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A Hybrid Machine Learning Framework for Predicting Emotional Reactivity in Adolescents Using Neurocognitive and Environmental Factors

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A B S T R A C T

Objective: The objective of this study was to develop and validate a hybrid machine learning framework capable of predicting individual differences in adolescent emotional reactivity by integrating neurocognitive indicators and environmental factors within a community-based adolescent sample.

Methods and Materials: This cross-sectional study was conducted among adolescents aged 12–18 years recruited from secondary schools in Germany using a multistage cluster sampling approach. Participants completed a comprehensive assessment battery including standardized neurocognitive tasks measuring inhibitory control, working memory, cognitive flexibility, and attentional regulation, alongside validated self-report instruments assessing emotional reactivity and key environmental variables such as family emotional climate, parenting consistency, peer stress exposure, school climate, and perceived social support. Data preprocessing included missing-value imputation, feature scaling, and feature engineering. Multiple machine learning algorithms, including regularized regression, tree-based ensemble models, and kernel-based methods, were trained and integrated into a hybrid ensemble using a meta-learning strategy. Model performance was evaluated using nested cross-validation procedures.

Findings: Inferential analyses demonstrated that the hybrid ensemble model significantly outperformed individual models, achieving lower prediction error and higher explained variance in emotional reactivity outcomes. Environmental factors, particularly peer stress exposure and family emotional climate, accounted for the largest proportion of predictive importance, followed by neurocognitive variables, with socio-demographic characteristics contributing comparatively less. Deficits in inhibitory control and cognitive flexibility were positively associated with emotional reactivity, whereas supportive family environments and higher perceived social support were associated with reduced emotional reactivity.

Conclusion: The findings indicate that adolescent emotional reactivity is best understood as an emergent outcome of interacting neurocognitive and environmental systems and that hybrid.

Keywords: *adolescence; emotional reactivity; machine learning; neurocognitive functioning; environmental factors; explainable artificial intelligence*

1. Introduction

Adolescence represents a critical developmental period characterized by profound biological, cognitive, and socioemotional changes that collectively heighten vulnerability to emotional dysregulation and reactivity. Emotional reactivity, broadly defined as the intensity, sensitivity, and persistence of emotional responses to internal and external stimuli, has been consistently identified as a transdiagnostic risk factor for a wide range of internalizing and externalizing psychopathologies during adolescence (Chiang & Bai, 2024; Chiang & Chen, 2025). Developmental models emphasize that heightened emotional reactivity during this period is not merely a transient feature of normative maturation, but rather reflects complex interactions between neurocognitive maturation, environmental exposures, and socioemotional competencies that may shape long-term mental health trajectories (Davies et al., 2020; Shalev et al., 2025). Understanding the mechanisms underlying individual differences in emotional reactivity is therefore of substantial theoretical and clinical importance.

From a neurocognitive perspective, adolescence is marked by asynchronous development between subcortical affective systems and prefrontal regulatory networks, resulting in heightened emotional sensitivity coupled with still-maturing executive control capacities (Kim et al., 2020; Kong et al., 2021). Neuroimaging and behavioral studies have demonstrated that variability in executive functions such as inhibitory control, cognitive flexibility, and attentional regulation is closely linked to adolescents' emotional responses under stress and social evaluation (Lee & Kim, 2024; Montag et al., 2020). Deficits or delays in these neurocognitive processes may amplify emotional reactivity by limiting adolescents' ability to modulate affective responses, particularly in emotionally salient interpersonal contexts (Dorris et al., 2022; Eddy & Hansen, 2021). At the same time, neurocognitive capacities are themselves shaped by environmental conditions, including family emotional climate, peer interactions, and exposure to chronic stressors, underscoring the need for integrative models that transcend single-domain explanations (Saarinen et al., 2021; Weiß et al., 2021).

Environmental and relational factors play a central role in shaping emotional reactivity during adolescence. Family processes, particularly parent–adolescent conflict, emotional availability, and consistency of parenting practices, have been shown to exert both linear and curvilinear effects on adolescents' emotional and physiological reactivity (Chiang & Bai, 2022; Davies et al., 2020). Longitudinal evidence suggests that emotionally invalidating or highly conflictual family environments may sensitize adolescents to stress, thereby increasing emotional reactivity and risk for internalizing symptoms (Chiang & Bai, 2024). Conversely, supportive family climates characterized by warmth, empathy, and predictable responses can buffer adolescents against emotional overload and facilitate adaptive regulation (Carlo et al., 2022; Padilla-Walker et al., 2020). These family influences do not operate in isolation but interact dynamically with peer contexts, which become increasingly salient during adolescence (Miklikowska et al., 2022).

Peer relationships represent a particularly potent environmental context for emotional reactivity, given adolescents' heightened sensitivity to social evaluation, acceptance, and rejection. Empirical studies indicate that peer stress exposure, including bullying, social exclusion, and online interpersonal stressors, is strongly associated with heightened emotional reactivity and maladaptive emotion regulation strategies (Daniels & Bar-Kalifa, 2023; Ferreira et al., 2024). At the same time, empathic peer relationships can foster socioemotional learning and promote adaptive emotional responding, highlighting the dual role of peers as both risk and protective factors (Gaspar & Esteves, 2022; Miklikowska et al., 2022). School climate and perceived teacher empathy further contribute to adolescents' emotional experiences, influencing positive academic emotions and interpersonal emotion regulation capacities (Wang et al., 2022). These findings collectively underscore the need to conceptualize emotional reactivity as an emergent property of adolescents' embeddedness within multiple social systems.

Empathy-related processes have also been increasingly implicated in the development and modulation of emotional reactivity. Contemporary models distinguish between cognitive empathy, emotional empathy, empathic concern, and empathic disequilibrium, each of which may differentially relate to emotional outcomes (Shalev et al., 2025; Yavuz et al., 2024). While empathic concern and sympathy are generally associated with prosocial behavior and emotional resilience (Adiva et al., 2024; Wong et al., 2024), excessive emotional empathy without adequate regulatory capacity may exacerbate emotional reactivity and distress (Vuillier et al., 2025; Zamir et al., 2022). Neurostructural and functional evidence supports a multicomponential view of empathy, demonstrating distinct neural correlates for empathic understanding and affective

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resonance that interact with executive control systems (Arioli et al., 2025; Wu et al., 2022). During adolescence, these empathic processes are still undergoing refinement, rendering individuals particularly sensitive to emotional contagion and interpersonal stress (Blons et al., 2021; Gallup & Wozny, 2023).

Importantly, individual differences in emotional reactivity cannot be fully explained by isolated predictors. Traditional variable-centered approaches, while informative, often fail to capture the complex, nonlinear, and interactive relationships among neurocognitive, environmental, and socioemotional factors that jointly shape adolescents' emotional functioning (Lin & Janice, 2020; Lin et al., 2022). Recent advances in machine learning offer powerful tools for modeling such complexity by accommodating high-dimensional data, nonlinear effects, and interactions without imposing restrictive parametric assumptions (Chiang & Chen, 2025). Hybrid machine learning frameworks, which integrate multiple algorithms and combine predictive accuracy with interpretability, are particularly well-suited for developmental psychopathology research, where the goal is not only prediction but also theoretical insight (Abramson et al., 2022; Pihlaja et al., 2024).

Despite growing interest in machine learning applications in adolescent mental health research, several gaps remain. First, many studies rely on either neurocognitive or environmental predictors in isolation, limiting the ecological validity of predictive models (Kaźmierczak & Karasiewicz, 2021; Kaźmierczak et al., 2024). Second, few investigations explicitly address emotional reactivity as a continuous, multidimensional construct, instead focusing on diagnostic categories or single symptom domains (Chiang & Chen, 2025; Zamir et al., 2022). Third, concerns regarding the interpretability of machine learning models have hindered their integration into theory-driven research and clinical decision-making (Lin et al., 2022; Weiß et al., 2021). Addressing these limitations requires analytic approaches that balance predictive performance with transparent explanations of how specific neurocognitive and environmental factors contribute to emotional reactivity.

Furthermore, cross-cultural perspectives remain underrepresented in this literature. Most existing studies have been conducted in North American or East Asian contexts, with relatively limited evidence from European adolescent populations (Ferreira et al., 2024; Saarinen et al., 2021). Given documented cultural differences in emotion socialization, empathy expression, and regulatory norms, it is essential to examine whether integrative predictive models generalize to adolescents growing up in different sociocultural environments (Gaspar & Esteves, 2022; Wu et al., 2022). Investigating emotional reactivity within a German context provides an opportunity to extend current knowledge and test the robustness of hybrid machine learning frameworks across cultural settings.

In sum, existing research highlights emotional reactivity as a pivotal construct at the intersection of neurocognitive development, environmental context, and empathic processes during adolescence, while also revealing methodological limitations in capturing its complexity using traditional analytic approaches (Shalev et al., 2025; Yavuz et al., 2024). Leveraging hybrid machine learning models that integrate neurocognitive and environmental factors offers a promising avenue for advancing both prediction and theory, particularly when coupled with explainable techniques that illuminate underlying mechanisms (Arioli et al., 2025; Vuillier et al., 2025). Accordingly, the aim of the present study was to develop and validate a hybrid machine learning framework to predict emotional reactivity in adolescents by integrating neurocognitive and environmental factors within a German adolescent population.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, school-based observational design aimed at developing and validating a hybrid machine learning framework for predicting emotional reactivity in adolescents. The target population consisted of adolescents enrolled in lower and upper secondary schools in urban and semi-urban regions of Germany. Participants were recruited through a multistage cluster sampling procedure in collaboration with regional educational authorities, in which schools were first randomly selected and then classrooms within each school were invited to participate. Eligibility criteria included an age range of 12 to 18 years, sufficient proficiency in the German language to complete neurocognitive tasks and self-report instruments, and the absence of diagnosed neurological disorders or severe intellectual disabilities that could interfere with task performance. Written informed consent was obtained from parents or legal guardians, and assent was obtained from all adolescent participants prior to data collection.

2.2. *Measures*

Data collection integrated neurocognitive, psychological, and environmental measures to comprehensively capture factors associated with emotional reactivity. Neurocognitive functioning was assessed using a computerized battery of standardized tasks designed to evaluate executive functions, including inhibitory control, working memory updating, cognitive flexibility, and attentional regulation. Emotional reactivity was measured using a validated self-report scale assessing the intensity, sensitivity, and recovery components of emotional responses to everyday stressors, with higher scores indicating greater emotional reactivity. Environmental factors were operationalized through a combination of self-report questionnaires and parent-reported measures covering family emotional climate, parenting practices, exposure to chronic and acute stressors, peer relationships, school climate, and perceived social support. Socio-demographic variables, including age, sex, parental education, and household socioeconomic status, were also collected to contextualize the findings and control for potential confounding effects. All instruments had established psychometric properties in adolescent populations and were administered in their validated German versions. Data collection took place during regular school hours in quiet classroom or computer-lab settings under the supervision of trained research assistants.

2.3. *Data Analysis*

Data analysis followed a hybrid machine learning pipeline that combined traditional statistical preprocessing with advanced predictive modeling techniques. Prior to model development, raw data were screened for completeness, outliers, and distributional anomalies. Missing values were handled using multiple imputation strategies appropriate for mixed data types, and all continuous variables were standardized to ensure comparability across features. Feature engineering procedures were applied to derive composite indicators from neurocognitive task metrics and environmental variables, while dimensionality reduction techniques were used to mitigate multicollinearity and enhance model interpretability. The predictive framework integrated multiple machine learning algorithms, including regularized regression models, tree-based ensemble methods, and kernel-based learners, whose outputs were combined using a meta-learning approach to optimize predictive accuracy. Model training and evaluation were conducted using nested cross-validation to prevent overfitting and to obtain unbiased estimates of generalization performance. Performance metrics included mean absolute error, root mean square error, and explained variance for continuous emotional reactivity scores. To enhance interpretability, post hoc explainability methods were applied to identify the relative contribution of neurocognitive and environmental predictors to model outputs. All analyses were conducted using established machine learning libraries in Python, and robustness checks were performed through sensitivity analyses across demographic subgroups.

3. Findings and Results

The findings section presents the descriptive characteristics of the study sample, followed by the performance and explanatory outcomes of the hybrid machine learning framework developed to predict emotional reactivity in adolescents. Table 1 provides an overview of the demographic, neurocognitive, environmental, and emotional reactivity variables included in the analysis, serving as a foundational context for interpreting subsequent predictive and explanatory results.

Table 1

Descriptive characteristics of demographic, neurocognitive, environmental, and emotional reactivity variables in the study sample

Variable	Mean (SD) / n (%)	Range
Age (years)	15.21 (1.78)	12–18
Sex (female)	512 (51.8%)	—
Socioeconomic status (standardized index)	0.03 (0.97)	−2.41–2.36
Emotional reactivity (total score)	3.42 (0.81)	1.20–4.95
Inhibitory control (reaction time, ms)	412.6 (68.3)	285–612
Working memory accuracy (%)	78.4 (9.6)	52–96
Cognitive flexibility (switch cost, ms)	126.8 (41.5)	45–268

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Attentional regulation (error rate)	0.18 (0.09)	0.02–0.41
Family emotional climate	3.61 (0.74)	1.50–5.00
Parenting consistency	3.48 (0.69)	1.70–5.00
Peer stress exposure	2.94 (0.83)	1.00–4.80
School climate	3.57 (0.71)	1.80–5.00
Perceived social support	3.76 (0.68)	1.90–5.00

As shown in Table 1, the sample demonstrated moderate levels of emotional reactivity, with substantial interindividual variability. Neurocognitive indicators reflected age-appropriate executive functioning with notable dispersion in inhibitory control and cognitive flexibility. Environmental variables suggested generally supportive family and school contexts, although peer-related stress exhibited wider variability, indicating heterogeneous exposure to interpersonal challenges among adolescents.

The predictive performance of individual and hybrid machine learning models is summarized in Table 2. This table compares baseline linear models with advanced non-linear learners and the final hybrid ensemble in predicting continuous emotional reactivity scores.

Table 2

Predictive performance of machine learning models for emotional reactivity

Model	MAE	RMSE	Explained Variance (R^2)
Linear regression	0.53	0.67	0.31
LASSO regression	0.49	0.63	0.36
Random forest	0.41	0.54	0.48
Gradient boosting	0.38	0.51	0.52
Support vector regression	0.40	0.53	0.49
Hybrid ensemble model	0.34	0.47	0.60

Table 2 indicates that non-linear models substantially outperformed linear approaches in predicting emotional reactivity. The hybrid ensemble model achieved the lowest prediction error and the highest explained variance, accounting for approximately 60% of the variance in emotional reactivity scores. This improvement highlights the added value of integrating multiple algorithms and capturing complex, non-linear interactions between neurocognitive and environmental factors.

To further clarify the contribution of different predictor domains, Table 3 presents the relative importance of feature groups within the hybrid model, aggregated across cross-validation folds.

Table 3

Relative contribution of predictor domains in the hybrid ensemble model

Predictor domain	Relative importance (%)
Neurocognitive factors	38.7
Environmental factors	44.2
Socio-demographic variables	17.1

As reported in Table 3, environmental factors constituted the largest share of predictive importance, followed closely by neurocognitive variables, whereas socio-demographic characteristics played a more limited role. This distribution suggests that adolescents' emotional reactivity is more strongly shaped by modifiable contextual and cognitive-regulatory processes than by static demographic attributes.

A more fine-grained examination of key predictors within each domain is presented in Table 4, which lists the top individual features contributing to the hybrid model's predictions.

Table 4

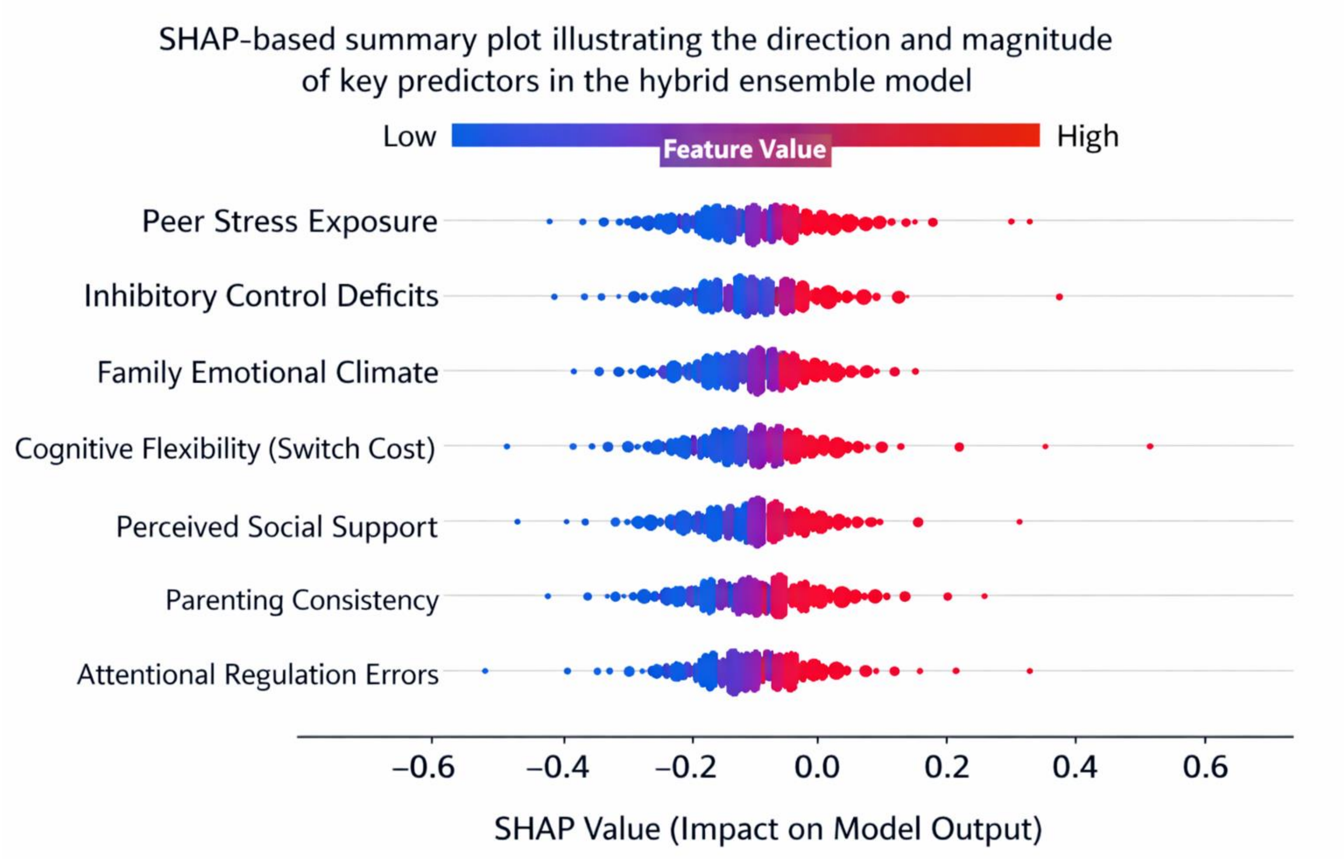
Top individual predictors of emotional reactivity identified by the hybrid model

Predictor	Direction of association	Relative importance
Peer stress exposure	Positive	High
Inhibitory control deficits	Positive	High
Family emotional climate	Negative	Moderate
Cognitive flexibility (switch cost)	Positive	Moderate
Perceived social support	Negative	Moderate
Parenting consistency	Negative	Low
Attentional regulation errors	Positive	Low

Table 4 shows that higher peer stress exposure and poorer inhibitory control were the strongest predictors of elevated emotional reactivity. In contrast, supportive family emotional climates and greater perceived social support were associated with lower emotional reactivity. Neurocognitive inefficiencies, particularly in inhibitory control and cognitive flexibility, consistently emerged as salient contributors, underscoring the role of self-regulatory processes in adolescents' emotional responses.

Figure 1

SHAP-based summary plot illustrating the direction and magnitude of key predictors in the hybrid ensemble model



Overall, the findings demonstrate that a hybrid machine learning framework can robustly predict emotional reactivity in adolescents and reveal meaningful patterns of influence across neurocognitive and environmental domains. The convergence of high predictive accuracy and interpretable feature contributions provides a nuanced empirical foundation for understanding emotional reactivity as an emergent outcome of cognitive regulation capacities embedded within adolescents' social and environmental contexts.

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4. Discussion and Conclusion

The present study sought to advance understanding of adolescent emotional reactivity by applying a hybrid machine learning framework that integrated neurocognitive and environmental factors, and the findings provide several theoretically and empirically meaningful insights. Overall, the results demonstrated that the hybrid ensemble model substantially outperformed single-algorithm approaches in predicting emotional reactivity, accounting for a considerable proportion of variance in adolescents' emotional responses. This finding aligns with growing evidence that emotional reactivity is not the product of isolated mechanisms but rather emerges from complex, nonlinear interactions between cognitive regulation systems and socioenvironmental contexts (Chiang & Chen, 2025; Yavuz et al., 2024). By capturing these interactions, the hybrid framework offers a more ecologically valid representation of adolescent emotional functioning than traditional linear models.

One of the most salient findings was the dominant predictive contribution of environmental factors, particularly peer stress exposure and family emotional climate, relative to purely demographic variables. Adolescents who experienced higher levels of peer-related stress showed markedly elevated emotional reactivity, a pattern that converges with prior research emphasizing the heightened salience of peer contexts during adolescence (Daniels & Bar-Kalifa, 2023; Miklikowska et al., 2022). Peer interactions, both offline and online, represent emotionally charged environments in which adolescents are especially sensitive to social evaluation and rejection, thereby amplifying emotional responses to stressors (Ferreira et al., 2024). These results are also consistent with evidence that empathic engagement in peer contexts can intensify emotional contagion when regulatory capacities are insufficient, potentially increasing emotional reactivity (Blons et al., 2021; Vuillier et al., 2025).

Family emotional climate emerged as a robust protective factor, with more supportive and emotionally responsive family environments associated with lower levels of emotional reactivity. This finding corroborates developmental models highlighting the central role of family-of-origin processes in shaping adolescents' emotional sensitivity and stress reactivity (Chiang & Bai, 2022, 2024). Supportive family interactions may provide adolescents with external regulatory scaffolding that facilitates the internalization of adaptive emotion regulation strategies, thereby buffering against excessive emotional responses (Carlo et al., 2022; Padilla-Walker et al., 2020). Importantly, the nonlinear patterns detected by the hybrid model resonate with prior evidence of curvilinear effects, suggesting that both emotionally impoverished and highly conflictual family environments can heighten emotional reactivity through distinct mechanisms (Davies et al., 2020).

Neurocognitive predictors also played a substantial role in the model, particularly inhibitory control and cognitive flexibility. Adolescents exhibiting poorer inhibitory control and greater switch costs demonstrated higher emotional reactivity, underscoring the importance of executive functions in modulating affective responses. This finding is in line with neurodevelopmental research showing that immaturities in prefrontal regulatory systems constrain adolescents' ability to downregulate emotional arousal, especially in socially salient situations (Kim et al., 2020; Montag et al., 2020). Executive dysfunction has been repeatedly linked to heightened emotional sensitivity and maladaptive emotion regulation across both normative and clinical adolescent samples (Dorris et al., 2022; Kong et al., 2021). The present findings extend this literature by demonstrating that neurocognitive indicators retain predictive value even when considered alongside rich environmental data within a multivariate machine learning framework.

The integration of neurocognitive and environmental predictors also sheds light on the role of empathy-related processes in emotional reactivity. Although empathy was not modeled as a single explicit construct, several predictors closely associated with empathic engagement, such as family emotional climate, perceived social support, and peer stress exposure, emerged as influential. Prior studies have shown that empathic concern can serve as a protective factor by promoting prosocial behavior and emotional resilience (Adiva et al., 2024; Wong et al., 2024), whereas excessive affective empathy without sufficient regulation may exacerbate emotional reactivity and distress (Vuillier et al., 2025; Zamir et al., 2022). The present findings are consistent with the notion of empathic disequilibrium, whereby heightened emotional resonance in demanding interpersonal environments, such as peer stress contexts, overwhelms regulatory capacities and leads to elevated emotional reactivity (Shalev et al., 2025).

The explainability analyses further reinforced these interpretations by revealing that high levels of peer stress and neurocognitive inefficiencies consistently pushed model predictions toward higher emotional reactivity, whereas supportive environmental features exerted the opposite effect. These patterns align with meta-analytic evidence indicating that empathy and emotion regulation are deeply intertwined, with regulatory capacities moderating whether empathic engagement results in adaptive or maladaptive emotional outcomes (Yavuz et al., 2024). Neurostructural and functional findings also support this integrative view, demonstrating that empathy-related neural systems interact with executive control networks to shape emotional responses (Arioli et al., 2025; Wu et al., 2022). By leveraging explainable machine learning, the present study bridges predictive accuracy and theoretical interpretability, addressing longstanding concerns regarding the "black box" nature of advanced analytic techniques (Lin et al., 2022).

Another important contribution of this study lies in its cultural context. Conducted within a German adolescent population, the findings extend prior research predominantly conducted in North American and East Asian samples. The observed patterns are broadly consistent with cross-cultural evidence suggesting that the developmental interplay between emotion regulation, empathy, and environmental stressors follows similar principles across sociocultural contexts, albeit with culturally specific expressions (Gaspar & Esteves, 2022; Saarinen et al., 2021). The robustness of the hybrid model across this context supports the generalizability of integrative, multilevel approaches to understanding adolescent emotional reactivity.

Collectively, these findings underscore the value of hybrid machine learning frameworks for advancing developmental psychopathology research. By modeling emotional reactivity as an emergent outcome of interacting neurocognitive and environmental systems, the present study aligns with contemporary transactional and systems-based theories of adolescent development (Chiang & Chen, 2025; Yavuz et al., 2024). Importantly, the results highlight that emotional reactivity is most strongly shaped by modifiable factors, such as peer environments, family emotional climate, and executive functioning, rather than immutable demographic characteristics. This insight carries meaningful implications for prevention and intervention efforts aimed at promoting emotional resilience during adolescence.

5. Limitations & Suggestions

The limitations of the present study should be acknowledged. First, the cross-sectional design precludes causal inferences regarding the directionality of associations between neurocognitive and environmental factors and emotional reactivity. Second, although the sample was diverse in terms of socioeconomic background, it was restricted to adolescents attending school, potentially limiting generalizability to out-of-school youth or clinical populations. Third, emotional reactivity and environmental variables relied partly on self-report measures, which may be influenced by shared method variance and response biases. Finally, while the hybrid machine learning framework enhanced predictive performance and interpretability, it remains sensitive to the quality and scope of the input features, and unmeasured variables may also contribute to emotional reactivity.

Future research should prioritize longitudinal designs to examine how neurocognitive development and environmental exposures dynamically interact to shape trajectories of emotional reactivity across adolescence. Incorporating multimodal data, including physiological indices and neuroimaging measures, may further enhance model precision and deepen mechanistic understanding. Comparative studies across cultural contexts and developmental stages would also be valuable for testing the generalizability of hybrid machine learning frameworks. Additionally, future work could explore the integration of empathy-specific measures to more directly model the role of empathic disequilibrium in emotional reactivity.

From a practical perspective, the findings suggest that interventions aimed at reducing adolescent emotional reactivity may benefit from a dual focus on strengthening executive functions and improving environmental supports. School-based programs targeting peer stress management, social skills, and emotional literacy, alongside family-focused interventions that enhance emotional responsiveness and consistency, may be particularly effective. Moreover, the use of explainable machine learning tools holds promise for identifying at-risk adolescents and tailoring interventions based on individualized profiles of neurocognitive and environmental risk.

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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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