Predicting Adolescent Emotional Dysregulation Using Ensemble Machine Learning Models Integrating Family, School, and Digital Behavior Indicators

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Article Info	ABSTRACT
Article type: *Original Research* **How to cite this article:** 	**Objective:** The objective of this study was to develop and evaluate an ensemble machine learning framework for predicting adolescent emotional dysregulation by integrating family, school, and digital behavior indicators. **Methods and Materials:** This study adopted a cross-sectional predictive design and was conducted among secondary school adolescents in Mexico. Data were collected using validated self-report instruments assessing emotional dysregulation, family functioning, school climate, and digital behavior patterns, alongside demographic variables. After data preprocessing, including normalization, imputation of missing values, and feature selection, multiple supervised machine learning models were developed. These included linear regression, support vector regression, random forest, gradient boosting, and a stacked ensemble model combining heterogeneous base learners. Model training and evaluation were performed using repeated k-fold cross-validation to ensure robustness and to minimize overfitting. Predictive performance was assessed using root mean square error, mean absolute error, and explained variance. **Findings:** Inferential analyses demonstrated that ensemble-based machine learning models significantly outperformed traditional linear and single-algorithm approaches in predicting emotional dysregulation. The stacked ensemble model achieved the highest explained variance and the lowest prediction error. Digital behavior indicators accounted for the largest proportion of predictive importance, followed closely by family-related factors and school-related variables. At the individual predictor level, problematic digital use, family conflict, parental warmth, nighttime device use, and teacher support emerged as the most influential features. Risk-related predictors showed positive associations with emotional dysregulation, whereas relational and contextual support variables showed negative associations. **Conclusion:** The findings indicate that adolescent emotional dysregulation is best predicted through integrative, non-linear models that simultaneously account for family, school, and digital contexts. ***Keywords:*** *Adolescence; Emotional Dysregulation; Ensemble Machine Learning; Digital Behavior; Family Context; School Climate*

1.   Introduction

Adolescence represents a critical developmental period marked by profound biological, cognitive, emotional, and social transformations that collectively shape mental health trajectories across the life span. Among the psychological processes undergoing substantial reorganization during this stage, emotional regulation occupies a central role, as it underpins adolescents' capacity to manage internal emotional states, navigate interpersonal relationships, and adapt to environmental demands. Emotional dysregulation, characterized by heightened emotional reactivity, poor impulse control, limited access to adaptive regulation strategies, and difficulty recovering from negative affect, has been consistently associated with a wide range of adverse outcomes, including internalizing symptoms, externalizing behaviors, academic difficulties, and problematic social functioning. Recent advances in developmental neuroscience have further demonstrated that emotional regulation during adolescence is closely tied to ongoing maturation of fronto-limbic neural networks, rendering adolescents particularly sensitive to contextual influences from family, school, and increasingly, digital environments (Marano, Anesini, et al., 2025; Marano, Lisci, et al., 2025).

Within the family context, parenting practices, emotional climate, and communication patterns have long been recognized as foundational determinants of adolescents' emotional development. Warm, supportive, and structured family environments are generally associated with more adaptive emotion regulation skills, whereas high levels of family conflict, inconsistency, and emotional invalidation elevate vulnerability to dysregulation. Empirical evidence indicates that familial influences extend beyond early childhood, continuing to shape adolescents' coping strategies and emotional stability in interaction with emerging autonomy (Douglas et al., 2020; Paulus et al., 2024). At the same time, contemporary families are increasingly embedded within digital ecosystems, where parental mediation of technology use, joint media engagement, and communication about online experiences play a pivotal role in moderating adolescents' emotional responses to digital stressors (Adigwe, 2024; Ellis et al., 2025). These dynamics suggest that family-related factors cannot be disentangled from adolescents' digital lives when examining emotional dysregulation.

The school environment constitutes a second critical ecological context influencing emotional regulation during adolescence. Schools provide not only academic instruction but also social structures, norms, and relational experiences that profoundly affect emotional well-being. Teacher support, school connectedness, peer acceptance, and exposure to bullying or academic stress have all been linked to adolescents' emotional adjustment and regulatory capacities. Cross-national evidence demonstrates that school stress and dissatisfaction are positively associated with excessive screen use and emotional difficulties, highlighting the interdependence of educational and digital domains (Khan et al., 2022). Furthermore, school-based interventions aimed at enhancing digital balance, emotional skills, and mindfulness have shown promising effects in reducing emotional distress and maladaptive technology use among adolescents (Guath, 2025; Ünlü et al., 2025). These findings underscore the importance of incorporating school-level indicators when modeling emotional dysregulation in digitally mediated developmental contexts.

Over the past decade, adolescents' emotional lives have become increasingly intertwined with digital media, particularly smartphones and social networking platforms. Digital environments offer opportunities for social connection, self-expression, and emotional support, but they also introduce novel risks, including social comparison, cyberbullying, sleep disruption, and compulsive engagement patterns. Systematic reviews and meta-analyses consistently report associations between high screen time, problematic social media use, and poorer emotional regulation and mental health outcomes (Bahadur & Karaca, 2023; Santos et al., 2023; Vannucci et al., 2020). Importantly, recent conceptual work cautions against simplistic narratives that frame digital media as uniformly harmful, emphasizing instead the need to differentiate between types of use, underlying motivations, and contextual moderators (Livingstone, 2024; Schoon et al., 2024). For instance, adolescents may deliberately use digital technologies as tools for emotion regulation, seeking distraction or social reassurance, which can either alleviate or exacerbate emotional distress depending on individual vulnerabilities and usage patterns (Scott et al., 2023).

A growing body of empirical research has sought to unpack the mechanisms linking digital behavior to emotional dysregulation. Studies have identified pathways involving fear of missing out, social media addiction, attentional control deficits, and disrupted sleep, all of which contribute to heightened emotional reactivity and reduced regulatory capacity (Gansner et al., 2021; Kokoç, 2021; Ntumi et al., 2025). Qualitative investigations further reveal

adolescents' nuanced perceptions of social media as simultaneously supportive and emotionally taxing, reinforcing the complexity of these relationships (Larivière-Bastien et al., 2022; Popat & Tarrant, 2022). Moreover, patterns of smartphone and app use vary substantially across adolescents, with latent class analyses demonstrating distinct profiles that differentially relate to well-being and emotional outcomes (Fortunato et al., 2023). These findings collectively suggest that emotional dysregulation emerges from the dynamic interplay of individual characteristics and multiple contextual domains, rather than from isolated risk factors.

Despite the richness of this literature, much of the existing research relies on linear statistical models that may be ill-suited to capture the complex, non-linear, and interactive relationships among family, school, and digital behavior indicators. Methodological scholars in digital media research have increasingly highlighted the limitations of traditional approaches and called for more sophisticated analytical techniques capable of modeling high-dimensional data and heterogeneous effects (Subrahmanyam & Michikyan, 2022). In parallel, advances in machine learning have opened new avenues for psychological research, enabling the integration of diverse predictors and the identification of complex patterns that enhance predictive accuracy without imposing restrictive parametric assumptions (Wood et al., 2023). Ensemble machine learning models, which combine multiple algorithms to leverage their complementary strengths, are particularly well-suited for studying multifactorial phenomena such as emotional dysregulation.

Recent applications of machine learning in adolescent mental health research demonstrate its potential to improve prediction of emotional and behavioral outcomes, yet many studies remain narrowly focused on single domains, such as digital use or individual traits, without adequately integrating family and school contexts. Moreover, much of the evidence originates from high-income Western countries, limiting the generalizability of findings to diverse sociocultural settings. Emerging research from low- and middle-income contexts highlights both shared and context-specific dynamics in adolescents' digital engagement and emotional experiences, underscoring the importance of culturally sensitive, integrative models (Adigwe, 2024; Ntumi et al., 2025). Addressing these gaps requires predictive frameworks that simultaneously incorporate family functioning, school climate, and nuanced digital behavior indicators within diverse adolescent populations.

In addition to predictive accuracy, interpretability remains a critical concern when applying machine learning in psychological research. Without transparent explanation of model outputs, the practical utility of predictive models for prevention and intervention remains limited. Recent developments in explainable artificial intelligence, such as SHAP-based feature attribution, offer promising tools for disentangling the relative contribution and directionality of predictors within complex models. Such approaches align with calls for psychologically meaningful and policy-relevant insights that can inform family guidance, school policies, and digital well-being interventions (Throuvala et al., 2021; Žmavc et al., 2025). By identifying which contextual factors most strongly predict emotional dysregulation, researchers and practitioners can better target resources toward modifiable risk and protective factors.

Taken together, the existing literature converges on the view that adolescent emotional dysregulation is a multidetermined phenomenon shaped by intersecting family, school, and digital environments, yet methodological limitations have constrained the field's ability to model these interactions comprehensively. Integrating ensemble machine learning with a developmental-ecological framework offers a novel and timely approach to advancing understanding in this area. Such an approach is particularly relevant in contemporary adolescence, where emotional development unfolds within increasingly hybrid offline–online contexts that challenge traditional theoretical and analytical boundaries (Casteele et al., 2023; Gaspar et al., 2023; Lamash et al., 2023).

Accordingly, the aim of the present study was to predict adolescent emotional dysregulation using ensemble machine learning models that integrate family, school, and digital behavior indicators within a sample of secondary school students.

2. Methods and Materials

2.1. Study Design and Participants

The present study employed a cross-sectional, predictive-analytic design with a methodological emphasis on supervised ensemble machine learning to model adolescent emotional dysregulation based on multi-contextual indicators. The target population consisted of adolescents enrolled in public secondary schools in urban and semi-urban regions of Mexico. Participants were recruited using a multistage cluster sampling approach in collaboration with regional educational authorities, whereby schools were first

selected, followed by intact classrooms within each school. Eligibility criteria included being between 12 and 18 years of age, current enrollment in a formal secondary education program, sufficient literacy to complete self-report instruments, and access to a personal digital device such as a smartphone or tablet. Adolescents with diagnosed neurodevelopmental disorders or severe psychiatric conditions that could substantially impair self-report reliability were excluded based on school counseling records. Data collection was conducted during the academic year under standardized classroom conditions, with trained research assistants present to ensure procedural consistency. Prior to participation, written informed consent was obtained from parents or legal guardians, and assent was obtained from the adolescents themselves. All procedures complied with ethical standards for research with minors, including confidentiality safeguards, anonymization of data, and the right to withdraw at any stage without penalty.

2.2.   Measures

Data were collected using a comprehensive battery of validated self-report instruments and structured indicators designed to capture family, school, and digital behavior domains relevant to emotional regulation processes. Emotional dysregulation, the primary outcome variable, was operationalized through a multidimensional self-report scale assessing difficulties in emotional awareness, impulse control under emotional distress, limited access to adaptive emotion regulation strategies, and emotional reactivity intensity. Family-related indicators included perceived parental warmth, consistency of discipline, family cohesion, conflict frequency, and emotional communication patterns, measured through standardized adolescent-report family functioning questionnaires. School-related indicators encompassed perceived teacher support, peer relationship quality, experiences of academic stress, school engagement, and exposure to bullying or social exclusion, all assessed via psychometrically established school climate and adjustment measures. Digital behavior indicators were derived from self-reported patterns of daily screen time, social media engagement intensity, nighttime device use, exposure to online social comparison, and problematic or compulsive digital use behaviors. In addition to scale-based measures, demographic covariates such as age, gender, socioeconomic status proxy indicators, and school type were collected to control for background variability. All instruments were administered in Spanish using culturally adapted versions

previously validated for Mexican adolescent populations, and internal consistency indices were examined prior to modeling to ensure acceptable measurement reliability.

2.3.   Data Analysis

Data analysis followed a structured machine learning pipeline designed to maximize predictive accuracy while maintaining interpretability and generalizability. Prior to model development, raw data were screened for completeness, plausibility, and outliers, with missing values handled using multiple imputation methods appropriate for mixed-scale data. Continuous variables were standardized, and categorical variables were encoded using appropriate transformation techniques to ensure compatibility across algorithms. Feature selection was conducted using a combination of correlation-based filtering and model-driven importance ranking to reduce redundancy and multicollinearity while preserving theoretically meaningful predictors. The primary analytical strategy involved the development and comparison of multiple ensemble machine learning models, including random forest, gradient boosting machines, and stacked ensemble architectures integrating predictions from heterogeneous base learners. Model training and validation were conducted using repeated k-fold cross-validation to minimize overfitting and to obtain stable estimates of predictive performance. Model evaluation metrics included root mean square error, mean absolute error, and explained variance for continuous emotional dysregulation scores. In addition, permutation-based feature importance and SHAP value analyses were employed to examine the relative contribution and directional influence of family, school, and digital behavior indicators within the final optimized ensemble model. All analyses were conducted using open-source statistical and machine learning libraries, and analytic decisions were pre-specified to enhance reproducibility and transparency of the modeling process.

3.   Findings and Results

The findings section presents the descriptive characteristics of the study variables, followed by the predictive performance of the ensemble machine learning models and the relative contribution of family, school, and digital behavior indicators in predicting adolescent emotional dysregulation. To ensure transparency and interpretability, the results are organized sequentially from descriptive statistics to model-level performance and

feature-level importance. Table 1 provides an overview of the demographic characteristics and core study variables, establishing the empirical context for subsequent predictive analyses.

Table 1

Demographic characteristics and descriptive statistics of key study variables

Variable	Mean	SD	Minimum	Maximum
Age (years)	15.21	1.73	12	18
Emotional dysregulation (total score)	61.84	14.27	32	98
Family functioning (overall)	3.42	0.68	1.45	4.92
Parental warmth	3.58	0.74	1.33	5.00
Family conflict	2.71	0.81	1.00	4.83
School engagement	3.36	0.65	1.57	4.89
Teacher support	3.49	0.71	1.42	5.00
Peer relationship quality	3.41	0.69	1.50	4.88
Daily screen time (hours)	5.18	2.04	1.00	11.00
Social media intensity	3.62	0.77	1.40	5.00
Problematic digital use	3.29	0.83	1.12	4.94

As shown in Table 1, the sample consisted of mid-adolescents with a relatively balanced distribution across the eligible age range. The mean emotional dysregulation score indicated moderate to elevated difficulties in emotion regulation, with substantial interindividual variability. Family functioning and school-related indicators were generally in the moderate range, suggesting heterogeneous psychosocial environments among participants. Digital behavior indicators revealed high average daily screen time and moderate levels of social media intensity and problematic digital use, underscoring the relevance of digital context variables for subsequent predictive modeling.

Table 2

Predictive performance of individual and ensemble machine learning models

Model	RMSE	MAE	Explained Variance (R^2)
Linear regression	10.94	8.61	0.41
Support vector regression	9.86	7.74	0.52
Random forest	8.72	6.91	0.63
Gradient boosting machine	8.29	6.54	0.68
Stacked ensemble model	7.84	6.12	0.73

Table 2 demonstrates that ensemble-based approaches substantially outperformed traditional and single-model machine learning techniques in predicting emotional dysregulation. While linear regression explained a limited proportion of variance, non-linear models, particularly random forest and gradient boosting, yielded marked improvements in predictive accuracy. The stacked ensemble model achieved the lowest prediction error and the highest explained variance, indicating that integrating complementary learning algorithms enhanced the model's ability to capture complex, non-linear interactions among family, school, and digital behavior indicators.

Table 3

Relative contribution of predictor domains in the optimized ensemble model

Predictor domain	Relative importance (%)
Family indicators	34.7
School indicators	29.3
Digital behavior indicators	36.0

The results presented in Table 3 indicate that all three domains contributed substantially to the prediction of emotional dysregulation. Digital behavior indicators emerged as the most influential domain, marginally

surpassing family-related variables, while school-related indicators also accounted for a considerable proportion of model importance. This pattern suggests that emotional dysregulation in adolescents is best understood as a multidimensional phenomenon shaped by both offline relational contexts and online behavioral patterns.

Table 4

Top individual predictors of emotional dysregulation based on SHAP values

Predictor	Mean absolute SHAP value
Problematic digital use	0.184
Family conflict	0.162
Parental warmth	0.149
Nighttime device use	0.138
Teacher support	0.131
Social media intensity	0.126
Peer relationship quality	0.119

As shown in Table 4, problematic digital use was the strongest individual predictor of emotional dysregulation, followed closely by family conflict and parental warmth. School-related variables, particularly teacher support and peer relationship quality, also demonstrated meaningful contributions. The SHAP-based results highlight that both risk-related factors, such as excessive or dysregulated digital engagement and family conflict, and protective factors, such as parental warmth and supportive school relationships, play critical roles in shaping adolescents' emotional regulation capacities.

Figure 1

Feature importance and directionality of effects in the stacked ensemble model
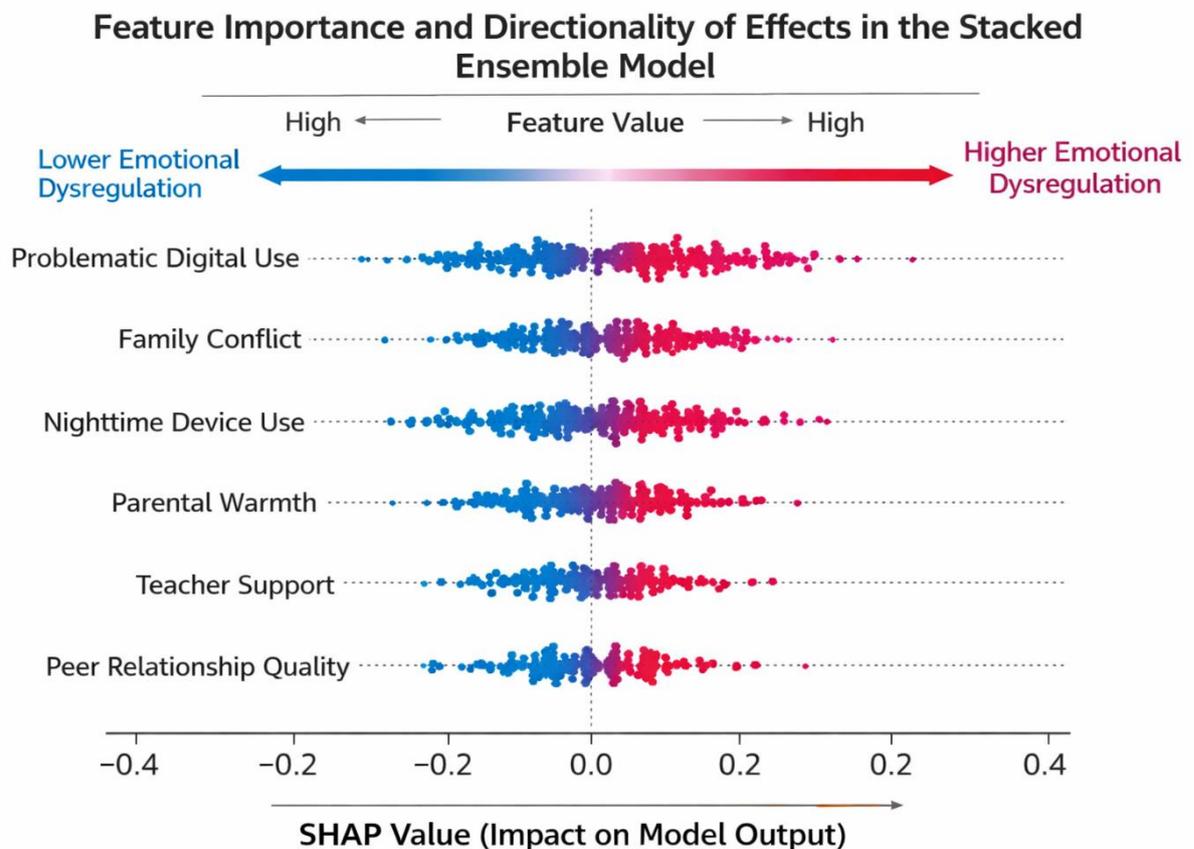
The figure illustrates the relative importance and directional influence of the most salient predictors within the stacked ensemble model. Higher levels of problematic digital use, family conflict, and nighttime device engagement were associated with increased emotional dysregulation, whereas greater parental warmth, teacher support, and positive peer relationships showed a protective association, corresponding to lower predicted dysregulation scores.

4.   Discussion and Conclusion

The present study sought to predict adolescent emotional dysregulation through an integrative ensemble machine learning framework incorporating family, school, and digital behavior indicators, and the findings provide several theoretically and empirically meaningful insights. At the descriptive level, adolescents demonstrated moderate to elevated levels of emotional dysregulation alongside substantial variability in family functioning, school experiences, and digital engagement patterns. This heterogeneity is consistent with contemporary developmental perspectives emphasizing adolescence as a period of heightened emotional sensitivity and contextual susceptibility, shaped by rapid neurodevelopmental changes and expanding social environments (Marano, Anesini, et al., 2025; Marano, Lisci, et al., 2025). The observed variability underscores the appropriateness of predictive approaches capable of modeling non-linear and interactive effects across multiple domains.

The predictive analyses revealed that ensemble machine learning models, particularly the stacked ensemble approach, substantially outperformed traditional linear and single-algorithm models in explaining variance in emotional dysregulation. This finding aligns with methodological arguments that emotional and behavioral outcomes in adolescence are rarely driven by additive, linear relationships, but rather by complex configurations of risk and protective factors (Subrahmanyam & Michikyan, 2022). By integrating multiple base learners, the ensemble model was better able to capture subtle interactions among family, school, and digital variables, supporting recent calls for more advanced analytical techniques in adolescent digital life research (Wood et al., 2023). Importantly, the strong performance of the ensemble model suggests that predictive accuracy in this domain benefits from methodological pluralism rather than reliance on a single theoretical lens.

A key finding of this study was the relatively balanced contribution of digital behavior, family, and school indicators to the prediction of emotional dysregulation, with digital behavior emerging as the most influential domain. This result adds nuance to ongoing debates regarding the role of digital media in adolescent mental health. Consistent with systematic reviews and meta-analyses, problematic digital use and excessive screen engagement were strongly associated with poorer emotional regulation (Bahadur & Karaca, 2023; Santos et al., 2023; Vannucci et al., 2020). However, the present findings extend this literature by demonstrating that digital indicators retain their predictive salience even when family and school contexts are simultaneously modeled, reinforcing the argument that digital behavior represents a distinct and powerful ecological influence rather than a mere proxy for offline difficulties (Livingstone, 2024; Schoon et al., 2024).

At the level of individual predictors, problematic digital use emerged as the strongest contributor to emotional dysregulation. This finding is consistent with prior evidence linking compulsive or dysregulated technology use to emotional reactivity, impaired impulse control, and difficulties disengaging from negative affect (Gansner et al., 2021; Ntumi et al., 2025). The prominence of nighttime device use further highlights the role of sleep disruption as a mechanism through which digital behavior may undermine emotional regulation. Adolescents who engage with digital devices late at night are more likely to experience reduced sleep quality, which in turn compromises emotional stability and recovery from stress (Bahadur & Karaca, 2023; Thomas et al., 2020). These results align with biopsychosocial models emphasizing the interconnectedness of behavioral routines, physiological regulation, and emotional functioning during adolescence (Gaspar et al., 2023).

Family-related predictors, particularly family conflict and parental warmth, also demonstrated strong associations with emotional dysregulation. High levels of family conflict were linked to increased dysregulation, whereas parental warmth showed a protective pattern, mirroring a robust body of developmental research (Douglas et al., 2020; Paulus et al., 2024). Notably, the persistence of these effects within a model that also included digital variables suggests that family emotional climate continues to exert a substantial influence even in highly digitized adolescent lives. This finding resonates with dyadic and ecological perspectives highlighting that parental communication, emotional validation, and mediation practices shape how adolescents interpret and emotionally respond to online experiences

(Adigwe, 2024; Ellis et al., 2025). In this sense, family processes may function both as direct regulators of emotional development and as moderators of digital risk exposure.

School-related indicators, including teacher support and peer relationship quality, contributed meaningfully to the prediction of emotional dysregulation, albeit to a slightly lesser extent than family and digital domains. This pattern is consistent with evidence that supportive school climates and positive peer relationships buffer against emotional distress, whereas academic stress and social exclusion exacerbate regulatory difficulties (Khan et al., 2022; Lan et al., 2022). The findings also align with research demonstrating that adolescents increasingly use digital media to cope with school-related stress and loneliness, sometimes adaptively and sometimes in ways that reinforce dysregulation (Lamash et al., 2023; Scott et al., 2023). The joint contribution of school and digital indicators thus supports integrative models in which offline stressors and online coping strategies dynamically interact.

The explainable machine learning analyses further clarified the directional nature of these relationships, showing that risk-related factors such as problematic digital use, family conflict, and nighttime device engagement were associated with higher predicted levels of emotional dysregulation, whereas protective factors such as parental warmth, teacher support, and positive peer relationships were associated with lower predicted dysregulation. This pattern is congruent with qualitative and mixed-methods research highlighting adolescents' reliance on supportive relationships to mitigate emotional strain in both offline and online contexts (Larivière-Bastien et al., 2022; Popat & Tarrant, 2022). Moreover, the results echo intervention-focused studies demonstrating that enhancing psychosocial skills, digital literacy, and relational support within schools can reduce online harms and improve emotional well-being (Guath, 2025; Throuvala et al., 2021; Žmavc et al., 2025).

From a broader theoretical perspective, the findings lend support to developmental-ecological frameworks that conceptualize emotional dysregulation as an emergent property of interacting systems rather than a trait confined to the individual. The comparable weight of family, school, and digital domains suggests that interventions narrowly targeting screen time reduction may be insufficient unless accompanied by efforts to strengthen family relationships and school support structures (Hampton & Shin, 2022; Jones et al., 2021). At the same time, the strong predictive role of digital behavior underscores the need to move beyond simplistic exposure metrics toward more nuanced assessments of how, why, and when adolescents engage with digital technologies (Casteele et al., 2023; Fortunato et al., 2023). By demonstrating the utility of ensemble machine learning in integrating these perspectives, the present study contributes methodologically to a growing body of work seeking to bridge psychological theory and data-driven modeling.

5. Limitations & Suggestions

Several limitations of the present study should be acknowledged. First, the cross-sectional design precludes causal inference, and the observed associations cannot determine the temporal ordering between emotional dysregulation and contextual predictors. Second, reliance on self-report measures may introduce shared method variance and reporting biases, particularly in the assessment of digital behavior. Third, although the ensemble model demonstrated strong predictive performance, its results may be sample-specific, and external validation in other cultural or socioeconomic contexts is necessary. Finally, despite the use of explainable machine learning techniques, some degree of model complexity remains, which may limit interpretability for non-technical stakeholders.

Future research should prioritize longitudinal designs to examine how family, school, and digital factors dynamically interact over time to shape trajectories of emotional regulation. Incorporating objective digital trace data, physiological indicators, and multi-informant reports would enhance measurement precision and reduce bias. Additionally, cross-cultural comparative studies are needed to assess the generalizability of predictive models and to identify context-specific versus universal predictors. Further methodological work could also explore hybrid models combining machine learning with theory-driven structural approaches to balance prediction and explanation.

From a practical standpoint, the findings highlight the importance of integrated prevention and intervention strategies. Schools should be supported in fostering emotionally supportive climates and in implementing evidence-based digital well-being and mindfulness programs. Parents may benefit from guidance on cultivating warm, communicative relationships and on adopting balanced mediation strategies rather than purely restrictive approaches. At a policy level, adolescent mental health initiatives should recognize digital behavior as a core component of emotional development, addressing it

alongside family and educational contexts rather than in isolation.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

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

Transparency of Data

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

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Authors' Contributions

All authors equally contributed to this article.

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