Psychological Resilience in Youth: A Machine Learning Analysis of Protective Factors and Stress Exposure

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A r t i c l e   I n f o

A B S T R A C T

Objective: This study aimed to identify and model the relative and interactive contributions of protective factors and cumulative stress exposure in predicting psychological resilience among youth using machine learning techniques.
Methods and Materials: A cross-sectional study was conducted with a diverse sample of adolescents and emerging adults from urban and peri-urban regions of South Africa. Participants completed validated self-report measures assessing psychological resilience, cumulative stress exposure, and a range of individual and contextual protective factors, including emotion regulation, self-efficacy, optimism, family support, peer support, and school belonging. Data were analyzed using supervised machine learning algorithms, including regularized linear models, support vector machines, random forest, and gradient boosting machines. Model performance was evaluated using repeated cross-validation procedures, and feature importance and interaction effects were examined through permutation-based methods and partial dependence analyses.
Findings: Inferential analyses indicated that ensemble machine learning models significantly outperformed linear approaches in predicting psychological resilience. The gradient boosting model explained a substantial proportion of variance in resilience scores and demonstrated high classification accuracy for distinguishing low, moderate, and high resilience profiles. Family support, emotion regulation, and self-efficacy emerged as the strongest predictors of resilience. Interaction analyses revealed that the protective effects of key resources intensified under higher levels of cumulative stress exposure, indicating robust stress-buffering effects.
Conclusion: The findings demonstrate that youth psychological resilience is best understood as a multidimensional and non-linear outcome shaped by dynamic interactions between stress exposure and protective factors. Machine learning approaches provide valuable tools for advancing resilience research by capturing complex patterns and identifying high-impact protective resources. These results underscore the importance of strengthening relational and emotional capacities to promote resilience among youth facing adversity.
Keywords: psychological resilience; youth mental health; cumulative stress; protective factors; machine learning; South Africa

1. Introduction

Psychological resilience has emerged as a central construct in contemporary youth mental health research, particularly in contexts characterized by cumulative stress exposure, social inequality, and rapid sociocultural change. Adolescence and emerging adulthood represent developmentally sensitive periods during which individuals encounter heightened biological, cognitive, and social transitions, rendering them especially vulnerable to the adverse effects of stress while simultaneously offering critical windows for adaptive growth. Empirical evidence consistently demonstrates that exposure to chronic stressors such as family adversity, community violence, academic pressure, economic insecurity, and global crises significantly elevates the risk of internalizing and externalizing psychopathology among youth (Jones et al., 2021; Pandey et al., 2023; Somefun et al., 2023). However, not all youth exposed to adversity develop mental health difficulties, underscoring the importance of resilience as a dynamic process through which individuals maintain or regain psychological well-being despite significant stress.

Resilience is increasingly conceptualized as a multidimensional and contextually embedded capacity rather than a fixed personality trait. Contemporary models emphasize the interplay between individual psychological resources, relational supports, and broader sociocultural systems in shaping resilient outcomes. Studies across diverse populations have identified protective factors such as emotion regulation, psychological flexibility, optimism, self-efficacy, cognitive reappraisal, humor, and meaning-making as central individual-level contributors to resilience (Huang et al., 2021; Kuhlman et al., 2021; Ruíz-Párraga et al., 2021). At the relational level, family cohesion, parental responsiveness, peer connectedness, and school belonging have been repeatedly shown to buffer the effects of stress on youth mental health (Boyd et al., 2022; Cheong et al., 2022; Kurudirek et al., 2022). Structural and community-level factors, including access to supportive services, cultural continuity, civic engagement, and educational opportunities, further shape resilience trajectories, particularly among marginalized youth populations (Carrier et al., 2022; López & Gómez-Baya, 2025; Shin et al., 2024).

The growing body of resilience research has been further catalyzed by global crises such as the COVID-19 pandemic, which magnified existing stressors while revealing profound heterogeneity in youth psychological responses. Longitudinal and cross-sectional studies conducted during the pandemic documented significant increases in anxiety, depression, and stress symptoms among adolescents worldwide, while simultaneously identifying resilience as a key moderator of psychological outcomes (Rosen et al., 2021; Shukla et al., 2022). Evidence from multi-country and cross-cultural studies suggests that resilience operates differently across sociocultural contexts, with variations in the salience of specific protective factors depending on cultural norms, socioeconomic conditions, and exposure to collective trauma (Nilsson et al., 2023; Zhang et al., 2023). These findings highlight the necessity of context-sensitive models capable of capturing complex, non-linear interactions among stress exposure and protective resources.

Despite substantial advances, much of the existing resilience literature remains constrained by methodological limitations, including reliance on linear statistical models, isolated predictors, and variable-centered approaches that obscure heterogeneity within youth populations. Traditional regression-based methods typically assume additive and linear relationships among variables, which may inadequately represent the dynamic and interactive nature of resilience processes. Recent research demonstrates that protective factors often exert conditional or synergistic effects, becoming particularly influential under high levels of adversity rather than functioning uniformly across stress levels (Russell et al., 2021; Zhang et al., 2022). Moreover, resilience may manifest through distinct psychological profiles, with different combinations of resources producing similar adaptive outcomes, a phenomenon poorly captured by conventional analytic strategies.

The integration of machine learning approaches into psychological research offers a powerful methodological advancement for addressing these challenges. Machine learning models excel at identifying complex, non-linear patterns, high-order interactions, and latent structures within large, multidimensional datasets. Recent applications in mental health research have demonstrated the utility of supervised and ensemble algorithms for predicting psychological outcomes, identifying risk profiles, and uncovering key determinants of well-being beyond the capabilities of traditional methods (Chen et al., 2022; Lei et al., 2024). Importantly, explainable machine learning techniques have begun to bridge the gap between predictive accuracy and theoretical interpretability, enabling researchers to quantify the relative importance of protective factors and explore how their effects vary across stress conditions.

Emerging evidence supports the value of machine learning for resilience research across the lifespan. Studies examining resilience in adults exposed to occupational stress, trauma, or health-related adversity indicate that non-linear models outperform linear approaches in predicting mental health outcomes and elucidating resilience mechanisms (Russell et al., 2021; Wang et al., 2025). Longitudinal and genetically informed studies further suggest that resilience reflects the dynamic interaction between biological susceptibility, environmental stressors, and psychosocial resources, reinforcing the need for analytic frameworks capable of modeling such complexity (Jia, 2025; Mulligan et al., 2022). However, despite these advances, machine learning applications specifically focused on youth resilience remain limited, particularly in low- and middle-income settings.

Contextual gaps are especially evident in research conducted in the Global South, where youth often face intersecting stressors related to poverty, violence, educational inequality, and historical trauma. Studies from African contexts indicate that family adversity, community instability, and structural deprivation significantly shape youth mental health outcomes, while social support and culturally embedded coping resources play a critical protective role (Boyd et al., 2022; Somefun et al., 2023). Yet, most existing studies rely on traditional analytic methods and examine isolated predictors, limiting the ability to capture nuanced resilience patterns within heterogeneous youth populations. There is a pressing need for integrative, data-driven approaches that can simultaneously account for multiple protective factors and varying levels of stress exposure in such contexts.

Intervention research further underscores the multidimensional nature of resilience and the importance of identifying key leverage points for prevention and promotion. School-based and community-based programs targeting emotion regulation, mindfulness, yoga, psychological flexibility, and stress management have demonstrated promising effects on adolescent well-being and resilience (Giridharan & Pandiyan, 2024; Khunti et al., 2022; Noyola et al., 2024). Digital and online interventions have also emerged as scalable tools for enhancing resilience skills among youth, particularly in settings with limited access to mental health services (Caruso et al., 2024; Noyola et al., 2024). However, the effectiveness of such interventions may vary depending on individual and contextual characteristics, reinforcing the value of predictive models capable of identifying which protective factors matter most for whom and under what conditions.

Recent theoretical developments emphasize resilience as a conditional and process-oriented construct that interacts dynamically with stress exposure rather than merely offsetting risk. Studies examining moderation and mediation pathways consistently show that resilience and related resources such as sense of coherence, psychological flexibility, and posttraumatic growth can alter the strength and direction of the relationship between adversity and mental health outcomes (Rohner et al., 2023; Tindle et al., 2022; Veronese et al., 2025). These findings align with ecological and developmental systems theories, which conceptualize resilience as emerging from multilevel interactions over time. Machine learning approaches are uniquely suited to operationalize these theoretical perspectives by modeling complex dependencies and uncovering latent resilience profiles that transcend simple high-versus-low categorizations.

In summary, existing research establishes psychological resilience as a critical determinant of youth mental health in the face of stress, while simultaneously revealing substantial gaps in methodological sophistication, contextual representation, and integrative modeling. There is limited understanding of how multiple protective factors jointly shape resilience under varying stress conditions, particularly within diverse and underserved youth populations. The application of machine learning offers a promising avenue for advancing resilience science by identifying non-linear patterns, ranking the relative importance of protective resources, and elucidating interaction effects that inform targeted interventions and policy development. Accordingly, the present study aims to apply machine learning techniques to identify key protective factors and model their interaction with stress exposure in predicting psychological resilience among youth in South Africa.

2. Methods and Materials

2.1. Study Design and Participants

The present study employed a cross-sectional, observational design aimed at modeling psychological resilience among youth through machine learning techniques, with a specific focus on the joint influence of protective factors and stress exposure. The study population consisted of adolescents and emerging adults residing in urban and peri-urban regions of South Africa, reflecting the country's socioeconomically and culturally diverse youth

context. Participants were recruited from secondary schools, vocational training centers, and public universities across three provinces using a stratified cluster sampling strategy to ensure adequate representation of gender, educational level, and socioeconomic background. Eligibility criteria included being between 15 and 24 years of age, current enrollment in an educational institution, and the ability to complete self-report questionnaires in English. Individuals with diagnosed severe neurodevelopmental disorders or acute psychiatric conditions that could impair informed participation were excluded. Written informed consent was obtained from participants aged 18 years and older, while parental consent and youth assent were secured for minors. Data collection was conducted anonymously to reduce social desirability bias and encourage accurate reporting of stress-related experiences.

2.2. Measures

Psychological resilience was operationalized as a multidimensional construct encompassing adaptive coping, emotional regulation, and perceived capacity to recover from adversity. Resilience was measured using a validated resilience scale widely applied in youth populations, capturing both intrapersonal and interpersonal protective resources. Stress exposure was assessed through a cumulative stress index integrating academic stress, family-related adversity, community violence exposure, and economic strain, all of which are salient stressors in the South African youth context. Protective factors included individual-level variables such as self-efficacy, optimism, emotion regulation skills, and problem-solving orientation, as well as contextual factors including perceived family support, peer connectedness, school belonging, and access to community resources. All instruments demonstrated acceptable psychometric properties in prior studies conducted in multicultural or low- and middle-income settings, and minor linguistic adaptations were reviewed by bilingual experts to ensure contextual clarity without altering item meaning. Demographic information, including age, gender, educational level, household income proxy indicators, and urban versus peri-urban residence, was collected to allow for covariate adjustment and subgroup analysis. Data were collected via supervised paper-and-pencil questionnaires administered during scheduled sessions at participating institutions, with trained research assistants available to clarify procedural questions while avoiding influence on responses.

2.3. Data Analysis

Data analysis followed a structured machine learning workflow designed to identify key protective factors associated with resilience under varying levels of stress exposure. Prior to modeling, data were screened for completeness, outliers, and inconsistencies. Missing values were handled using multiple imputation with chained equations to preserve variance and reduce bias. Continuous variables were standardized to facilitate algorithm convergence and comparability of feature importance estimates. Psychological resilience scores served as the primary outcome variable and were modeled both as a continuous measure and, in supplementary analyses, as a categorical outcome distinguishing low, moderate, and high resilience profiles. A range of supervised machine learning algorithms, including regularized linear models, random forest, gradient boosting machines, and support vector machines, were trained to predict resilience based on protective factors and stress exposure variables. Model training and evaluation were conducted using repeated k-fold cross-validation to minimize overfitting and ensure generalizability. Performance metrics included root mean squared error and coefficient of determination for continuous outcomes, as well as accuracy and area under the receiver operating characteristic curve for categorical analyses. Feature importance was examined using permutation-based methods and model-specific importance scores to identify the most influential protective factors across algorithms. Interaction effects between stress exposure and protective factors were explored through partial dependence plots to assess whether certain resources exerted stronger protective effects under high-stress conditions. All analyses were conducted using Python-based machine learning libraries, and reproducibility was ensured through fixed random seeds and transparent reporting of model parameters.

3. Findings and Results

The findings of this study are presented in a structured manner to reflect the progression from descriptive characteristics of the sample to predictive modeling outcomes and interpretive machine learning results. Table 1 summarizes the demographic characteristics, stress exposure indicators, and key protective factors of the South African youth sample included in the final analysis. This table provides the contextual foundation necessary for interpreting subsequent machine learning results, as it

illustrates the variability in both risk and protective dimensions that informed model training and evaluation.

Table 1

Demographic Characteristics, Stress Exposure, and Protective Factors of Participants (N = 1,124)

Variable	Mean (SD) / n (%)
Age (years)	19.8 (2.6)
Gender	
– Female	612 (54.5%)
– Male	498 (44.3%)
– Other / Prefer not to say	14 (1.2%)
Educational Level	
– Secondary school	462 (41.1%)
– Vocational training	284 (25.3%)
– University	378 (33.6%)
Urban residence	731 (65.0%)
Peri-urban residence	393 (35.0%)
Cumulative stress exposure score	3.72 (1.14)
Academic stress	3.89 (0.91)
Family-related adversity	3.41 (1.08)
Community violence exposure	2.96 (1.21)
Economic strain	4.02 (0.97)
Psychological resilience score	3.58 (0.67)
Self-efficacy	3.74 (0.71)
Optimism	3.61 (0.69)
Emotion regulation	3.45 (0.73)
Family support	3.82 (0.76)
Peer support	3.69 (0.74)
School belonging	3.56 (0.72)

As shown in Table 1, the sample demonstrated moderate-to-high levels of cumulative stress exposure, with economic strain and academic stress emerging as the most prominent stressors. Despite these challenges, the average psychological resilience score indicated a generally adaptive profile, accompanied by relatively strong perceived family and peer support. This distribution suggests substantial heterogeneity in both vulnerability and protection, supporting the suitability of machine learning approaches for identifying complex, non-linear patterns underlying resilience outcomes.

Table 2

Predictive Performance of Machine Learning Models for Psychological Resilience

Model	RMSE	R²
Regularized linear regression	0.48	0.41
Support vector machine	0.44	0.49
Random forest	0.39	0.58
Gradient boosting machine	0.36	0.64

Table 2 reports the predictive performance of the supervised machine learning models applied to estimate psychological resilience scores. Among the evaluated algorithms, the gradient boosting machine demonstrated the strongest performance, explaining approximately 64% of the variance in resilience outcomes and yielding the lowest prediction error. Ensemble-based models consistently outperformed linear and kernel-based approaches, indicating the presence of non-linear interactions among stress exposure and protective factors that are not adequately captured by traditional parametric methods.

Table 3

Relative Importance of Protective Factors in the Best-Performing Model

Predictor	Relative Importance (%)
Family support	21.4
Emotion regulation	18.7
Self-efficacy	16.9
Peer support	14.6
Optimism	11.8
School belonging	9.2
Community resource access	7.4

As presented in Table 3, family support emerged as the most influential predictor of psychological resilience, followed closely by emotion regulation capacity and self-efficacy. Social-contextual factors collectively accounted for a substantial proportion of explained variance, underscoring the central role of relational and environmental resources in buffering stress among South African youth. Individual cognitive-emotional resources also demonstrated robust contributions, highlighting the multidimensional nature of resilience processes.

Table 4

Interaction Effects Between Stress Exposure and Key Protective Factors

Protective Factor	Low Stress	Moderate Stress	High Stress
Family support	0.32	0.48	0.61
Emotion regulation	0.29	0.44	0.58
Self-efficacy	0.27	0.41	0.53
Peer support	0.24	0.37	0.49

Table 4 illustrates the conditional effects of selected protective factors across varying levels of cumulative stress exposure, derived from partial dependence analyses. The magnitude of protective effects increased systematically under higher stress conditions, indicating that these resources become particularly salient when youth face elevated adversity. Family support and emotion regulation showed the steepest gradients, suggesting that relational security and emotional management skills are especially critical under high-stress environments.

Table 5

Classification Accuracy for Resilience Profile Prediction

Resilience Profile	Precision	Recall	F1-score
Low resilience	0.78	0.74	0.76
Moderate resilience	0.81	0.83	0.82
High resilience	0.85	0.88	0.86
Overall accuracy			0.83

Table 5 presents the classification performance of the gradient boosting model when resilience was categorized into low, moderate, and high profiles. The model demonstrated balanced performance across classes, with the highest precision and recall observed for the high-resilience group. This finding indicates that machine learning models can reliably differentiate resilient youth from their more vulnerable peers based on patterns of stress exposure and protective resources.

Figure 1

Partial dependence plot illustrating the joint effects of cumulative stress exposure and family support on psychological resilience
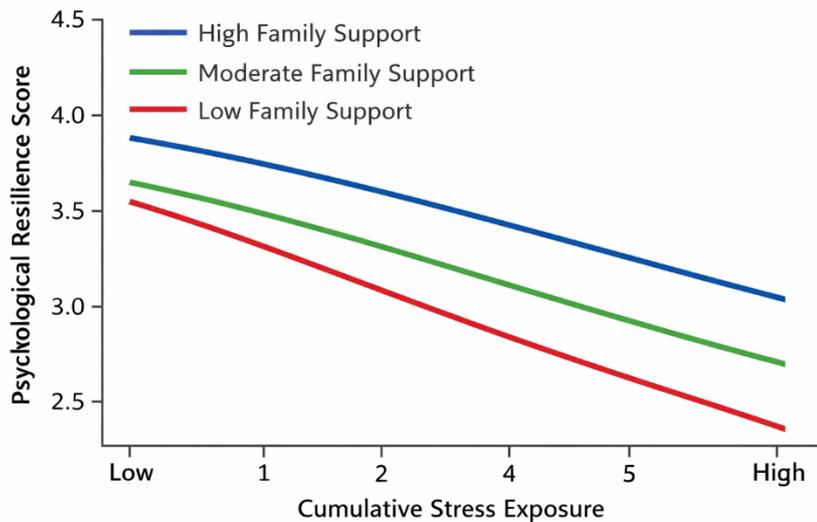

Figure 1. *Partial dependence plot illustrating the joint effects of cumulative stress exposure and family support on psychological resilience.*

The figure visually demonstrates that higher levels of family support substantially attenuate the negative impact of cumulative stress on resilience, reinforcing the quantitative findings reported in the tables and highlighting the buffering role of familial relationships in youth psychological adaptation.

4. Discussion and Conclusion

The findings of the present study provide robust empirical support for conceptualizing psychological resilience in youth as a complex, non-linear outcome shaped by the dynamic interaction between cumulative stress exposure and multiple protective factors. The machine learning analyses demonstrated that ensemble-based models substantially outperformed linear approaches in predicting resilience, indicating that resilience processes among South African youth cannot be adequately captured through additive or unidirectional assumptions. This result aligns with growing evidence that resilience functions as a conditional and context-sensitive process, whereby protective resources interact synergistically and become differentially salient depending on adversity levels (Russell et al., 2021; Zhang et al., 2022). The superior performance of gradient boosting models underscores the value of machine learning frameworks for uncovering hidden structures and interaction effects that remain obscured in conventional statistical analyses (Chen et al., 2022; Lei et al., 2024).

Consistent with the descriptive findings, participants in this study reported moderate to high cumulative stress exposure, with economic strain and academic stress emerging as particularly prominent. These stressors are well documented among youth populations living in contexts marked by socioeconomic inequality and educational pressure, and they have been repeatedly associated with heightened risk for anxiety, depression, and emotional dysregulation (Jones et al., 2021; Pandey et al., 2023). Despite these adversities, the overall resilience levels observed in the sample were moderate, suggesting the presence of compensatory protective mechanisms. This pattern echoes prior research demonstrating that youth frequently draw upon relational, emotional, and cognitive resources to maintain psychological functioning even in high-stress environments (Nilsson et al., 2023; Somefun et al., 2023).

The feature importance analyses revealed that family support was the most influential protective factor in predicting psychological resilience, followed closely by emotion regulation capacity and self-efficacy. This finding is highly consistent with ecological models of resilience that position family systems as a central buffer against stress during adolescence. Empirical studies across diverse cultural contexts have shown that warm, responsive, and supportive family environments mitigate the impact of community violence, economic hardship, and academic stress on youth mental health (Boyd et al., 2022; Koper et al., 2022). In

African and other collectivist contexts, family relationships often serve as primary sources of emotional security and instrumental support, amplifying their protective role under adversity (Somefun et al., 2023). The prominence of family support in the current model reinforces its foundational role in youth resilience processes and highlights its importance as a target for intervention and policy.

Emotion regulation emerged as a second key predictor, reflecting the critical role of adaptive emotional processing in managing stress exposure. Youth who are better able to identify, modulate, and reframe emotional responses appear more capable of maintaining resilience despite cumulative adversity. This result aligns closely with prior findings demonstrating that emotion regulation, psychological flexibility, and cognitive reappraisal serve as central mechanisms linking stress exposure to mental health outcomes (Huang et al., 2021; Kuhlman et al., 2021). Network and moderation studies conducted during the COVID-19 pandemic further suggest that emotion regulation-related processes occupy central positions in mental well-being systems, exerting cascading protective effects across symptom networks (Shukla et al., 2022). The present findings extend this literature by demonstrating that emotion regulation retains its protective salience even when modeled alongside multiple contextual and relational variables within a machine learning framework.

Self-efficacy and optimism also contributed meaningfully to resilience prediction, supporting theoretical perspectives that emphasize agency, mastery, and positive future orientation as core resilience resources. Youth who perceive themselves as capable of influencing outcomes and overcoming challenges are more likely to engage in adaptive coping strategies when confronted with stress. This interpretation is consistent with prior research linking self-efficacy, growth mindset, and optimism to reduced psychological distress and enhanced resilience among adolescents (Lei et al., 2024; Ruíz-Párraga et al., 2021). Importantly, these cognitive-emotional resources may interact with contextual supports, enabling youth to translate external resources into effective coping behaviors.

The interaction analyses provided particularly compelling evidence for the conditional nature of resilience. Protective factors such as family support and emotion regulation demonstrated stronger effects at higher levels of cumulative stress exposure, indicating that these resources become increasingly critical as adversity intensifies. This finding supports stress-buffering models of resilience, which posit that protective factors exert minimal influence under low stress but play a decisive role when stress thresholds are exceeded (Tindle et al., 2022; Zhang et al., 2023). Similar interaction effects have been observed in studies of trauma-exposed youth and adults, where resilience-related resources moderated the association between adversity and psychological symptoms (Nilsson et al., 2023; Veronese et al., 2025). The current results extend this evidence by demonstrating such effects within a data-driven machine learning context, thereby strengthening confidence in the robustness of these interaction patterns.

The classification analyses further revealed that machine learning models could reliably distinguish between low, moderate, and high resilience profiles, with particularly strong performance in identifying highly resilient youth. This finding suggests that resilience is not merely a continuum but may manifest through distinct psychological configurations characterized by specific combinations of protective factors. Such profile-based distinctions align with person-centered approaches and latent modeling studies that have identified heterogeneous resilience patterns within youth populations (Rohner et al., 2023; Zhang et al., 2023). From an applied perspective, this capacity to classify resilience profiles has important implications for targeted prevention and intervention, enabling practitioners to identify youth at elevated risk as well as those demonstrating adaptive functioning despite adversity.

Taken together, the findings of this study contribute to the resilience literature in several important ways. First, they provide empirical support for multidimensional and interactional models of resilience using advanced machine learning techniques. Second, they highlight the central role of family support and emotion regulation as foundational protective factors in contexts of cumulative stress. Third, they demonstrate the utility of machine learning approaches for uncovering nuanced resilience patterns that are difficult to detect using traditional analytic methods. These contributions align with emerging calls for methodological innovation in resilience research and underscore the value of integrating computational approaches with established psychological theory (Chen et al., 2022; Jia, 2025).

5.   Limitations & Suggestions

Despite its strengths, this study has several limitations that should be acknowledged. The cross-sectional design precludes causal inference and limits conclusions regarding the temporal dynamics of resilience development. Reliance on self-report measures may introduce reporting biases,

including social desirability and recall bias. Additionally, although the sample captured socioeconomic and educational diversity, the findings may not generalize to out-of-school youth or those living in rural regions not represented in the study. Finally, while machine learning models offer strong predictive performance, their results remain dependent on the quality and scope of input variables, and unmeasured factors such as biological markers or longitudinal stress trajectories were not included.

Future research should prioritize longitudinal designs to examine how resilience profiles and protective factors evolve over time and in response to changing stress conditions. Integrating biological, behavioral, and digital data streams may further enhance predictive accuracy and theoretical insight. Comparative studies across cultural and national contexts would help clarify the generalizability of identified resilience patterns and the contextual specificity of key protective factors. Additionally, future work should continue to advance explainable machine learning methods to strengthen interpretability and facilitate translation into practice and policy.

From a practical perspective, the findings underscore the importance of strengthening family support systems and emotion regulation capacities in youth-focused interventions. Schools, community organizations, and mental health services should prioritize programs that enhance relational security, emotional skills, and self-efficacy, particularly for youth exposed to high levels of cumulative stress. Digital and school-based resilience programs may offer scalable and accessible avenues for intervention, while policy initiatives should address structural stressors such as economic insecurity and educational inequality to create environments that support resilient development.

Acknowledgments

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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