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The Impact of Childhood Trauma on Adolescent Resilience: An Explainable Machine Learning Analysis of Protective Factors in Low-Socioeconomic Contexts

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ABSTRACT

Objective: This study aims to utilize an explainable machine learning framework to identify and rank the critical protective factors that buffer against the deleterious effects of specific childhood trauma subtypes on adolescent resilience within low-socioeconomic Iraqi contexts.

Methods and Materials: A cross-sectional design was employed with a sample of 642adolescents (mean age = 15.34years; 52.3%female) from low-socioeconomic districts in Iraq. Data were collected using culturally adapted and validated instruments, including the Childhood Trauma Questionnaire-Short Form (CTQ-SF), the Connor-Davidson Resilience Scale (CD-RISC), and the Resilience Scale for Adolescents (READ). To analyze the complex, non-linear relationships between variables, an eXtreme Gradient Boosting (XGBoost) machine learning model was developed. The model's interpretability was enhanced using SHapley Additive exPlanations (SHAP) to calculate the global predictive importance and interaction effects of specific risk and protective factors.

Findings: The XGBoost model demonstrated robust predictive performance, explaining a significant portion of the variance in adolescent resilience ($R^2 = 0.68$, $RMSE = 8.35$). SHAP value analysis revealed that Family Cohesion emerged as the paramount protective factor (SHAP = 4.85), while Emotional Abuse (SHAP = 4.12) and Emotional Neglect (SHAP = 3.58) were identified as the most detrimental risk factors, surpassing physical and sexual abuse in predictive weight. Furthermore, a critical non-linear threshold effect was discovered: the protective utility of peer support increased significantly only when emotional neglect scores were below a specific clinical threshold (CTQ-SF <12).

Conclusion: Explainable machine learning provides granular insights into trauma recovery, highlighting that emotional maltreatment profoundly damages adolescent adaptation. Interventions in low-resource settings must prioritize systemic family-based therapies to foster cohesion and adopt a phased clinical approach that addresses foundational emotional neglect before introducing peer-based support systems.

Keywords: *Childhood Trauma; Adolescent Resilience; Machine Learning; XGBoost; SHAP; Low-Socioeconomic Status.*

1. Introduction

Childhood trauma represents one of the most pervasive and detrimental public health challenges globally, exerting a profound and lasting influence on human development. The exposure to adverse childhood experiences (ACEs)—ranging from physical, emotional, and sexual abuse to profound neglect—initiates a cascade of psychological and physiological dysregulations that can persist well into adulthood. Recent research has increasingly focused on the psychosomatic and long-term consequences of these early experiences, establishing that the scars of early adversity are not merely psychological but are deeply embedded in the biological and behavioral fabric of the survivor (Saadati et al., 2024). The gravity of this issue is underscored by findings linking lifetime trauma exposure not only to psychiatric morbidity but also to all-cause mortality, suggesting that the physiological toll of early stress compromises longevity and physical health through mechanisms involving perceived control and stress reactivity (Elliot et al., 2018). Furthermore, the scope of these consequences is vast, affecting self-rated health and personality dimensions even in middle-aged populations, which highlights the temporal endurance of early wounds (Linnemann et al., 2022).

However, the pathway from childhood adversity to adult psychopathology is rarely linear. Current theoretical frameworks emphasize a transdiagnostic model of risk, positing that childhood trauma disrupts fundamental mechanisms of emotional processing and cognitive control, thereby increasing vulnerability to a wide spectrum of disorders rather than a single specific outcome (McLaughlin et al., 2020). Within this complex landscape, psychological resilience emerges as a critical construct. Resilience is not merely the absence of pathology, but a dynamic developmental process encompassing the ability to adapt positively despite significant adversity. Studies investigating young adults have demonstrated that resilience acts as a vital buffer, moderating the relationship between personality traits, coping styles, and the onset of psychiatric symptoms (Campbell-Sills et al., 2006). This buffering effect is particularly evident in the mediation of depression; for instance, systematic reviews have identified that psychological factors, including resilience, play a pivotal role in determining whether childhood adversity manifests as clinical depression (Zhao et al., 2022). Similarly, in populations such as college students, resilience has been shown to mediate and moderate the effects of childhood trauma on depressive symptoms, suggesting that strengthening these adaptive capacities can sever the link between past abuse and current suffering (Chang et al., 2021).

The interaction between trauma and resilience is further complicated by the environment in which the adolescent develops, particularly the family unit. The intergenerational transmission of trauma is a well-documented phenomenon where the adverse experiences of parents influence their parenting behaviors and the subsequent mental health of their children. Recent qualitative explorations into sibling resilience have illuminated how trauma is transmitted across generations, affecting attachment styles and family dynamics (Nichol et al., 2025). This transmission often occurs through the perpetuation of early maladaptive schemas, where the cognitive structures developed by parents in response to their own trauma are passed down, creating a cycle of vulnerability (Zeynel & Uzer, 2020). Consequently, the resilience of the family unit itself becomes a determinant of individual outcomes. Research among undergraduate nursing students has shown that family resilience works in tandem with individual psychological resilience to mitigate the impact of childhood trauma, emphasizing that intervention strategies must consider the broader familial context (Dong et al., 2020). Furthermore, the role of parental emotional socialization serves as a significant moderator; the way parents teach adolescents to process emotions can either exacerbate or buffer the internalizing problems resulting from early trauma (Liao & Dong-mei, 2023).

The specific manifestations of childhood trauma are diverse and often depend on the interplay between the severity of the abuse and the availability of protective factors. In the realm of mood disorders, the severity of childhood trauma has been directly correlated with lower resilience levels, which in turn predicts a more severe clinical course for patients (Yoon Park et al., 2023). This relationship extends to anxiety disorders, where resilience has been found to moderate the indirect effect of emotion dysregulation, serving as a protective shield for adults with a history of childhood adversity (Poole et al., 2017). Beyond mood and anxiety, the impact of trauma penetrates deep into somatic and behavioral domains. For example, in patients with fibromyalgia, childhood trauma is a significant predictor of disease severity, a relationship that is partially mediated by deficits in psychological resilience (Kizilkurt et al., 2021). Similarly, in populations suffering from adjustment disorders, traumatic experiences are closely

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linked to alexithymia—the inability to identify and describe emotions—which significantly hampers resilient coping mechanisms (Öksüz & Özcan, 2018).

The behavioral consequences of unmitigated trauma are equally alarming, particularly regarding substance use and high-risk behaviors. Adolescents exposed to disasters and subsequent trauma are at heightened risk for substance use disorders, yet this risk is modifiable through the strengthening of resilience and the reduction of posttraumatic stress symptoms (Fuchs et al., 2021). In more severe clinical populations, such as individuals with established substance use issues, low resilience combined with high emotional regulation difficulty creates a potent risk profile for relapse and chronic addiction (Amini, 2023). Further research in this domain substantiates that the prediction of resiliency in substance-using individuals is fundamentally tied to their history of childhood trauma and current psychological distress, necessitating targeted interventions that address these root causes (Amini, 2023).

Moreover, the cognitive distortions resulting from childhood trauma can lead to profound psychiatric disturbances. In young adults, the relationship between childhood trauma and psychotic-like experiences is mediated by cognitive biases and depressive symptoms, with resilience acting as a crucial filter that can prevent the transition to psychosis (Mętel et al., 2020). These distortions also affect social and forensic outcomes. In forensic mental health populations, a strong correlation exists between adverse childhood experiences, insecure attachment, and psychological distress, painting a picture of trauma as a precursor to legal and social deviance (Finch et al., 2024). This is mirrored in studies of adult crime victims, where the severity of post-traumatic stress disorder (PTSD) is exacerbated by a history of childhood abuse, mediated by dysfunctional coping strategies and compromised resilience (Kim et al., 2021). Interestingly, the cognitive impact of trauma is not universally negative in all dimensions; some research suggests a link between childhood trauma and “malevolent creativity”—the use of creativity for harmful ends—which is moderated by aggression and resilience, highlighting the complex and sometimes paradoxical adaptations to early adversity (Li et al., 2022).

Given the ubiquity of these adverse outcomes, the importance of protective factors extends beyond the family to the broader community and professional environments. For professionals working with children, such as preschool teachers, their own history of childhood trauma and subsequent resilience can influence their pedagogical approach and emotional availability, suggesting that supporting the mental health of caregivers is a vital indirect intervention for children (ÖZaslan et al., 2022). To effectively counteract the widespread effects of early adversity, systematic approaches are required. Implementing trauma-informed care is essential for building resilience, shifting the focus from treating symptoms to understanding the root causes of behavior and fostering environments that promote safety and empowerment (Bartlett & Steber, 2019).

Despite the wealth of literature linking trauma, resilience, and psychopathology, significant methodological and contextual gaps remain. Much of the existing research relies on linear statistical models that may fail to capture the non-linear, interactive nature of protective factors, particularly in non-Western, low-socioeconomic contexts where resources are scarce and stressors are chronic. The interplay between specific types of trauma (e.g., emotional neglect vs. physical abuse) and specific protective factors (e.g., peer support vs. family cohesion) is likely complex and threshold-dependent. Furthermore, meta-analytic evidence suggests that while the associations between trauma, resilience, and depression are robust, there is substantial heterogeneity across studies, indicating the need for more granular, multivariate analyses to understand *how* these factors interact in specific populations (Watters et al., 2021). Traditional regression models often function as “black boxes,” offering limited insight into the relative importance and decision boundaries of different risk and protective factors for individual adolescents.

This study seeks to bridge these gaps by applying explainable machine learning techniques to a dataset of adolescents from low-socioeconomic backgrounds in Iraq. By moving beyond traditional linear analysis, this research aims to uncover the complex, non-linear relationships between childhood trauma subtypes and resilience, isolating the most potent protective factors in resource-constrained environments. This study aims to utilize an explainable machine learning framework to identify and rank the critical protective factors that buffer against the deleterious effects of specific childhood trauma subtypes on adolescent resilience within low-socioeconomic Iraqi contexts.

2. Methods and Materials

2.1. Study Design and Participants

This study employs a cross-sectional, quantitative research design to examine the complex interplay between early life adversity and psychological resilience among adolescents living in resource-constrained environments. The research was conducted in several high-density, low-socioeconomic urban and peri-urban districts across Iraq, specifically targeting regions where families face significant economic instability and limited access to social services. The final sample consisted of 642adolescents, aged between 13and 18years, recruited through a stratified random sampling technique from public secondary schools. To ensure the integrity of the data relative to the study's focus on low-socioeconomic contexts, participants were selected based on household income levels falling below the national poverty line and parental employment status. Ethical approval was obtained from the institutional review boards of the participating academic and governmental bodies, and informed consent was secured from both the legal guardians and the adolescent participants. The recruitment process emphasized confidentiality and the voluntary nature of participation, particularly given the sensitive nature of discussing childhood trauma. Inclusion criteria required participants to have resided in their current low-SES environment for at least five years, while exclusion criteria included the presence of severe neurodevelopmental disorders that might impede the completion of self-report measures.

2.2. Measures

Data collection was facilitated through a battery of validated psychometric instruments, adapted into Arabic using a rigorous forward and back-translation process to ensure linguistic and cultural equivalence. Childhood trauma was assessed using the Childhood Trauma Questionnaire-Short Form (CTQ-SF), a 28-item instrument that measures five distinct types of maltreatment: emotional abuse, physical abuse, sexual abuse, emotional neglect, and physical neglect. Participants responded to items on a five-point Likert scale, where higher scores indicated a greater frequency of traumatic experiences. Adolescent resilience was measured via the 25-item Connor-Davidson Resilience Scale (CD-RISC), which evaluates the ability to thrive in the face of adversity through domains such as personal competence, trust in one's instincts, and positive acceptance of change. To identify protective factors, the study utilized the Resilience Scale for Adolescents (READ), focusing specifically on subscales related to family cohesion, peer support, and institutional school support. Socioeconomic status was further verified using a demographic questionnaire that captured parental education levels, household size, and subjective financial security. The internal consistency for all scales in the current Iraqi sample was robust, with Cronbach's alpha coefficients ranging from $\alpha = 0.79$to $\alpha = 0.91$, indicating high reliability across the measured constructs.

2.3. Data Analysis

The data analysis strategy integrated traditional frequentist statistics with advanced explainable machine learning (XAI) techniques to provide both predictive power and clinical interpretability. Initially, descriptive statistics and correlation analyses were performed to map the baseline relationships between trauma scores and resilience levels. Subsequently, the primary analysis utilized an eXtreme Gradient Boosting (XGBoost) algorithm to model the impact of trauma subtypes and protective factors on the variance of adolescent resilience. The dataset was partitioned into a training set (80%) and a testing set (20%) to validate the model's predictive accuracy. To move beyond the "black box" nature of standard machine learning, SHapley Additive exPlanations (SHAP) values were calculated to determine the global and local importance of each feature. This XAI approach allowed for the identification of which specific protective factors—such as family cohesion or school support—exerted the strongest influence in mitigating the negative effects of high CTQ scores. All mathematical modeling and feature importance visualizations were executed using the Python programming language, specifically utilizing the Scikit-learn, XGBoost, and SHAP libraries, with statistical significance for the preliminary tests set at $p < .05$. This dual-methodological framework ensured that the findings were not only statistically rigorous but also offered granular insights into which variables served as the most critical levers for intervention in low-socioeconomic Iraqi contexts.

3. Findings and Results

The final analyzed sample consisted of $N =$ 642adolescents from low-socioeconomic districts in Iraq. The mean age of the participants was $M = 15.34$years ($SD = 1.62$), with a relatively balanced gender distribution comprising 52.3%females ($n = 336$) and 47.7%males ($n = 306$). An assessment of the Childhood Trauma Questionnaire-Short Form (CTQ-SF) revealed that emotional neglect and physical neglect were the most frequently reported forms of early adversity in this low-socioeconomic cohort, while sexual abuse was the least reported, though still present. The mean score for overall adolescent resilience, measured by the Connor-Davidson Resilience Scale (CD-RISC), indicated a moderate level of baseline psychological adaptation ($M = 58.42$, $SD = 14.75$). Detailed descriptive statistics detailing the sample's demographics and the mean scores across all primary psychometric instruments are presented in Table 1.

Table 1

Demographic Characteristics and Descriptive Statistics of the Sample (N=642)

Variable	Category / Measure	$\boldsymbol{n}$(%) or $\boldsymbol{M}(\boldsymbol{SD})$
Age (years)	Continuous	15.34(1.62)
Gender	Female	336(52.3%)
	Male	306(47.7%)
Parental Education	Primary or below	412(64.2%)
	Secondary	185(28.8%)
	Tertiary	45(7.0%)
Childhood Trauma (CTQ-SF)	Emotional Abuse	9.85(3.41)
	Physical Abuse	8.42(3.15)
	Sexual Abuse	6.12(2.05)
	Emotional Neglect	12.54(4.11)
	Physical Neglect	11.30(3.88)
Protective Factors (READ)	Family Cohesion	18.45(5.22)
	Peer Support	16.30(4.85)
	School Support	14.12(4.50)
Resilience (CD-RISC)	Total Score	58.42(14.75)

To explore the linear relationships between the measured constructs, a Pearson product-moment correlation matrix was computed. The correlational analysis revealed significant, inverse relationships between all subtypes of childhood trauma and overall adolescent resilience. Emotional abuse demonstrated the strongest negative correlation with resilience ($r = -0.52, p < .001$), followed closely by emotional neglect ($r = -0.48$, $p < .001$). Conversely, the protective factors measured by the READ scale exhibited robust positive correlations with the CD-RISC scores. Family cohesion emerged as the strongest linear correlate of resilience ($r = +0.56$, $p < .001$), underscoring the critical role of familial bonds in low-resource environments. Peer support and school support also showed significant positive associations with resilience ($r = +0.41$, $p < .001$and $r = +0.35$, $p < .001$, respectively). Interestingly, family cohesion was significantly negatively correlated with both emotional neglect ($r = -0.45$, $p < .001$) and physical neglect ($r = -0.39$, $p < .001$), suggesting that cohesive family units naturally buffer against neglectful environments. These bivariate relationships provided the foundational justification for integrating these variables into the subsequent machine learning pipeline. The complete correlation matrix is detailed in Table 2.

Table 2

Bivariate Correlations Between Childhood Trauma Subtypes, Protective Factors, and Resilience

Variable	1	2	3	4	5	6	7	8	9
1. Emotional Abuse	–								
2. Physical Abuse	0.45^{**}	–							
3. Sexual Abuse	0.28^{**}	0.35^{**}	–						
4. Emotional Neglect	0.51^{**}	0.31^{**}	0.18^{*}	–					
5. Physical Neglect	0.42^{**}	0.48^{**}	0.22^{**}	0.55^{**}	–				
6. Family Cohesion	-0.38^{**}	-0.29^{**}	-0.15^{*}	-0.45^{**}	-0.39^{**}	–			
7. Peer Support	-0.22^{**}	-0.18^{*}	-0.09	-0.25^{**}	-0.20^{**}	0.34^{**}	–		
8. School Support	-0.31^{**}	-0.25^{**}	-0.12^{*}	-0.30^{**}	-0.28^{**}	0.41^{**}	0.38^{**}	–	
9. Resilience	-0.52^{**}	-0.38^{**}	-0.25^{**}	-0.48^{**}	-0.41^{**}	0.56^{**}			

Following the correlational analysis, the dataset was subjected to the XGBoost machine learning algorithm to predict adolescent resilience scores based on demographic data, trauma subtypes, and protective factors. The model was trained on 80%of the data ($n = 513$) and evaluated on a held-out testing set of 20%($n = 129$). Hyperparameter tuning was conducted using grid search with five-fold cross-validation to prevent overfitting. The optimized model demonstrated excellent predictive capacity, accounting for a substantial proportion of the variance in adolescent resilience within the testing set. Specifically, the model achieved a Coefficient of Determination (R^2) of 0.68on the testing data, indicating that 68%of the variance in resilience can be explained by the included features. The Root Mean Square Error (RMSE) was 8.35, and the Mean Absolute Error (MAE) was 6.42. The minimal degradation in performance metrics between the training and testing sets confirms the model's generalizability to unseen data within similar demographic contexts. The performance metrics of the XGBoost model are summarized in Table 3.

Table 3

XGBoost Model Performance Metrics for Predicting Adolescent Resilience

Metric	Training Set ($\boldsymbol{n} = \mathbf{513}$)	Testing Set ($\boldsymbol{n} = \mathbf{129}$)
$\boldsymbol{R^2}$(Coefficient of Determination)	0.74	0.68
RMSE (Root Mean Square Error)	7.52	8.35
MAE (Mean Absolute Error)	5.81	6.42

To unpack the non-linear dynamics and feature contributions of the XGBoost model, SHapley Additive exPlanations (SHAP) values were computed. This explainable AI framework permitted the ranking of features by their global predictive importance, as well as an analysis of their directional impact on resilience. As illustrated in Table 4, Family Cohesion emerged as the most critical feature overall, yielding the highest mean absolute SHAP value (+4.85), indicating its paramount importance in driving model predictions. High levels of family cohesion consistently pushed the model's prediction of resilience higher. Emotional Abuse was identified as the most detrimental risk factor, ranking second in overall feature importance (SHAP = 4.12), where higher values of emotional abuse severely reduced predicted resilience. Interestingly, SHAP dependence plots (data reported in text) revealed complex threshold effects; for instance, the protective effect of Peer Support (SHAP = 2.75) increased exponentially only when Emotional Neglect was below a specific threshold (CTQ-SF score <12), suggesting that severe emotional neglect limits an adolescent's capacity to utilize peer networks effectively. School Support (SHAP = 2.10) acted as an independent protective factor, elevating resilience scores regardless of trauma severity, albeit with a smaller overall magnitude than familial support. Demographic variables such as age and parental education exhibited minimal predictive power, suggesting that the psychological variables (trauma and protective factors) are the primary determinants of resilience in this low-SES population.

Table 4

SHAP Feature Importance and Directionality for Predicting Resilience

Rank	Feature	Mean Absolute SHAP Value	Impact of High Feature Value on Resilience Prediction
1	Family Cohesion	4.85	Strong Positive (Increases Resilience)
2	Emotional Abuse	4.12	Strong Negative (Decreases Resilience)
3	Emotional Neglect	3.58	Strong Negative (Decreases Resilience)
4	Peer Support	2.75	Moderate Positive (Increases Resilience)
5	Physical Neglect	2.40	Moderate Negative (Decreases Resilience)
6	School Support	2.10	Moderate Positive (Increases Resilience)
7	Physical Abuse	1.95	Moderate Negative (Decreases Resilience)
8	Sexual Abuse	1.15	Weak Negative (Decreases Resilience)
9	Age	0.45	Neutral / Variable
10	Parental Education	0.32	Neutral / Variable

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4. Discussion

The present study aimed to elucidate the complex, non-linear relationships between childhood trauma subtypes and adolescent resilience within resource-constrained, low-socioeconomic contexts in Iraq, utilizing an advanced explainable machine learning framework. By deploying an eXtreme Gradient Boosting (XGBoost) algorithm augmented with SHapley Additive exPlanations (SHAP), this research moved beyond traditional correlational analyses to rank the global predictive importance of specific risk and protective factors. The primary results demonstrated that the machine learning model possessed substantial predictive power, explaining 68%of the variance in adolescent resilience ($R^2 = 0.68$). Crucially, the findings revealed that family cohesion was the most potent protective factor, while emotional abuse and emotional neglect emerged as the most detrimental risk factors undermining psychological adaptation. Furthermore, the explainable artificial intelligence approach uncovered a critical threshold effect, indicating that the protective utility of peer support is significantly compromised when an adolescent experiences severe emotional neglect. These results provide a highly granular understanding of how early life adversity interacts with socio-environmental buffers in vulnerable populations.

The profound negative impact of emotional abuse and emotional neglect on adolescent resilience, as identified by their high SHAP values (4.12 and 3.58, respectively) and strong inverse correlations ($r = -0.52$ and $r = -0.48$), aligns robustly with contemporary developmental psychopathology literature. While physical and sexual abuse are frequently the focus of clinical intervention due to their overt nature, the insidious and pervasive effects of emotional maltreatment profoundly disrupt the foundational architecture of resilience. This reflects the theoretical consensus that emotional trauma fundamentally alters emotional processing and cognitive control mechanisms, establishing a transdiagnostic vulnerability to future psychopathology (McLaughlin et al., 2020). Furthermore, the severity of such early childhood adversity is consistently linked to compromised psychological resilience, which in turn acts as a mediator for severe long-term outcomes, including depression and psychosomatic distress (Saadati et al., 2024; Zhao et al., 2022). The prominent role of emotional neglect in our model also corroborates findings in adult populations where early trauma predicts disease severity and somatic complaints, mediated heavily by a lack of resilient coping capacities (Kizilkurt et al., 2021). The fact that emotional abuse and neglect outweighed physical abuse in predictive importance suggests that the psychological dimensions of maltreatment—specifically those that invalidate the child's self-worth and emotional reality—are most destructive to the formulation of an adaptive, resilient self-concept (Yoon Park et al., 2023).

Conversely, the emergence of family cohesion as the paramount protective factor—yielding the highest overall mean absolute SHAP value (+4.85) and the strongest positive linear correlation with resilience ($r = +0.56$)—highlights the irreplaceable role of the primary caregiving environment, even within contexts marked by severe socioeconomic deprivation. This finding strongly supports the notion that the familial unit acts as the primary crucible for resilience generation. When the family environment is cohesive, it inherently buffers against the systemic stressors associated with poverty and external trauma. This aligns with research demonstrating that family resilience operates synergistically with individual psychological resilience to mitigate the sequelae of childhood trauma (Dong et al., 2020). Furthermore, cohesive families are more likely to engage in positive parental emotional socialization, which has been shown to moderate the internalizing problems resulting from childhood trauma, effectively teaching adolescents how to process and adapt to adverse experiences (Liao & Dong-mei, 2023). The critical nature of family dynamics is also echoed in qualitative studies emphasizing how adverse family experiences and the intergenerational transmission of trauma dictate the psychological trajectory of offspring, pointing to the family as both the primary source of risk and the greatest potential source of healing (Nichol et al., 2025).

One of the most compelling insights generated by the SHAP dependence analysis was the non-linear threshold effect regarding peer support. The model revealed that while peer support generally enhanced resilience (SHAP = 2.75), its protective efficacy increased exponentially only when emotional neglect scores were below a specific clinical threshold (CTQ-SF score <12). This suggests a complex psychological phenomenon wherein severe emotional neglect fundamentally impairs an adolescent's capacity to form, trust, or utilize external social support networks. This finding is deeply resonant with attachment theory and cognitive-behavioral models of trauma, which posit that early profound neglect fosters early maladaptive schemas—deeply ingrained beliefs about the unreliability and unavailability of others (Zeynel & Uzer, 2020). If an adolescent's primary caregivers are emotionally absent, the

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resulting cognitive biases may prevent the adolescent from perceiving or accepting support from peers, effectively neutralizing a vital community-level protective factor (Mętel et al., 2020). This threshold effect highlights why simplistic, linear models often fail to capture the reality of trauma recovery; the presence of a protective factor is not enough if the internal psychological architecture to utilize it has been destroyed by specific forms of neglect (Chang et al., 2021; Kim et al., 2021).

The secondary protective role of institutional support, specifically school support (SHAP = 2.10), further underscores the necessity of multi-systemic buffers. While less potent than family cohesion, school support provided a consistent positive upward pressure on resilience scores across varying levels of trauma severity. This finding validates the growing emphasis on trauma-informed educational environments.

5. Conclusion

For adolescents living in low-socioeconomic areas where family systems might be fractured by economic stress, the school represents the next logical safety net. Implementing trauma-informed care within these institutions is essential not only for academic success but for fundamental psychological survival (Bartlett & Steber, 2019). Furthermore, the mental health and resilience of the educators themselves play a crucial role in creating this supportive environment, as teachers with their own unresolved trauma histories may struggle to provide the emotional scaffolding required by traumatized students (ÖZaslan et al., 2022). The cumulative evidence from our machine learning model, contextualized within the broader literature, confirms that addressing childhood trauma requires a nuanced understanding of exactly which protective levers to pull, acknowledging the profound heterogeneity and multivariate nature of trauma responses (Finch et al., 2024; Watters et al., 2021).

6. Limitations & Suggestions

Despite the methodological rigor introduced by the explainable machine learning approach, several limitations must be acknowledged when interpreting the findings of this study. Primarily, the cross-sectional nature of the research design precludes the establishment of definitive causal relationships between childhood trauma, protective factors, and adolescent resilience. While the XGBoost model demonstrates high predictive accuracy, longitudinal data are required to map the temporal dynamics of how resilience fluctuates over time in response to ongoing adversity or intervention. Secondly, the reliance on retrospective self-report measures for assessing childhood trauma introduces the potential for recall bias and social desirability effects. Adolescents may underreport severe abuse due to stigma or fear of familial repercussions, or conversely, current psychological distress may negatively skew their recollection of early childhood events. Additionally, the sample was exclusively drawn from specific low-socioeconomic urban and peri-urban districts in Iraq. While this provides highly targeted insights for this demographic, it inherently limits the generalizability of the findings to adolescents in high-income contexts, rural areas, or different cultural backgrounds where the structural conceptualization of family and community support might differ significantly. Finally, while the model included key social and demographic variables, it did not account for potential biological or genetic markers of stress reactivity, which are known to interact with environmental trauma to shape resilience profiles.

To build upon the findings of this study, future research should prioritize longitudinal, multi-wave study designs that can track the developmental trajectory of resilience from early childhood through late adolescence. Such studies would allow researchers to pinpoint the exact developmental windows during which specific protective factors, such as peer support or school affiliation, are most effective at buffering against trauma. Furthermore, future investigations should aim to integrate subjective psychological self-reports with objective physiological and neurobiological markers of stress, such as cortisol reactivity, heart rate variability, or neuroimaging data. This biopsychosocial approach would provide a more holistic understanding of how trauma becomes biologically embedded and how resilience manifests at a physiological level. There is also a pressing need to apply these explainable machine learning frameworks to diverse, cross-cultural datasets. Comparing feature importance and threshold effects between low-income and high-income countries could isolate universal mechanisms of resilience versus context-specific adaptations. Finally, future studies should move beyond individual-level factors to include macro-systemic variables in their predictive models, such as neighborhood violence, community infrastructure, and access to psychiatric care, to fully capture the ecological landscape of adolescent development in adverse environments.

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The insights derived from this explainable machine learning analysis offer highly specific, actionable directives for clinical practice and community intervention in low-socioeconomic settings. Because family cohesion emerged as the most critical protective factor, interventions must pivot away from solely child-centric therapies to systemic, family-based approaches. Programs designed to enhance parental emotional regulation, improve family communication, and alleviate parental stress are likely to yield the highest dividends in boosting adolescent resilience. Furthermore, the discovery that severe emotional neglect neutralizes the benefits of peer support dictates a phased approach to clinical treatment. Practitioners must first work to address the profound attachment wounds and cognitive schemas associated with neglect—helping the adolescent build basic relational trust—before pushing them into group therapy or peer-mentoring programs. If the foundational emotional neglect is not addressed, peer-based interventions may fail or even exacerbate feelings of alienation. Finally, the consistent, independent protective value of school support mandates the widespread adoption of trauma-informed practices within educational systems. Schools in low-resource areas must be funded and equipped not just as centers of academic learning, but as primary hubs for psychological safety, requiring extensive training for educators to recognize trauma responses and foster environments that actively build resilience rather than inadvertently re-traumatizing vulnerable youth.

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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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