adaptive emotion processing, or reinforcing avoidance-based coping (Nathiya & Meenakshi, 2024). Neurobiological discussions have further raised concern that intensive exposure to technological devices during early developmental stages may be associated with molecular, cognitive, and regulatory imbalances, although such mechanisms require cautious interpretation and continued longitudinal investigation (Rizzo et al., 2025).

Digital-media behavior may also operate indirectly by contributing to other forms of psychopathology or maladaptive behavior. Prospective evidence has indicated that depression may mediate the association between screen time and binge-eating disorder, illustrating how digital exposure, emotional symptoms, and health-risk behaviors can become linked within a broader developmental pathway (Al-Shoaibi et al., 2024). Problematic social-media use and digital-gaming addiction have been associated with impaired mental and academic well-being, particularly during periods of remote schooling when adolescents' educational and social activities were heavily dependent on digital access (Bulut & Gökçe, 2023). Large-scale research among Chinese adolescents has also connected leisure screen time and internet-gaming disorder with mental-health outcomes, suggesting that gaming-related impairment and general screen exposure may provide partially distinct predictive information (Deng et al., 2026). The pandemic further accelerated children's reliance on social media and intensified concerns about excessive screen time, developmental effects, and changes in social interaction (Islam, 2023). Nevertheless, the presence of an association does not establish that digital-media use independently causes depression. Genetic and phenotypic analyses have shown that adolescent mental health and time spent on social media, gaming, and television may share underlying influences, indicating that pre-existing vulnerabilities can partly shape both media behavior and emotional symptoms (Frei et al., 2023). This possibility is essential because depressed adolescents may use digital media more intensively to cope with loneliness, avoid distress, seek reassurance, or maintain social contact, thereby producing reciprocal rather than purely causal relationships.

The distinction between high exposure and problematic use has direct implications for prevention and intervention. Interventions targeting digital addiction among children and adolescents have included psychoeducation, cognitive-behavioral methods, parental involvement, self-monitoring, environmental modification, and strategies for rebuilding offline routines, yet the evidence base remains heterogeneous with respect to intervention content and outcome measurement (Ding & Li, 2023). A prevention model based only on fixed screen-time limits may therefore overlook the adolescent who spends considerable time online for school, creativity, or supportive communication while failing to identify another adolescent whose shorter use is characterized by compulsivity, nighttime checking, cybervictimization, or severe social comparison. Similarly, digital-media variables cannot be interpreted independently of parenting, family resilience, cultural expectations, peer attachment, sleep, and physical activity. The clinical value of prediction lies not merely in labeling adolescents as high or low risk, but in identifying the combinations of factors that contribute most strongly to an individual estimate. This requirement creates a need for computational methods that can model nonlinear effects and interactions while remaining interpretable to researchers, clinicians, educators, families, and policymakers.

Traditional regression models remain valuable for estimating average associations and testing prespecified hypotheses, but they may be constrained when predictors are numerous, correlated, nonlinear, or interactive. Machine-learning algorithms can accommodate high-dimensional data and identify complex combinations of risk and protective factors without requiring every relationship to be specified in advance. A multinational analysis of adolescents from 46 countries demonstrated the potential of machine learning for identifying young people at high risk of mental-health difficulties across diverse social contexts (Chen et al., 2025). Machine-learning prediction of adolescent depression has also been strengthened by the inclusion of interactions between screen time and activity interests, indicating that the effect of one behavioral exposure may depend on the presence or absence of another (Mao et al., 2026). However, predictive accuracy alone is insufficient. A model that generates strong discrimination but offers no explanation for its classifications may be difficult to evaluate

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ethically, may reproduce subgroup inequalities, and may provide little guidance for intervention. Explainable artificial-intelligence methods are therefore required to reveal which variables shape predictions globally and why a particular adolescent receives a higher or lower estimated probability of depression.

SHapley Additive exPlanations provide a principled method for interpreting complex machine-learning models by estimating the contribution of each feature to an individual prediction. SHAP analysis can rank predictors according to their average absolute influence, indicate whether high or low feature values increase predicted risk, reveal nonlinear thresholds, and identify interactions among family, peer, cultural, and digital variables. This approach is particularly appropriate for adolescent depression because the same exposure may have different implications across individuals. For example, nighttime device use may generate a larger increase in predicted risk when it co-occurs with poor family functioning or problematic social-media symptoms, while cultural-value conflict may have a smaller effect when parenting is warm and communicative. Similarly, peer support may buffer the predictive contribution of cybervictimization, and family resilience may alter the relationship between media behavior and sleep. SHAP analysis does not establish causality, but it can make predictive reasoning visible and permit investigators to examine whether a model relies on plausible, modifiable, and ethically acceptable features.

Important gaps nevertheless remain. Many studies have examined screen time or problematic media use without simultaneously modeling family functioning, multiple parenting dimensions, peer attachment, cultural-value conflict, cybervictimization, sleep, and supportive online engagement. Other studies have relied on samples from a single cultural context, making it difficult to determine whether predictor importance is stable across countries. Canadian adolescents represent a particularly relevant population for this question because Canada is culturally and linguistically diverse and includes immigrant, bicultural, Indigenous, urban, rural, English-speaking, and French-speaking communities whose family and digital experiences may differ substantially. At the same time, a multicountry framework is needed to distinguish predictors that generalize across settings from those whose importance depends on cultural and social context. Fairness evaluation is also essential because a model may achieve acceptable average performance while producing lower sensitivity, weaker calibration, or higher false-negative rates for particular demographic, linguistic, socioeconomic, or cultural groups.

Accordingly, an integrated explainable machine-learning model should be evaluated not only according to discrimination but also according to calibration, robustness, subgroup performance, and the stability of feature contributions across national cohorts. The model should compare conventional and nonlinear algorithms, preserve an independent test sample, avoid information leakage during preprocessing, and examine whether family and peer variables add predictive value beyond digital-media measures. It should also assess whether digital-media variables provide incremental information after family functioning, parenting practices, cultural values, and peer relationships are considered. Such an approach can clarify whether adolescent depression is best predicted by isolated exposures or by configurations of interacting ecological risks and protections, while ensuring that machine-learning outputs remain interpretable as probabilistic estimates rather than clinical diagnoses. The aim of this study was to develop, validate, and explain a multicountry machine-learning model for predicting elevated adolescent depression from family functioning, parenting practices, peer relationships, cultural values, and digital-media behaviors using SHAP analysis.

2 Methods and Materials

2.1 Study Design and Participants

This study employed a cross-sectional, multicountry, predictive-correlational design to develop and interpret machine-learning models for identifying adolescents at increased risk of depression based on family functioning, parenting practices, peer relationships, cultural values, and digital-media behaviors. The study was conducted as part of a harmonized international research project in which participating countries followed a common protocol for participant recruitment, measurement, data management, and statistical analysis. The Canadian component of the study included exactly 1,000 adolescents between 13 and 18 years of age who were enrolled in public or private secondary schools at the time of data collection. A stratified multistage cluster-sampling procedure was used to recruit participants from schools located in different Canadian regions. The sampling framework was designed to increase variation in geographical location, urban and rural residence, school type, socioeconomic background, cultural and linguistic identity, and patterns of digital-media access.

Provinces and school districts constituted the initial sampling strata, schools were selected as clusters within each stratum, and eligible students were subsequently invited to participate. Recruitment quotas were applied to avoid substantial overrepresentation of a particular age group, gender, school grade, socioeconomic category, or residential setting. The Canadian sample was treated both as a country-specific cohort and as one component of the larger harmonized multicountry dataset, thereby permitting the examination of whether the predictors of adolescent depression operated consistently across cultural contexts.

Adolescents were eligible for participation when they were between 13 and 18 years of age, were currently enrolled in a participating Canadian school, had resided in Canada for at least one year, and possessed sufficient English or French proficiency to understand and complete the study questionnaires. Participants were also required to provide informed assent, while written informed consent was obtained from a parent or legal guardian for adolescents younger than the applicable age of independent consent. Adolescents were excluded when a documented cognitive, developmental, neurological, or language-related condition prevented independent comprehension of the questionnaires, when they were experiencing an acute psychiatric or medical crisis that made participation inappropriate, or when more than 20% of the questionnaire responses were missing. A small number of unanswered items within otherwise complete questionnaires did not automatically result in exclusion and were addressed through the predefined missing-data procedure. Participation was voluntary, and students were informed that they could discontinue the survey at any time without academic, social, or administrative consequences. Data were collected anonymously through a secure electronic survey platform during supervised school sessions or through protected remote access when in-person administration was not feasible. No directly identifying information was included in the analytical dataset. Participants who reported severe depressive symptoms or indicated thoughts of self-harm on the depression questionnaire were shown an immediate standardized support message containing national crisis resources, school counseling contacts, and instructions for seeking assistance from a trusted adult or qualified mental-health professional.

2.2 Measures

Data were collected using a structured questionnaire package consisting of validated psychological scales and standardized questions concerning demographic characteristics and digital-media behavior. The primary outcome variable was adolescent depression, which was assessed using the adolescent version of the Patient Health Questionnaire, commonly referred to as the PHQ-A. The PHQ-A contains nine items evaluating the frequency of depressive symptoms during the preceding two weeks, including reduced interest or pleasure, depressed mood, sleep disturbance, fatigue, appetite changes, negative self-evaluation, difficulty concentrating, psychomotor changes, and thoughts related to death or self-harm. Each item is scored on a four-point response scale ranging from zero, indicating that the symptom was not experienced, to three, indicating that it was experienced nearly every day. Total scores range from zero to 27, with higher scores representing greater depressive-symptom severity. For the primary machine-learning classification analysis, a total score of 10 or higher was used to indicate an elevated probability of clinically meaningful depressive symptoms. The continuous PHQ-A total score was retained for secondary regression analyses and sensitivity analyses so that the findings would not depend entirely on a single classification threshold. Responses to the self-harm item were reviewed through the automated safeguarding procedure regardless of the total depression score.

Family functioning was assessed with the General Functioning Subscale of the McMaster Family Assessment Device. This 12-item instrument measures the overall health of the family system by examining communication, emotional responsiveness, problem-solving, role clarity, mutual involvement, behavioral control, and the extent to which family members support one another. Participants rated each statement on a four-point scale ranging from strongly agree to strongly disagree. After reverse scoring the positively worded items, higher scores represented poorer family functioning. In addition to the total family-functioning score, item-level responses were retained during exploratory model development because particular dimensions of family life, such as emotional communication or perceived support, could contribute differently to depression prediction. Parenting practices were measured using the nine-item short form of the Alabama Parenting Questionnaire. The instrument assesses positive parenting, inconsistent discipline, and poor supervision, which

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represent theoretically distinct dimensions of parental behavior. Adolescents indicated how frequently each parenting practice occurred in their household. Subscale scores were calculated separately so that supportive parenting and maladaptive parenting practices would not be combined into a single index that could conceal their independent predictive effects. Where an adolescent lived with more than one parent or caregiver, responses were based on the adult who was most involved in the adolescent's daily care and supervision.

Peer relationships were evaluated using the peer-attachment section of the Inventory of Parent and Peer Attachment. This measure assesses adolescents' perceptions of trust, communication, acceptance, availability, conflict, and alienation within close peer relationships. Items were rated on a five-point scale reflecting how accurately each statement described the participant's experiences with friends. Positively worded and negatively worded items were scored according to the instrument guidelines, and a total peer-attachment score was calculated, with higher scores indicating stronger and more secure peer relationships. Trust, communication, and alienation scores were also retained as separate candidate predictors because supportive peer communication may operate differently from interpersonal isolation or alienation. To capture adverse peer experiences not fully represented by attachment quality, participants were additionally asked standardized questions regarding social exclusion, cybervictimization, face-to-face bullying, perceived loneliness, and the availability of at least one trusted friend. These variables were included because adolescents may simultaneously report close attachment to selected friends and exposure to harmful behaviors within the wider peer environment.

Cultural values were assessed using an adolescent-appropriate version of the Portrait Values Questionnaire derived from Schwartz's theory of basic human values. The questionnaire presents brief descriptions of individuals with particular goals, beliefs, or priorities and asks respondents to indicate how similar each described person is to themselves. The instrument measures value domains related to self-transcendence, conservation, openness to change, and self-enhancement, as well as more specific values such as benevolence, universalism, conformity, tradition, security, achievement, power, self-direction, stimulation, and hedonism. Scores were centered within each participant before domain-level indices were calculated, thereby reducing the influence of individual differences in response style. Because the Canadian population is culturally heterogeneous, participants also completed brief questions concerning family cultural orientation, intergenerational value agreement, perceived pressure to conform to cultural expectations, and the importance of family obligation. These measures were intended to capture the possibility that cultural values may function as either protective or risk-related factors depending on the level of compatibility between adolescents' personal values, family expectations, peer norms, and the wider social environment. Participants were not classified into rigid cultural categories, and cultural identity variables were used descriptively and analytically without assuming that all members of a cultural, linguistic, immigrant, Indigenous, or ethnocultural group shared identical values.

Digital-media behaviors were assessed through a combination of validated symptom measures and standardized behavioral questions. Problematic social-media use was measured using the nine-item Social Media Disorder Scale, which evaluates preoccupation, tolerance, withdrawal, persistence, displacement of other activities, interpersonal conflict, deception, escape, and problems resulting from social-media engagement. Participants responded according to whether each experience had occurred during the preceding year. The questionnaire package also assessed average daily time spent using social-media platforms, video-sharing services, online games, streaming services, instant messaging, and general smartphone functions on school days and non-school days. Participants reported nighttime device use, device use after going to bed, sleep interruption caused by notifications, habitual checking, simultaneous use of multiple platforms, active content creation, passive browsing, exposure to appearance-focused content, online social comparison, cybervictimization, participation in supportive online communities, and parental mediation of digital-media use. Where participants had access to device-based screen-time summaries, they were invited to consult the previous seven days of recorded use when estimating daily duration, thereby reducing exclusive reliance on unaided recall. Digital-media exposure was not treated as uniformly harmful; the analytical framework distinguished between duration, timing, compulsivity, content, social context, and purpose of use.

The questionnaire further collected information on age, gender, school grade, province or territory, urban or rural residence, household composition, parental education, perceived household financial status, cultural and linguistic background, immigration generation, self-reported physical

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health, sleep duration, chronic health conditions, previous mental-health service use, and current use of psychological or psychiatric treatment. These variables were included as descriptive characteristics and potential covariates. English and French versions of all instruments were administered according to the participant's language preference. When a validated French-language form was available, that version was used. Any supplementary items developed specifically for the multicountry project were translated and independently back-translated, after which discrepancies were reviewed by bilingual researchers familiar with adolescent mental-health terminology. Before the main data collection, the complete survey was pilot-tested with adolescents from the target age range to assess clarity, completion time, cultural appropriateness, technical functionality, and the acceptability of sensitive questions. Internal consistency was evaluated separately for each multi-item scale in the Canadian sample before the variables were entered into the predictive models.

2.3 Data Analysis

Data analysis was performed using an integrated statistical and machine-learning framework designed to maximize predictive performance while preserving transparency, reproducibility, and protection against data leakage. Initial data screening included the examination of duplicate records, impossible values, response-pattern anomalies, questionnaire completion time, inconsistent demographic responses, and missing data. Participants with more than 20% missing questionnaire information were excluded in accordance with the predefined eligibility criteria. For the remaining participants, missing continuous and ordinal values were imputed using a multivariate procedure fitted exclusively within the training data. Categorical variables were imputed using the most frequent category or a designated missing category when the absence of a response could contain relevant information. All imputation, scaling, encoding, feature selection, and resampling procedures were performed within the cross-validation pipeline so that information from the validation or test data could not influence model development. Continuous predictors were standardized when required by the algorithm, while categorical predictors were transformed using one-hot encoding. Highly correlated variables were inspected to identify potential redundancy; however, theoretically important variables were not automatically removed solely because of intercorrelation, particularly when tree-based algorithms could evaluate nonlinear and conditional relationships.

The primary outcome was binary depression status based on the PHQ-A threshold, while the secondary outcome was the continuous depression-severity score. The Canadian dataset was divided through stratified random sampling into a development set containing 80% of the participants and an independent holdout test set containing 20%. Stratification preserved the proportion of adolescents with and without elevated depressive symptoms. Within the development set, repeated stratified cross-validation was used for model training, hyperparameter optimization, and preliminary comparison. The holdout test set remained untouched until the final model and all preprocessing decisions had been selected. As part of the broader multicountry analysis, the same preprocessing and modeling procedures were applied to each participating national cohort, and pooled models were evaluated using country-stratified validation and leave-one-country-out validation. The Canadian cohort was therefore used both to estimate country-specific predictive performance and to assess the transportability of models developed from data obtained in other cultural settings.

Several supervised-learning algorithms were compared to determine whether complex nonlinear models provided meaningful advantages over a conventional statistical baseline. The candidate models included penalized logistic regression with elastic-net regularization, random forest classification, gradient-boosted decision trees, extreme gradient boosting, support-vector machines, and a multilayer perceptron neural network. For the secondary continuous outcome, corresponding regression versions of the algorithms were examined. Hyperparameters were optimized within the training folds using randomized or Bayesian search procedures. Model selection was based primarily on discrimination, calibration, stability across cross-validation folds, and interpretability rather than on accuracy alone. Because clinically meaningful depressive symptoms may be less frequent than nonclinical scores, class-weighted learning was used to reduce bias toward the majority class. Any resampling procedure used to address class imbalance was restricted to the training fold and was never applied before the data split or to the independent test set.

Classification performance was evaluated using the area under the receiver-operating-characteristic curve, the area under the precision-recall curve, balanced accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and the F1 score. The probability threshold

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for classification was determined within the development data according to the intended screening purpose of the model, with greater emphasis placed on sensitivity so that adolescents at elevated risk were not systematically overlooked. Calibration was assessed using the Brier score, calibration intercept, calibration slope, and graphical comparison of predicted and observed risk. Confidence intervals for test-set performance estimates were calculated through bootstrap resampling. For continuous depression prediction, performance was evaluated using the mean absolute error, root mean squared error, and coefficient of determination. The final machine-learning model was compared with penalized logistic regression to determine whether increases in predictive performance justified the additional complexity. Sensitivity analyses examined alternative PHQ-A thresholds, continuous depression scores, exclusion of adolescents currently receiving mental-health treatment, models based only on psychosocial variables, models based only on digital-media variables, and models that included demographic and socioeconomic covariates.

Explainability analysis was conducted using SHapley Additive exPlanations, or SHAP, to identify how individual predictors contributed to the model's estimated depression risk. SHAP values were computed for the best-performing model using an algorithm appropriate to the model architecture, including TreeSHAP for tree-based models and model-agnostic SHAP procedures for models without a specialized explainer. Global predictor importance was determined from the mean absolute SHAP value of each feature across participants. Summary plots were used to evaluate both the magnitude and direction of predictor contributions, while SHAP dependence analyses were used to examine nonlinear relationships and potential threshold effects. Interaction analyses were conducted to investigate whether the contribution of one predictor depended on another predictor, such as whether intensive nighttime social-media use was more strongly associated with predicted depression among adolescents reporting poor family functioning, inconsistent parenting, weak peer attachment, cultural conflict, or cybervictimization. Local SHAP explanations were generated for selected correctly classified, incorrectly classified, high-risk, and low-risk cases to demonstrate how the model combined multiple features when estimating an individual adolescent's probability of depression.

To evaluate the cross-cultural robustness of the explanations, global SHAP rankings and feature-direction patterns were compared across the Canadian cohort and the other participating country samples. The analysis examined whether the same predictors consistently increased or decreased predicted depression risk and whether the relative importance of family, parenting, peer, cultural, and digital-media domains varied across national contexts. Differences in SHAP values were interpreted as differences in the model's predictive use of variables rather than as direct evidence of causality. Fairness analyses compared model discrimination, calibration, sensitivity, and false-negative rates across age groups, gender categories, socioeconomic groups, linguistic groups, urban and rural participants, and major cultural-background categories when subgroup sample sizes were sufficient for stable estimation. Predictors that directly represented protected or potentially sensitive characteristics were evaluated carefully, and models were also estimated without these variables to determine whether their inclusion materially improved prediction or produced unacceptable subgroup disparities. The final model was selected only after considering predictive performance, calibration, explanation stability, subgroup fairness, and consistency across the country-specific and pooled analyses. All statistical tests were two-sided, and inferential analyses used a significance level of .05. The machine-learning workflow, preprocessing pipeline, random seeds, hyperparameter ranges, model specifications, performance metrics, and SHAP procedures were documented to support reproducibility.

3 Findings and Results

The final analytical sample consisted of 1,000 Canadian adolescents, and no participant meeting the predefined data-quality criteria was removed from the primary analysis. Participants ranged from 13 to 18 years of age, with a mean age of 15.50 years and a standard deviation of 1.66 years. The age distribution was balanced across early and later adolescence: 153 participants were 13 years old, 166 were 14 years old, 181 were 15 years old, 177 were 16 years old, 170 were 17 years old, and 153 were 18 years old. A total of 512 participants identified as girls, representing 51.2% of the sample, 469 identified as boys, representing 46.9%, and 19 identified as gender-diverse, nonbinary, or another gender identity, representing 1.9%. Most participants attended public schools, with 872 adolescents accounting for 87.2% of the sample, while 128 participants, or 12.8%, attended private schools. A total of 812 adolescents, representing 81.2%, lived in urban or suburban communities, whereas 188 participants, representing 18.8%, lived in rural or remote

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communities. English was selected as the preferred survey language by 735 participants, or 73.5%, and French was selected by 265 participants, or 26.5%. Regarding household structure, 681 adolescents, representing 68.1%, lived with two parents or primary caregivers, 211, representing 21.1%, lived in single-parent households, and 108, representing 10.8%, lived in blended, extended-family, shared-custody, or other caregiving arrangements. Based on perceived household financial adequacy, 218 participants, or 21.8%, reported low financial adequacy, 524, or 52.4%, reported moderate financial adequacy, and 258, or 25.8%, reported relatively high financial adequacy.

The mean PHQ-A depression score was 7.84 with a standard deviation of 5.62, and scores ranged from 0 to 26. Based on the established cutoff score of 10 or higher, 286 adolescents met the criterion for elevated and potentially clinically meaningful depressive symptoms, corresponding to a prevalence of 28.6% with a 95% confidence interval from 25.9% to 31.5%. More specifically, 337 participants, or 33.7%, were classified in the minimal symptom range, 377, or 37.7%, in the mild symptom range, 175, or 17.5%, in the moderate range, 57, or 5.7%, in the moderately severe range, and 54, or 5.4%, in the severe range. Elevated depressive symptoms were observed among 174 of the 512 girls, corresponding to 34.0%, 103 of the 469 boys, corresponding to 22.0%, and 9 of the 19 gender-diverse adolescents, corresponding to 47.4%. A total of 139 participants, or 13.9%, reported currently receiving psychological, counseling, or psychiatric services, 174, or 17.4%, reported previous but not current mental-health service use, and 687, or 68.7%, reported no previous formal mental-health treatment. Item-level missingness before imputation was low and ranged from 0.2% to 2.7%. No evidence of extensive careless responding, duplicate survey completion, or implausibly short completion times was identified among the retained participants.

Table 1

Descriptive Statistics, Internal Consistency, and Correlations Among the Principal Study Variables

Variable	Possible range	Mean	SD	Cronbach's α	1	2	3	4	5	6	7	8
1. Depressive symptoms	0–27	7.84	5.62	.89	—							
2. Poor family functioning	1–4	2.19	0.54	.91	.47***	—						
3. Positive parenting	1–5	3.62	0.71	.84	−.31***	−.49***	—					
4. Inconsistent discipline	1–5	2.41	0.68	.79	.34***	.43***	−.32***	—				
5. Peer attachment	1–5	3.71	0.66	.92	−.45***	−.46***	.38***	−.30***	—			
6. Cultural-value conflict	1–5	2.26	0.73	.86	.36***	.32***	−.24***	.26***	−.31***	—		
7. Problematic social-media use	0–9	3.12	2.38	.88	.42***	.29***	−.19***	.25***	−.29***	.24***	—	
8. Nighttime digital-media use	0–6 hours	2.37	1.28	—	.33***	.22***	−.15***	.19***	−.21***			

As shown in Table 1, all principal psychosocial and digital-media variables were significantly associated with depressive-symptom severity in the theoretically expected directions. Poor family functioning demonstrated the strongest positive bivariate association with depressive symptoms, with a correlation of .47, indicating that adolescents who perceived greater difficulty in family communication, emotional responsiveness, problem-solving, and mutual support also tended to report more severe depressive symptoms. Peer attachment showed a similarly substantial but inverse association with depression, with a correlation of −.45, demonstrating that greater trust, communication, acceptance, and security in peer relationships were associated with lower depressive-symptom scores. Problematic social-media use was positively related to depressive symptoms at .42, while cultural-value conflict was correlated with depressive symptoms at .36, inconsistent discipline at .34, and nighttime digital-media use at .33. Positive parenting showed a negative correlation of −.31 with depression, indicating that parental warmth, recognition, involvement, and supportive reinforcement were associated with fewer depressive symptoms. Although several predictors were moderately intercorrelated, none of the correlations approached a level indicating complete redundancy. The largest predictor-to-predictor correlations were observed between positive parenting and poor family functioning at −.49, problematic social-media use and nighttime digital-media use at .48, poor family functioning and peer attachment at −.46, and poor family functioning and inconsistent discipline at .43. These

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findings supported the inclusion of the variables as related but distinguishable components of the predictive framework. Internal consistency was acceptable to excellent for all multi-item measures, with Cronbach's alpha coefficients ranging from .79 for inconsistent discipline to .92 for peer attachment. The pattern of correlations also indicated that adolescent depression was not associated exclusively with one ecological domain; rather, symptom severity was related simultaneously to family functioning, parenting behavior, peer connectedness, cultural congruence, and the manner and timing of digital-media engagement.

Table 2

Predictive Performance of the Candidate Machine-Learning Models in the Independent Holdout Test Sample

Model	ROC-AUC, 95% CI	PR-AUC	Balanced accuracy	Sensitivity	Specificity	Positive predictive value	Negative predictive value	F1 score	Brier score
Elastic-net logistic regression	.825 (.765–.882)	.661	.734	.754	.714	.568	.858	.648	.161
Random forest	.846 (.791–.896)	.694	.756	.772	.740	.598	.868	.674	.151
Gradient-boosted decision trees	.861 (.808–.909)	.724	.775	.807	.743	.610	.887	.695	.143
Extreme gradient boosting	.879 (.831–.922)	.756	.802	.842	.762	.634	.907	.723	.132
Support-vector machine	.838 (.780–.889)	.681	.749	.789	.709	.573	.876	.664	.155
Multilayer perceptron	.852 (.797–.901)	.704	.764	.789	.739	.597	.875	.6	

Table 2 presents the performance of the six candidate classification models in the independent holdout sample. Extreme gradient boosting produced the strongest overall predictive performance and was therefore selected as the final model for the subsequent explainability and fairness analyses. The model achieved a ROC-AUC of .879, with a 95% confidence interval from .831 to .922, indicating good discrimination between adolescents with and without elevated depressive symptoms. Its precision-recall area under the curve was .756, which was superior to the corresponding values obtained for all alternative models and indicated that the model retained useful precision despite the lower prevalence of elevated depression relative to non-elevated depression in the sample. At the prespecified probability threshold, the extreme gradient-boosting model achieved a sensitivity of .842, meaning that it correctly identified approximately 84% of adolescents who met the depression criterion. Its specificity was .762, indicating that approximately 76% of adolescents without elevated depressive symptoms were correctly classified as lower risk. The negative predictive value was .907, showing that adolescents classified by the model as lower risk had a relatively low probability of meeting the PHQ-A depression criterion. The positive predictive value was .634, which reflected the fact that the model was developed as a screening-oriented rather than diagnostic instrument and that some adolescents classified as higher risk did not meet the questionnaire cutoff. The balanced accuracy was .802, the F1 score was .723, and the Brier score was .132, demonstrating a favorable combination of classification accuracy and probability calibration.

The performance advantage of extreme gradient boosting was not attributable solely to greater sensitivity. Compared with elastic-net logistic regression, the final model increased ROC-AUC by .054, precision-recall area by .095, sensitivity by .088, specificity by .048, and F1 score by .075, while reducing the Brier score from .161 to .132. The nonlinear tree-based models generally outperformed the linear logistic model, indicating that the relationships between the predictors and depression risk were not entirely additive or linear. Gradient-boosted decision trees provided the second-best performance, with a ROC-AUC of .861, whereas the random forest, multilayer perceptron, support-vector machine, and elastic-net logistic regression produced ROC-AUC values ranging from .825 to .852. Calibration assessment of the final extreme gradient-boosting model produced a calibration slope of .97 and a calibration intercept of .02 in the holdout sample. These values were close to the ideal values of 1.00 and 0.00, respectively, and indicated that the model did not substantially overestimate or underestimate depression probabilities across the observed risk range. Examination of the calibration curve showed

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close agreement between predicted and observed probabilities in the low- and moderate-risk groups, with only slight overprediction among participants assigned predicted probabilities above .80. Overall, the results supported the use of extreme gradient boosting as the principal model because it offered the most favorable balance of discrimination, sensitivity, specificity, calibration, and interpretability through SHAP analysis.

Table 3

Global SHAP Importance of the Principal Predictors in the Final Extreme Gradient-Boosting Model

Rank	Predictor	Predictor domain	Mean absolute SHAP value	Normalized contribution, %	Direction associated with greater predicted depression risk
1	Poor family functioning	Family functioning	0.412	14.2	Higher scores increased predicted risk
2	Peer alienation	Peer relationships	0.358	12.3	Higher alienation increased predicted risk
3	Problematic social-media use	Digital-media behavior	0.327	11.3	Higher symptom counts increased predicted risk
4	Nighttime device use	Digital-media behavior	0.291	10.0	Longer use after bedtime increased predicted risk
5	Cybervictimization	Peer and digital context	0.264	9.1	More frequent victimization increased predicted risk
6	Inconsistent discipline	Parenting practices	0.238	8.2	Greater inconsistency increased predicted risk
7	Cultural-value conflict	Cultural values	0.211	7.3	Greater conflict increased predicted risk
8	Positive parenting	Parenting practices	0.192	6.6	Higher positive parenting reduced predicted risk
9	Average nightly sleep duration	Health and behavioral covariate	0.165	5.7	Longer sleep reduced predicted risk
10	Appearance-focused online social comparison	Digital-media behavior	0.144	5.0	More frequent comparison increased predicted risk
11	Availability of a trusted friend	Peer relationships	0.121	4.2	Greater availability reduced predicted risk
12	Poor parental supervision	Parenting practices	0.103	3.6	Poorer supervision increased predicted risk
13	Supportive online-community engagement	Digital-media behavior	0.074	2.6	Greater supportive engagement reduced predicted risk

The global SHAP analysis demonstrated that the final model drew predictive information from all five principal domains included in the conceptual framework rather than relying disproportionately on a single variable category. Poor family functioning was the most influential feature, with a mean absolute SHAP value of 0.412 and a normalized contribution of 14.2% among the displayed predictors. High scores reflecting ineffective communication, low emotional responsiveness, unresolved conflict, limited support, and impaired family problem-solving consistently shifted model predictions toward a greater probability of elevated depression. Peer alienation was the second most influential predictor, contributing 12.3%, and was more influential than the overall peer-attachment score because it captured the specific experience of emotional distance, perceived rejection, and inability to rely on friends during distress. Problematic social-media use ranked third, with a contribution of 11.3%, while nighttime device use ranked fourth, with a contribution of 10.0%. This distinction indicated that the model considered compulsive or dysregulated social-media behavior and the timing of media exposure as related but independently informative risk markers. Cybervictimization contributed an additional 9.1%, demonstrating that the interpersonal context of digital-media use was more predictive than duration alone.

Parenting practices also made substantial contributions to the model. Inconsistent discipline increased predicted risk and accounted for 8.2% of the importance represented in Table 3, whereas positive parenting reduced predicted risk and accounted for 6.6%. Poor parental supervision contributed 3.6%, particularly when it co-occurred with extensive nighttime media use or cybervictimization. Cultural-value conflict accounted for 7.3% of global importance and increased predicted depression risk when adolescents reported a strong discrepancy between their personal values and the expectations of parents, extended

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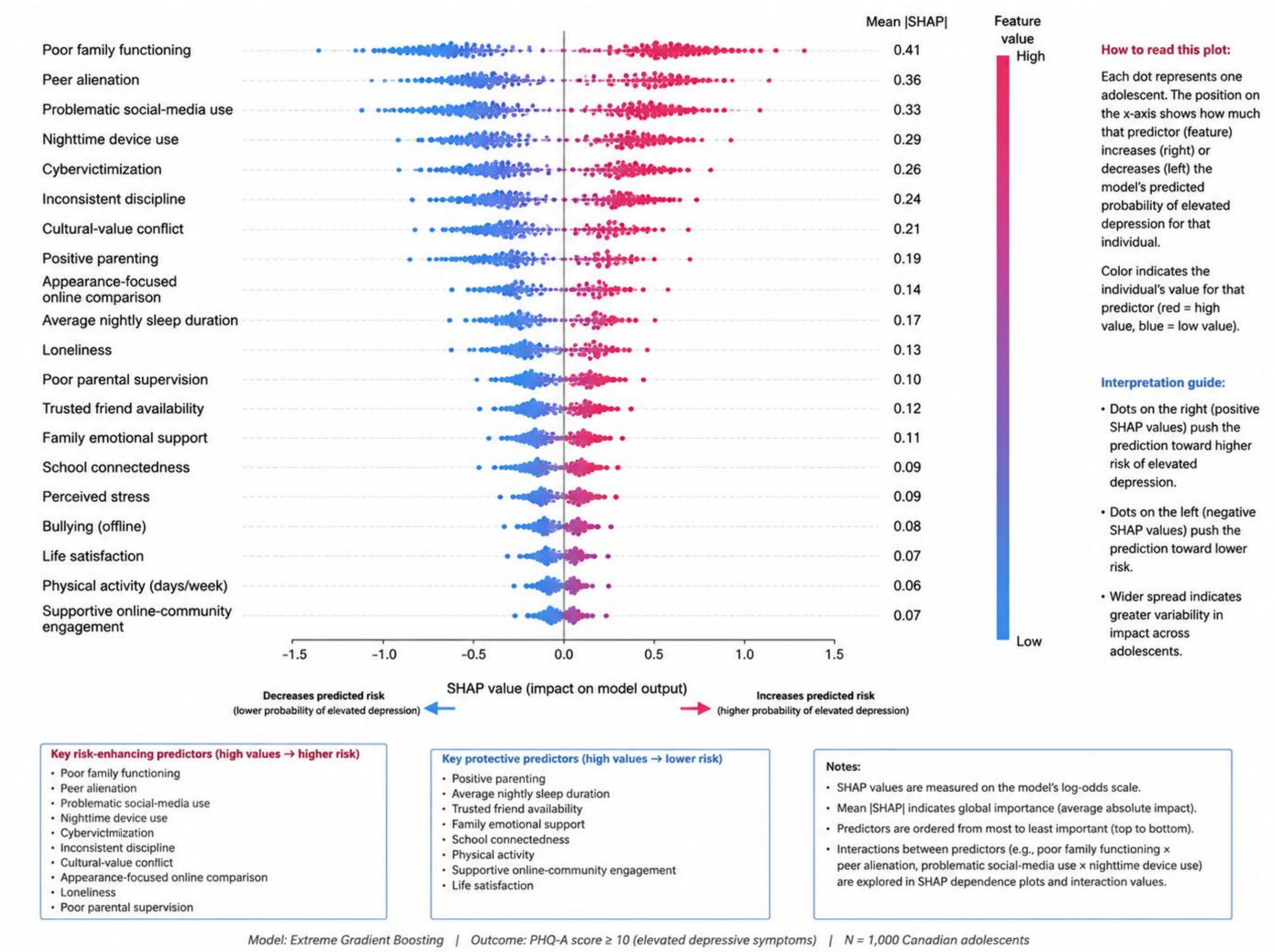
family members, or cultural communities. The direction of the SHAP values did not indicate that cultural commitment or family obligation was inherently harmful. Rather, elevated risk was associated specifically with perceived conflict, coercion, incompatibility, or a lack of acceptable negotiation between personal and collective expectations. Sleep duration, appearance-focused online social comparison, the availability of a trusted friend, and supportive engagement in online communities also contributed to prediction. Longer sleep, stronger access to a trusted friend, positive parenting, and supportive online-community participation shifted predictions toward lower depression probabilities. The protective SHAP contribution of supportive online engagement further demonstrated that digital-media participation was not uniformly associated with greater risk; its predictive meaning depended on whether online activity involved compulsivity, comparison, victimization, sleep disruption, or meaningful social support.

Figure 1

SHAP Summary Plot Showing the Direction and Magnitude of the Twenty Most Influential Predictors of Elevated Adolescent Depression



The SHAP summary plot showed clear directional patterns in the distribution of individual predictor contributions. High values for poor family functioning, peer alienation, problematic social-media use, nighttime device use, cybervictimization, inconsistent discipline, cultural-value conflict, appearance-focused comparison, poor supervision, and loneliness were concentrated on the positive side of the SHAP axis, indicating that these values generally increased the model's predicted probability of elevated depression. In contrast, high values for positive parenting, peer trust, availability of a trusted friend, sleep duration, family emotional support, and supportive online-community engagement were concentrated on the negative side of the axis and generally reduced predicted risk. The spread of SHAP values was widest for poor family functioning and peer alienation, demonstrating that these variables exerted particularly heterogeneous effects across adolescents. For some participants, poor family functioning

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generated only a modest increase in predicted risk, whereas for others it produced a large positive shift, particularly when accompanied by peer alienation, inconsistent discipline, or cultural-value conflict.

The dependence patterns indicated several nonlinear thresholds. Poor family-functioning scores below approximately 1.8 generally contributed little to predicted depression risk, whereas scores above approximately 2.4 produced increasingly positive SHAP values. Problematic social-media-use scores between zero and three showed relatively small contributions, but the contribution rose more sharply when five or more symptoms were endorsed. Nighttime device use had a limited average effect below approximately one hour after bedtime, became progressively risk-enhancing between one and three hours, and showed the strongest positive contribution when use exceeded approximately three hours. Sleep duration had a nonlinear protective pattern: the greatest increase in predicted risk occurred below seven hours per night, while additional sleep above approximately eight hours produced comparatively small changes. Cultural-value conflict demonstrated a similar threshold pattern, with moderate conflict producing variable contributions and high conflict consistently shifting predictions toward elevated risk.

The strongest SHAP interaction was observed between poor family functioning and peer alienation. Adolescents with difficulty in one of these domains but relative strength in the other often received only moderately elevated predictions, whereas the combination of poor family functioning and high peer alienation generated a substantially greater increase in predicted risk. A second important interaction involved problematic social-media use and nighttime device use, such that extensive nighttime media exposure was most strongly associated with predicted depression among adolescents who also endorsed multiple symptoms of compulsive social-media engagement. Cybervictimization interacted with trusted-friend availability: exposure to online victimization produced a smaller positive SHAP contribution when adolescents reported access to a dependable friend, but a markedly larger contribution when trusted peer support was absent. Cultural-value conflict also interacted with positive parenting. High cultural conflict was less strongly risk-enhancing when adolescents simultaneously perceived parental warmth and open communication, suggesting that supportive parenting altered the predictive significance of disagreement over cultural expectations. These interaction patterns explained part of the performance advantage of the nonlinear extreme gradient-boosting model over the additive logistic-regression model.

Table 4

Robustness, Sensitivity, and Subgroup Performance of the Final Extreme Gradient-Boosting Model

Analysis or subgroup	n	ROC-AUC	Sensitivity	Specificity	Balanced accuracy	Brier score
Primary independent holdout analysis	200	.879	.842	.762	.802	.132
Repeated out-of-fold predictions, full sample	1,000	.872	.829	.759	.794	.136
Alternative PHQ-A cutoff of 11 or higher	1,000	.875	.824	.773	.799	.130
Alternative PHQ-A cutoff of 12 or higher	1,000	.878	.819	.781	.800	.124
Participants not currently receiving treatment	861	.865	.812	.766	.789	.134
Model excluding demographic and cultural-identity indicators	1,000	.869	.825	.755	.790	.138
Psychosocial predictors without digital-media variables	1,000	.846	.798	.731	.765	.149
Digital-media predictors without family and peer variables	1,000	.768	.721	.694	.708	.178
Girls	512	.868	.836	.748	.792	.139
Boys	469	.876	.820	.770	.795	.132
Ages 13–15 years	500	.869	.821	.755	.788	.138
Ages 16–18 years	500	.875	.837	.763	.800	.134
Low perceived household financial adequacy	218	.859	.842	.721	.782	.148
Moderate or high financial adequacy	782	.878	.824	.770	.797	.132
English-language respondents	735	.874	.831	.761	.796	.135
French-language respondents	265	.867	.824	.752	.788	.139
Urban or suburban residents	812	.873	.830	.758	.794	.136
Rural or remote residents	188	.868	.824	.764	.794	.137

The sensitivity and robustness analyses presented in Table 4 indicated that the final model's performance was not dependent on a particular random data split or on the use of a single depression threshold. Repeated out-of-fold

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predictions across the full sample produced a ROC-AUC of .872, sensitivity of .829, specificity of .759, and Brier score of .136, all of which were close to the estimates obtained in the independent holdout sample. Increasing the PHQ-A threshold from 10 to 11 or 12 resulted in small improvements in specificity and the Brier score while preserving ROC-AUC values between .875 and .878. These findings indicated that the model continued to discriminate effectively when the outcome was restricted to adolescents with somewhat greater symptom severity. Excluding the 139 adolescents who were currently receiving mental-health treatment produced a ROC-AUC of .865, showing that the predictive performance was not explained merely by treatment-related characteristics or by the inclusion of participants whose depression had already been formally recognized. Removal of demographic and cultural-identity indicators caused only a small decline in ROC-AUC from .872 to .869 in the out-of-fold analysis, demonstrating that most of the model's predictive information was obtained from modifiable psychosocial and behavioral characteristics rather than from protected or fixed demographic attributes.

The domain-restriction analyses further demonstrated the value of the study's integrated ecological framework. A model based on family functioning, parenting practices, peer relationships, cultural-value conflict, and related psychosocial variables but excluding digital-media predictors achieved a ROC-AUC of .846. Although this level of discrimination remained useful, it was lower than that of the complete model, indicating that digital-media behavior contributed incremental predictive information. In contrast, a model based only on digital-media predictors achieved a ROC-AUC of .768, sensitivity of .721, specificity of .694, and Brier score of .178. Thus, digital-media variables alone did not predict depression as effectively as the broader psychosocial model. The difference between the digital-only and complete models showed that adolescent depression could not be adequately predicted from screen exposure or social-media behavior without considering family, parenting, peer, cultural, and sleep-related contexts. The strongest performance was obtained when variables from these domains were analyzed jointly.

Subgroup analyses showed broadly comparable discrimination across gender, age, survey language, and residential setting. ROC-AUC values were .868 for girls and .876 for boys, with a difference of only .008. Sensitivity was slightly higher among girls, whereas specificity was slightly higher among boys. Adolescents aged 16 to 18 years had a ROC-AUC of .875 compared with .869 among those aged 13 to 15 years. Performance was also similar for English- and French-language respondents, with ROC-AUC values of .874 and .867, respectively, and for urban or suburban and rural or remote participants, with values of .873 and .868. These relatively small differences indicated that the model's ability to rank adolescents according to depression risk was stable across the principal demographic and linguistic groups represented in the Canadian cohort.

The largest subgroup difference involved perceived household financial adequacy. The model achieved a ROC-AUC of .859 among adolescents reporting low financial adequacy and .878 among those reporting moderate or high financial adequacy. Sensitivity was slightly higher in the low-financial-adequacy group, but specificity was lower at .721 compared with .770. This pattern indicated that the model was somewhat more likely to classify financially disadvantaged adolescents as higher risk when they did not meet the PHQ-A cutoff. However, the model did not show evidence of systematically reduced sensitivity in this group, which would have been a more consequential limitation for a screening application. Examination of false-negative cases showed that misclassified adolescents frequently had moderate PHQ-A scores close to the threshold and relatively favorable family or peer scores despite reporting internal depressive symptoms. False-positive cases commonly presented with multiple psychosocial risk indicators, including family conflict, peer alienation, cybervictimization, disrupted sleep, and problematic social-media use, despite having PHQ-A scores below 10. Some of these cases may therefore have represented adolescents experiencing substantial vulnerability that was not fully captured by the binary depression criterion. Taken together, the robustness, sensitivity, and fairness analyses supported the stability of the final model while also indicating that its predictions should be interpreted as probabilistic risk estimates rather than clinical diagnoses.

4 Discussion

The present study developed and evaluated an explainable machine-learning model for predicting elevated depressive symptoms among 1,000 Canadian adolescents using an integrated set of family, parenting, peer, cultural, and digital-media variables. The findings showed that the extreme gradient-boosting model achieved the strongest predictive performance among the candidate algorithms, with a ROC-AUC of .879, sensitivity of .842, specificity of .762, and a Brier score of .132 in the independent holdout sample. These results indicate that adolescent depression was predicted more accurately when nonlinear relationships and interactions among ecological and behavioral variables were modeled than when the same information was analyzed through a conventional linear approach. The superior performance of extreme gradient boosting over elastic-net logistic regression is consistent with evidence that adolescent mental-health risk is multidimensional and may be better represented through combinations of mutually dependent factors rather than isolated average effects. Large-scale machine-learning analyses across multiple countries have similarly demonstrated that adolescent mental-health difficulties can be identified from broad configurations of behavioral, social, and contextual characteristics (Chen et al., 2025). The present findings also align with predictive research showing that interactions between screen time and activity-related factors contribute meaningfully to depression-risk estimation (Mao et al., 2026). The current model extended this work by demonstrating that predictive accuracy improved when digital-media variables were analyzed together with family functioning, parenting practices, peer relationships, cultural-value conflict, sleep, and social support.

Poor family functioning emerged as the most influential predictor in the global SHAP analysis. Adolescents who reported ineffective family communication, weak emotional responsiveness, unresolved conflict, impaired problem-solving, and limited support were assigned a higher predicted probability of elevated depression. This result is consistent with the view that the family constitutes the principal developmental environment in which adolescents learn emotional regulation, interpersonal trust, and coping strategies. It also corresponds with evidence that parental mental health and family lifestyle conditions are closely associated with psychosocial problems among children and adolescents (Barbieri et al., 2024). The importance of family functioning in the present model was not limited to a direct main effect. SHAP interaction analysis showed that poor family functioning was particularly consequential when it co-occurred with peer alienation, indicating that adolescents may be at greatest risk when both family-based and peer-based sources of emotional security are impaired. This finding supports an ecological interpretation of depression in which risk accumulates across relational contexts. Family resilience has previously been shown to alter the relationship between digital-media use and mental health, with sleep functioning as a possible mediating pathway (Uddin & Hasan, 2023). The current results expand this perspective by indicating that family functioning also changes the predictive meaning of peer and digital-media experiences.

Parenting practices provided additional information beyond general family functioning. Inconsistent discipline and poor parental supervision increased predicted depression risk, whereas positive parenting reduced it. These results suggest that the emotional and organizational quality of the family system should be distinguished from the specific behaviors through which parents respond to adolescents. Warmth, recognition, involvement, and consistent reinforcement may provide adolescents with a sense of predictability and personal worth, while inconsistent consequences and inadequate supervision may create confusion, insecurity, and conflict. The protective SHAP contribution of positive parenting was especially evident when adolescents reported cultural-value conflict. High cultural conflict produced a smaller increase in predicted depression when adolescents simultaneously perceived warmth and open communication from parents. This interaction indicates that disagreement over autonomy, identity, cultural expectations, or family obligations may be less psychologically harmful when parents communicate respectfully and maintain emotional support. The result is compatible with research showing that school and bicultural processes may mediate associations between parental acculturative stress and adolescent depression (Lim, 2023). It also reflects evidence that acculturation gaps within immigrant families are complex, multidirectional, and distributed across adolescent–mother–father relationships rather than reducible to a single cultural difference score (Li et al., 2026).

Peer alienation was the second most influential predictor and showed a strong positive relationship with depression risk, whereas trusted-friend availability and broader peer attachment were protective. These findings support the central developmental role of peer belonging during adolescence. Adolescents who feel unable to rely on friends, perceive themselves as rejected, or experience emotional distance from their peer group may lack opportunities for disclosure, reassurance, and validation. The model's emphasis on peer alienation rather than peer contact alone suggests that the subjective quality of relationships is more important than the mere presence of social interaction. This distinction is particularly relevant in digital environments, where adolescents may maintain frequent communication without experiencing genuine closeness or security. Research on online-only friendships has shown that intimate disclosure can predict depressive symptoms, suggesting that

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online relational intensity does not necessarily indicate psychological protection and may sometimes reflect unmet offline needs or heightened emotional vulnerability (Kilic et al., 2026). In the present study, cybervictimization also ranked among the strongest predictors, but its contribution was partly moderated by trusted-friend availability. Adolescents exposed to cybervictimization received a smaller increase in predicted risk when they reported access to a dependable friend, indicating a possible buffering effect of peer support.

Problematic social-media use was the third most influential predictor, while nighttime device use was the fourth. The importance of both variables supports the argument that digital-media exposure should not be reduced to a single measure of daily screen duration. Problematic use captured compulsivity, loss of control, displacement of responsibilities, interpersonal conflict, and emotional dependence, whereas nighttime use reflected the timing of exposure and its potential interference with sleep. This pattern aligns with the Digital Media-Use Effects model, which emphasizes that digital-media outcomes depend on the interaction of individual characteristics, motives, content, and context rather than on screen time alone (Liebherr et al., 2025). It is also consistent with clinical perspectives suggesting that digital media may support communication while simultaneously increasing social comparison, avoidance, overstimulation, and emotional dysregulation (Moreno & Jolliff, 2022). The current findings therefore support a differentiated interpretation in which problematic and poorly timed use are more informative than total duration.

The nonlinear SHAP patterns showed that problematic social-media use contributed relatively little to depression risk at low symptom levels but increased sharply when adolescents endorsed five or more problematic-use indicators. A similar threshold was observed for nighttime device use, with the strongest positive contribution occurring when use extended beyond approximately three hours after bedtime. These results are compatible with studies linking excessive screen time and problematic social-media or gaming behavior with impaired mental and academic well-being (Bulut & Gökçe, 2023). Large-scale evidence has also associated leisure screen time and internet-gaming disorder with adolescent mental-health difficulties (Deng et al., 2026). The present findings add precision by suggesting that the relationship is not linear across the full range of exposure. Moderate use may contribute little to prediction, whereas compulsive engagement, nighttime use, and associated functional impairment may indicate substantially greater risk.

Sleep duration was an important protective predictor, and its SHAP pattern showed a marked increase in depression risk below approximately seven hours of nightly sleep. This finding supports the hypothesis that sleep is one of the main pathways through which digital-media behaviors may be connected with adolescent mental health. Reviews have associated increased screen time with declining psychological health and disrupted sleep patterns (Nakshine et al., 2022), while research on biological-rhythm disturbance has identified strong associations with depression and anxiety symptoms among adolescents (Zeng et al., 2022). The present model suggests that sleep should not be treated merely as a background covariate because it may represent a central behavioral mechanism linking nighttime media engagement to emotional distress. Intensive device use after bedtime can delay sleep onset, increase cognitive arousal, expose adolescents to emotionally activating content, and cause repeated interruption through notifications. At the same time, depression itself may contribute to insomnia, irregular routines, or late-night media use, meaning that the relationship may be reciprocal.

Appearance-focused online social comparison also increased predicted depression risk. This result indicates that the psychological content of digital engagement may be more consequential than exposure duration alone. Adolescents who repeatedly compare appearance, popularity, achievements, or lifestyles may experience lower self-worth and greater emotional distress even when their total screen time is not exceptionally high. Screen use has been associated with emotional-regulation difficulties, suggesting that intensive engagement may amplify maladaptive comparison or avoidance-based coping (Nathiya & Meenakshi, 2024). The association between screen time, depression, and binge-eating risk further illustrates how digital exposure can become connected with body image, mood, and maladaptive health behaviors (Al-Shoaibi et al., 2024). The present findings therefore suggest that digital-media assessment should examine what adolescents do online, how they interpret content, and whether their use is driven by comparison, reassurance seeking, or emotional escape.

Cybervictimization was another major contributor to predicted depression. Its high SHAP importance indicates that the social risks embedded in digital platforms may be more important than technology use itself. Cybervictimization can extend peer conflict beyond school hours, increase perceived inescapability, broaden the audience for humiliation, and expose adolescents to repeated reminders of harmful interactions. The strong interaction between cybervictimization and trusted-friend availability suggests that the emotional impact of online victimization depends partly on whether adolescents possess reliable offline or online support. This result is consistent with systematic evidence showing associations between screen-related experiences and adolescent mental-health outcomes while emphasizing substantial heterogeneity across exposure types (Santos et al., 2023). It also supports findings that digital-media use is associated with depression and anxiety across both cross-sectional and longitudinal designs, although the strength of the relationship varies according to context and measurement (Li et al., 2025).

The model also identified supportive online-community engagement as a protective predictor. This finding is important because it challenges interpretations that treat all digital-media use as harmful. Online communities may provide belonging, identity affirmation, emotional disclosure, informational support, and access to peers with shared experiences. The protective effect was smaller than the risk contributions of problematic use, cybervictimization, or nighttime exposure, but it remained independently informative. This pattern supports conceptual approaches that distinguish functional from dysfunctional digital-media use (Liebherr et al., 2025). It also helps explain why research findings concerning screen time are sometimes inconsistent: adolescents may spend similar amounts of time online while having fundamentally different experiences. One adolescent may engage in supportive communication and creative activity, whereas another may experience compulsive checking, social comparison, sleep disruption, or harassment.

The association between digital-media use and depression should also be interpreted in light of possible bidirectionality and shared vulnerability. Genetic and phenotypic research has shown that adolescent mental health and time spent on social media, gaming, and television may share common influences (Frei et al., 2023). Depressive symptoms may lead adolescents to seek distraction, reassurance, or social contact online, while problematic digital engagement may further intensify low mood through sleep disruption, comparison, inactivity, and interpersonal stress. The developmental cascade linking fear of missing out, depression, and problematic smartphone use among Canadian adolescents provides further support for reciprocal pathways (Xiao et al., 2026). Accordingly, the SHAP values in the present study should be interpreted as indicators of predictive contribution rather than evidence that a particular behavior independently causes depression.

The model's domain-restriction analyses further clarified the relative importance of digital and psychosocial factors. The psychosocial model without digital-media variables retained a ROC-AUC of .846, whereas the digital-only model produced a substantially lower ROC-AUC of .768. These results indicate that digital-media behavior contributed incremental information but was insufficient as a stand-alone explanation of adolescent depression. This finding agrees with reviews showing associations between screen exposure and mental-health difficulties while cautioning against oversimplified causal interpretations (Ranjit et al., 2022). It also corresponds with pandemic-related research demonstrating that increased screen use occurred within a broader context of disrupted schooling, reduced physical activity, family stress, and social isolation (Abdoli et al., 2024). The weaker performance of the digital-only model suggests that screening programs focused exclusively on screen time would miss important sources of risk and may incorrectly classify adolescents whose digital behavior is extensive but not dysfunctional.

Physical activity and lifestyle displacement may help explain part of the digital-media contribution. Digital-media use has been associated with insufficient physical exercise among middle-school adolescents (Kim et al., 2023). Reduced physical activity can affect sleep, social participation, stress regulation, and self-perception, all of which may influence depressive symptoms. The pandemic intensified reliance on social media and altered children's developmental environments, making it difficult to separate the influence of screen exposure from changes in education, family routines, and peer contact (Islam, 2023). These considerations reinforce the value of models that integrate several domains rather than attributing psychological outcomes to a single technological behavior.

The subgroup analyses showed broadly comparable model performance across girls and boys, younger and older adolescents, English- and French-language respondents, and urban and rural residents. These findings provide preliminary support for the transportability of the model within the Canadian sample. However, performance was modestly lower among adolescents reporting low household financial adequacy, particularly with respect to specificity. This pattern may indicate that socioeconomic adversity generates psychosocial risk profiles similar to those associated with depression even when adolescents do not

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meet the PHQ-A cutoff. Family conflict, limited supervision, sleep disruption, peer stress, and digital vulnerability may therefore lead the model to identify genuine psychosocial burden that is not fully represented by a binary symptom threshold. The retention of high sensitivity in the financially disadvantaged subgroup is encouraging for screening, but the lower specificity indicates that socioeconomic context should be considered when interpreting high-risk predictions.

The robustness analyses also showed that model performance remained stable across alternative PHQ-A cutoffs, repeated out-of-fold validation, exclusion of adolescents currently receiving treatment, and removal of demographic and cultural-identity indicators. The small reduction in performance after protected demographic indicators were removed suggests that the model relied primarily on psychosocial and behavioral variables rather than fixed identity characteristics. This is ethically important because prediction systems that depend heavily on demographic proxies may reproduce existing inequalities without identifying modifiable intervention targets. The stability of the model across thresholds also indicates that the results were not an artifact of a single definition of elevated depression. Nevertheless, the positive predictive value remained lower than the negative predictive value, confirming that the model is more appropriate for preliminary risk identification than for diagnosis. Adolescents classified as high risk would require further clinical assessment.

5 Conclusion

The findings have implications for digital-addiction intervention research. Existing interventions have included cognitive-behavioral techniques, self-monitoring, parental involvement, and modification of daily routines, but evidence remains heterogeneous (Ding & Li, 2023). The current results suggest that intervention should not focus solely on reducing screen duration. More precise targets may include nighttime use, compulsive checking, cybervictimization, appearance-focused comparison, inconsistent parenting, family communication, and peer alienation. The potential neurobiological and developmental consequences of intensive technological exposure have also been discussed in relation to regulatory imbalance during childhood and adolescence (Rizzo et al., 2025). However, the protective association of supportive online engagement indicates that indiscriminate restriction may remove valuable sources of connection. Interventions should therefore differentiate harmful patterns from adaptive digital participation.

This study had several limitations. Its cross-sectional design prevented determination of temporal or causal direction, and the predictive associations may reflect reciprocal relationships between depressive symptoms and family, peer, cultural, or digital-media experiences. Most variables were self-reported and may have been affected by recall error, social-desirability bias, mood-congruent reporting, or inaccurate estimation of screen exposure. Although participants were encouraged to consult device-based summaries, objective digital-use records were not available for all adolescents. The PHQ-A provided a validated measure of depressive symptoms but did not constitute a clinical diagnosis. The Canadian sample was diverse but may not represent every provincial, territorial, Indigenous, immigrant, linguistic, or remote community. Some subgroup sizes, particularly the gender-diverse group, were too small for stable fairness estimates. SHAP values improved interpretability but did not establish causation and may be affected by correlations among predictors. Finally, although the broader protocol was designed for multicountry application, the present results were centered on the Canadian cohort and require external validation in independent national samples.

Future studies should use longitudinal and intensive repeated-measures designs to determine whether changes in family functioning, peer relationships, cultural conflict, sleep, and digital-media behavior precede changes in depressive symptoms. Passive sensing, device logs, ecological momentary assessment, sleep monitoring, and multi-informant reports from adolescents, parents, teachers, and clinicians could reduce reliance on retrospective self-report. Larger samples should be recruited to permit reliable analyses of gender-diverse adolescents, Indigenous communities, recent immigrants, rural populations, and culturally specific subgroups. Future research should also examine whether SHAP patterns remain stable across countries, developmental stages, and time periods and whether models trained in one cultural setting generalize to another. Experimental or quasi-experimental studies are needed to test whether modifying the most influential predictors leads to measurable reductions in depression risk. Model development should additionally compare causal, temporal, and multimodal machine-learning approaches and evaluate whether prediction improves when symptom trajectories replace a single binary outcome.

In practice, the model should be used as a supportive screening instrument rather than as an autonomous diagnostic system. Schools, primary-care services, and adolescent mental-health programs could incorporate brief assessments of family functioning, parenting consistency, peer alienation, cultural-value conflict, cybervictimization, problematic social-media use, nighttime device use, and sleep duration into stepped-care screening procedures. High-risk predictions should trigger confidential follow-up by trained professionals and should never result in punishment, surveillance, or automatic restriction of technology. Prevention programs should combine family communication training, positive-parenting support, peer-belonging initiatives, cyberbullying response systems, culturally responsive counseling, sleep education, and digital-literacy interventions. Guidance for families should emphasize the quality, timing, purpose, and emotional consequences of media use rather than relying exclusively on fixed screen-time limits. Any clinical deployment should include transparent explanation of predictions, informed consent, privacy protection, regular fairness audits, and clear procedures for human review.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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

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