

Utilizing Machine Learning to Predict Protective Factors for Childhood Exposure to Violence

Iris Chen

chenmiaoyan2009@gmail.com

ABSTRACT

Childhood exposure to violence is defined as the victimization or witnessing of violence by a child under 18 years of age, and affects over 60% of children in the United States. Though children exposed to violence consistently display more negative behaviors and outcomes, research has identified certain protective factors that mitigate negative effects and increase the likelihood of resilience. This study aims to investigate the relationship between various protective factors (family support, community support, community involvement, mentorship) and violence-impacted outcomes (behavior, self-motivation, academic performance, and emotional and developmental well-being) in a nationally representative population of children with exposure to violence. Utilizing data from the National Survey of Children's Health, we examined the significance and relationship directionality of all four key protective factors in each outcome. Results were compared across three predictive models – logistic regression, decision tree, and Random Forest – revealing no substantive differences between the odds ratios and the feature importances of the non-parametric models. Family support emerged as the strongest predictor of positive outcomes across all three algorithms, with community involvement also demonstrating consistent importance. Additionally, factors such as bullying victimization and overall health status were identified as highly significant, despite not being included in the original set of key independent variables. Findings suggest that family-centered support and community engagement are particularly effective in buffering negative consequences of childhood exposure to violence. These results shed light on the importance of interventions that prioritize family-based programming, anti-bullying initiatives, and structured extracurricular opportunities to strengthen resilience and improve outcomes.

INTRODUCTION

Childhood exposure to violence is defined as the victimization or witnessing of violence by a child under 18 years of age. In a nationally representative survey of the United States, over 60% of children experienced some kind of violence exposure either in their home or in their community (Finkelhor et al., 2009). Empirical research has consistently found associations between early experiences of violence and adverse academic outcomes, including lower grades, poor school attendance, suspension or expulsion, and delays in developmental and academic milestones (Artz et al., 2018). Furthermore, children who

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experience or witness violence are at higher risk for developing internalization psychopathologies – such as depression and anxiety – as well as externalization problems, including aggressive behavior and poor social skills (Doroudchi et al., 2023; Chen, 2024; Mitchell et al., 2019). Yet, some studies have found that some children display a certain level of resilience and aren't impacted as strongly by the negative effects (Yoon et al., 2020).

Given the high prevalence and wide-ranging consequences of childhood exposure to violence, it is critical to identify the protective factors that can improve outcomes for affected children. Higher levels of family and community support and the presence of a parental figure have all been associated with improved mental health and emotional resilience, as well as the development of healthy coping mechanisms in children with adverse childhood experiences (Jain et al., 2011; Tonsing, 2025). Higher scores for protective factors like neighborhood safety and family relationship quality predicted higher motivation and effort in school (Robles et al., 2019). In a study examining protective factors of child maltreatment, involvement in extracurriculars and community events have also been found to be generally predictive of better academic outcomes, lower levels of depression, and increased self-motivation (Jean-Thorn et al., 2022). Factors like family support, community support, religious involvement, and child self-regulation have been identified in previous systematic reviews to be associated with resilience after childhood adversity (Abate et al., 2024). However, there is a lack of literature comparing the effectiveness of different protective factors across multiple different outcomes. Most research has been centered on individual-level modifiers and mental health, and there's a need for more investigation into how family- and community-level factors affect outcomes like academic performance and risky behaviors (Valrie et al., 2024). Additionally, studies are often conducted with restricted samples with specific experiences like child abuse or maltreatment, and not enough research studies have been broadened to include children with exposure to community-level violence or general violence (Valrie et al., 2024).

Bronfenbrenner's ecological systems theory provides a useful framework for understanding these dynamics, as it emphasizes that child development is shaped by multiple, interacting layers of context – from the microsystem of family and school to broader community structures, cultural norms, and societal policies (Bronfenbrenner, 1977; Bronfenbrenner, 1993). Applying this perspective highlights the importance of examining protective factors across multiple ecological levels, rather than focusing solely on individual traits or family dynamics. The multi-level approach can help explain how protective factors at the individual, family, community, and societal levels interact to influence resilience in children exposed to violence (Sabri et al., 2013).

As a result, more research is required to study how multiple different levels of protective factors impact children with exposure to all kinds of violence, and how the significance of each factor's positive influence changes between different outcomes.

STATEMENT OF PURPOSE/HYPOTHESIS

The purpose of our research was to explore how protective factors like family support, community support, community involvement, and the presence of a mentor affected academic performance, emotional and developmental well-being, self-motivation, and behavior in children exposed to violence. We aimed to identify the most effective protective factor for each outcome, and compare the results across different statistical and machine learning models. We hypothesized that family support will be the most significant protective factor for better academic performance, better behavioral outcomes, higher rates of emotional and developmental well-being, and higher self-motivation. We also expected that family support will remain the strongest predictor across all different models.

MATERIALS AND METHODS

This study analyzed data from the 2023 National Survey of Children's Health (NSCH), a nationally representative, address-based public dataset conducted by the U.S. Census Bureau in collaboration with the Maternal and Child Health Bureau of the Health Resources and Service Administration from June 23, 2023 to January 19, 2024 (U.S. Census Bureau, 2025). All data used for analysis was de-identified by those with necessary approval for this study, and only the participant's answers in the survey were shared with us.

The study was parent/caregiver-reported and had two phases: the screener questionnaire and the topical questionnaire. The sample for our research was taken from the population (n 55,162) of participants that completed both questionnaires. For the purposes of our research, we only studied data from children who were victims or witnesses to violence, had valid school grades, and were between the ages of 12 and 17. To ensure consistency and completeness in the modeling dataset, rows containing missing values in the key independent and dependent variables were removed. We utilized a listwise deletion approach, only retaining cases with complete sets of data across the variables necessary for analysis. After narrowing the sample based on the eligibility criteria and removing rows with missing values, the final analytic sample size was 1,754.

Each dependent variable was defined categorically: a scale of 1 (mostly D's or lower) to 5 (mostly A's) for academic performance, a binary scale of 1 to 2 for emotional and developmental well-being (defined by emotional or developmental problems), a scale of 0 to 3 for self-motivation (defined by interest in learning, completion of tasks, and calmness when facing challenges), and a scale of 0 to 3 for behavioral problems (defined by difficulty in making friends, bullying others, and school contacting the household about problems concerning the child). Each key independent variable was also defined categorically: a scale of 0 (absence of an extrafamilial adult to rely on) to 1 (presence of an extrafamilial adult to rely on) for the presence of a mentor, a scale of 0 to 5 for community involvement (defined by participation in clubs, sports teams, religious activities, volunteer activities, and other organized activities), a scale of 0 to 5 for community support (defined by the extent to which people in the neighborhood help each other and

watch out for each other's children, the level of safety in the neighborhood, the level of safety at school, and the knowledge of where to go for help in the community), and a scale of 0 to 3 for family support (defined by how often the family ate meals together, how often family members attended the child's events, and how well the child could share ideas and talk with the family). Higher numbers on the scale indicate greater levels of support and involvement for community involvement, community support, and family support. Control variables included demographics, socioeconomic status, bullying victimization, family structure, and parental level of education. The variables *white* and *less_than_highschool* (lowest level of parental education) served as reference variables, and were dropped to avoid collinearity in regression models.

The data was analyzed using Python code, with $P < 0.05$ considered as statistically significant. For each dependent variable, we utilized three different models and compared results across all three. To ensure that our methods encompassed all the different complex interactions between the protective factors and the outcome variables, we used an ordinal logistic regression as our traditional statistical model and a baseline for interpreting results, a decision tree model as our non-parametric algorithm that could adapt to capture more complex relationships between variables, and a Random Forest model as a more robust algorithm that could enhance accuracy and reduce overfitting (Sesay et al., 2021; Singh et al., 2024; He et al., 2018). The three machine learning models were fitted to each of the four dependent variables, and we performed Monte Carlo cross-validations to guarantee that representation is balanced across different categories. The algorithms were compared using prediction accuracy as the evaluation metric.

Model parameters within the ordinal logistic regression were estimated using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization algorithm (Zhao, 2021). We then calculated the odds ratios and 95% confidence intervals to facilitate interpretation of predictor effects and assess statistical significance. Decision tree models were trained across a range of tree depths, and the optimal depth was selected based on highest average accuracy and lowest mean absolute error (MAE). Random Forest models were trained across the same depth range, and were selected based on the same criteria. Each forest comprised 100 decision trees. Feature importances from decision trees and Random Forest were computed and extracted to serve as points of comparison for the results of the ordinal logistic regression.

RESULTS

Table 1. Descriptive Statistics of Key Variables (Sample Size 1754)

Variable	Mean	Median	SD
Age of Selected Child (years)	15	15	1.7
Family Poverty Ratio	231	221	126
Number of Adverse Childhood Experiences for Child	2.82	3	1.7
Child's Participation in Community Service or Activities (0-5)	2.00	2	1.5
Community Safety and Support(0-5)	4.04	5	1.3
	Category	Frequency	Percent (%)
Grades Received in School	Mostly A's	324	19.49
	Mostly A's and B's	581	34.96
	Mostly B's and C's	448	26.96
	Mostly C's and D's	209	12.58
	Mostly D's or lower	100	6.02
Family Support	None or Low	134	7.64
	Medium	1246	71.04
	High	374	21.32
Be Bullied	Missing	19	1.08
	Yes	1023	58.96
	No	712	41.04
Sex of Selected Child	Male	875	49.89
	Female	879	50.11
Race of Selected Child	White	1003	57.18
	Black	162	9.24
	Hispanic	347	19.78
	Other	242	13.80
Highest Adult Education Level	< High School	66	3.76
	High School	388	22.12
	Some College	565	32.21
	College or Higher	735	41.9
General Health of Selected Child	Missing	4	0.23
	Poor	7	0.4
	Fair	72	4.11
	Good	327	18.69
	Very Good	625	35.71
	Excellent	719	41.09
Family Structure	Missing	14	0.77
	Two parents, currently married	662	38.05
	Two parents, not currently married	135	7.76
	Single Parent	673	38.68
	Other Relation	270	15.52

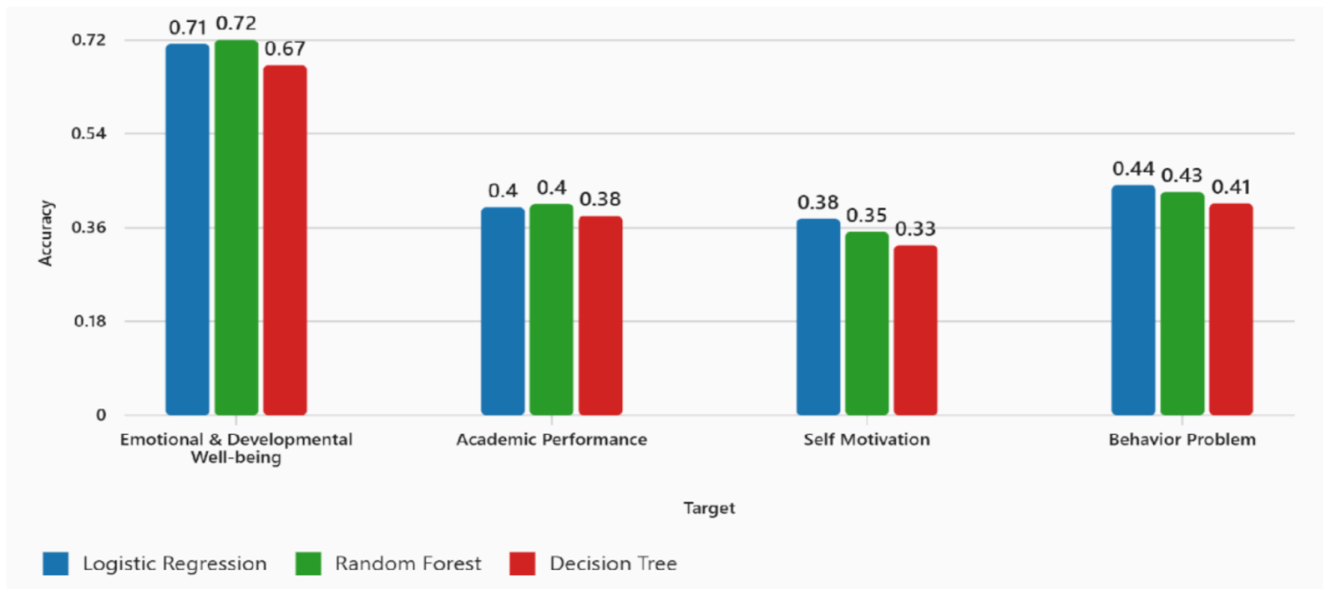


Figure 1. Prediction Accuracies Across Logistic Regressions, Random Forests, and Decision Trees

Table 2. Performance Across Models and Key Variables

	Model Feature	Family Support	Child's Community Involvement	Adverse Childhood Experience	Health Status	Has Been Bullied
Academic Performance	Odds Ratio (Ordinal Logistic)	1.62	1.38	0.88	1.17	0.53
	Random Forest Importance	0.08	0.16	0.13	0.08	0.05
	Decision Tree Importance	0.11	0.20	0.16	0.10	0.04
Self Motivation	Odds Ratio (Ordinal Logistic)	2.59	1.36	0.82	1.42	0.54
	Random Forest Importance	0.15	0.15	0.13	0.12	0.07
	Decision Tree Importance	0.36	0.12	0.09	0.18	0.06
Behavior Problem	Odds Ratio (Ordinal Logistic)	0.56	0.82	1.22	0.70	5.81
	Random Forest Importance	0.08	0.09	0.11	0.11	0.29
	Decision Tree Importance	0.11	0.03	0.12	0.12	0.46
Emotional and Developmental Problem	Odds Ratio (Logistic)	0.57	0.87	1.39	0.64	2.57
	Random Forest Importance	0.08	0.06	0.24	0.19	0.21

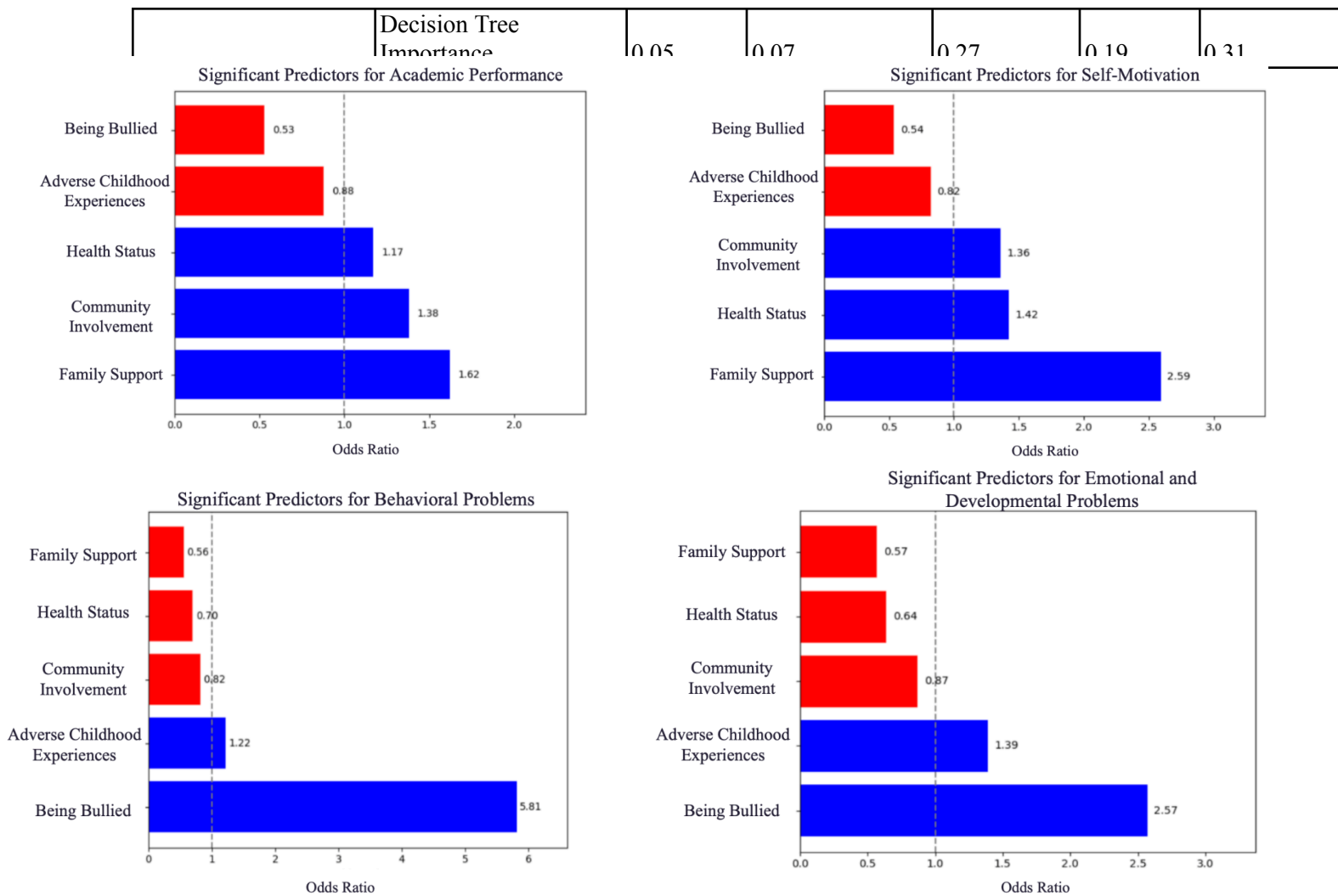


Figure 2. Significant Predictors for Key Dependent Variables

Model performance varied across the four dependent variables, and ensemble methods typically outperformed single-decision tree models (see Figure 1). When examining the results, we chose to focus on the logistic regressions. There were no significant performance differences between logistic regressions and the other two models (see Table 2), and the purpose of our study was to examine the direction of the relationships between our independent and dependent variables. The interpretability of the logistic regression made it more relevant and effective than decision tree and Random Forest towards our research topic, and as a result, we were able to better evaluate the level of impact each factor had on the outcome. Community support and the presence of a mentor weren't found to be significant in any of the models ($P > 0.05$), and subsequently didn't produce any significant results.

Academic Performance

All three models demonstrated some level of difficulty predicting academic performance outcomes, with accuracies ranging from 0.38 to 0.40 (see Figure 1). The Random Forest with an optimal depth of 6 achieved a slightly higher accuracy (0.40). The performance of the decision tree model with an optimal depth of 5 was comparable to the Random Forest (Accuracy = 0.38).

Family support was consistently ranked as the most influential predictor across all models, with an odds ratio of 1.62 in the logistic regression ($\beta = 0.49$, OR = 1.62, 95% CI [1.31, 2.01], $p < 0.001$). While decision tree models ranked family support as the most significant factor (importance = 0.108), the Random Forest importance scores identified both family support (importance = 0.076) and community involvement (importance = 0.161) as strong predictors. Community involvement was also shown to contribute positively to academic outcomes in the logistic regression ($\beta = 0.32$, OR = 1.38, 95% CI [1.12, 1.71], $p < 0.01$) (see Table 2). Other non-key variables like bullying were shown to be negatively associated with academic performance ($\beta = -0.64$, OR = 0.53, 95% CI [0.41, 0.69], $p < 0.001$), while demographic factors like sex and race also predicted lower grades (see Figure 2).

Behavioral Problems

The ordinal logistic regression achieved the best overall performance accuracy (Accuracy = 0.44), making it the most stable classifier for this domain. Random Forest models with an optimal depth of 6 performed less effectively (Accuracy = 0.43), while the decision tree models with an optimal depth of 5 performed the worst (Accuracy = 0.41) (see Figure 1).

Logistic regression results indicated that children who reported being bullied were more likely to experience social and behavioral difficulties ($\beta = 1.76$, OR = 5.81, 95% CI [4.12, 8.20], $p < 0.001$) (see Table 3). This effect size was substantially larger than any other predictor in the model. The results of the Random Forests and decision trees both ranked bully victimization as the most influential factor, with importance scores of 0.29 and 0.46, respectively (see Table 2). Among the key independent variables that were being examined in this study, family support stood out as the most significant protective factor ($\beta = -0.58$, OR = 0.56, 95% CI [0.43, 0.73], $p < 0.001$), with community involvement as a close second ($\beta = -0.20$, OR = 0.82, 95% CI [0.67, 0.99], $p < 0.05$). While community involvement had higher importance scores (importance = 0.09) in the Random Forest than family support (importance = 0.08), the decision tree ranked family support (importance = 0.11) higher than community involvement (importance = 0.03) in terms of significance. Additionally, Random Forest, which was at an optimal depth of 6, ranked ACEs (importance = 0.11) and health status (importance = 0.11) as the second and third most significant predictors. The decision tree gave ACEs (importance = 0.12) and health status (importance = 0.12) similar rankings.

Emotional and Developmental Well-being

The Random Forest model with a depth of five achieved the strongest predictive performance (Accuracy = 0.72), slightly outperforming logistic regression (Accuracy = 0.71). Decision tree models performed less effectively (Accuracy = 0.67) (see Figure 1).

The results from all three models highlighted bullying as the strongest risk factor ($\beta = 0.94$, OR = 2.57, 95% CI [2.01, 3.29], $p < 0.001$), followed by adverse childhood experiences (ACEs; $\beta = 0.33$, OR = 1.39, 95% CI [1.08, 1.79], $p < 0.01$) (see Table 2). Family support was the only key variable that was identified as a significant protective factor ($\beta = -0.56$, OR = 0.57, 95% CI [0.44, 0.74], $p < 0.001$) along with health status ($\beta = -0.45$, OR = 0.64, 95% CI [0.51, 0.81], $p < 0.001$). Family support was also ranked among the top importance factors in the decision tree models (importance = 0.27), while bullying was ranked first (importance = 0.31). Random Forests, however, pinpointed bullying (importance = 0.21) and ACEs (importance = 0.24) as the most significant predictors.

Self-Motivation

Evaluation metrics showed modest predictive performance across models. While the logistic regression models had the highest prediction accuracy (Accuracy = 0.38), the Random Forest models at an optimal depth of 6 (Accuracy = 0.35), achieved similar results to the decision tree models at an optimal depth of 5 (Accuracy = 0.33) (see Figure 1).

Family support was shown to be the strongest predictor for positive self-motivation in the logistic regression ($\beta = 0.95$, OR = 2.59, 95% CI [2.01, 3.34], $p < 0.001$), and was ranked as the most significant feature in both the Random Forest (importance = 0.15) and decision tree (importance = 0.36) (see Table 2). Community involvement contributed modestly but significantly ($\beta = 0.31$, OR = 1.36, 95% CI [1.08, 1.72], $p < 0.01$), and was also ranked fairly high within the Random Forest (importance = 0.15) and the decision tree (importance = 0.12). Other factors like health status ($\beta = 0.35$, OR = 1.42, 95% CI [1.12, 1.79], $p < 0.01$) were positively associated with self-motivation, while factors like bullying victimization ($\beta = -0.61$, OR = 0.54, 95% CI [0.42, 0.70], $p < 0.001$) and lower parental education ($\beta = -0.55$, OR = 0.58, 95% CI [0.44, 0.76], $p < 0.001$) reduced flourishing.

DISCUSSION

This study examined the relative importance of multiple protective factors – including family support, community support, community involvement, and presence of a mentor – in predicting academic performance, emotional well-being, self-motivation, and behavioral outcomes among children exposed to violence. There were several key findings.

Consistent with our hypotheses, family support emerged as a robust protective factor across multiple domains. It was found to be the key factor that was most significantly associated with better academic performance, increased self-motivation, and higher levels of emotional and developmental well-being, supporting our first, third, and fourth hypotheses. Increased family support proved to be a significant buffer against mental health difficulties and social problems. This finding aligns with prior research emphasizing the central role of family support in fostering resilience (Jain et al., 2011; Abate et al., 2024). Community involvement also emerged as a strong protective factor, demonstrating positive associations with self-motivation, child behavior, and academic achievement. The findings support literature that links extracurricular participation to improved motivation and school performance (Jean-Thorn et al., 2022). However, its effects were smaller than those of family support, suggesting that while engagement within the community contributes to resilience, family-level support remains more critical. Among the other factors, bullying victimization was consistently the strongest risk factor, especially for emotional health and social problems. This underscores the urgent need for anti-bullying interventions as a foundation for resilience-building strategies. Additionally, health status was found to be both a protective and risk factor, with better health predicting increased self-motivation and poor health increasing vulnerability to mental health challenges. The importance of the factor reflects the interconnectedness of physical and psychological well-being. Interestingly, community support and mentor presence did not demonstrate significance across any of the domains. This finding diverges from prior research, though it's possible that the two factors exerted indirect or moderating effects that were not explicitly modeled here. Mentorship and community support may have enhanced family functioning or facilitated community involvement rather than directly predicting child outcomes. Contextual variation could also explain the discrepancy with prior literature. Previous research often derived samples from targeted intervention studies or specific populations, whereas the present analysis used a nationally representative dataset. The protective effects of mentor presence and community support may be diluted by variability in larger samples.

Across the statistical and machine learning models, Random Forest models generally outperformed Decision Trees, confirming the higher efficacy of ensemble methods in exploring complex relationships between protective factors and outcomes. Logistic regression, as a parametric model, performed better in domains with clearer linear associations, particularly behavior problems, but had difficulty predicting academic performance and self-motivation. The complexity of the outcomes are highlighted by the generally modest predictive accuracies across the models, revealing the presence of unmeasured individual and contextual influences.

The results demonstrate the interplay of ecological influences consistent with Bronfenbrenner's ecological systems theory. Family support, community involvement, and bullying operate at the microsystem level, with family support emerging as the most influential protective factor and community involvement providing additional, though smaller, buffering effects. Within this same microsystem level, bullying exerted the strongest negative influence, emphasizing the importance of peer dynamics in developmental trajectories. By situating the findings within ecological systems theory, the study explores how resilience emerges from the interplay of protective and risk influences across multiple levels of a child's environment.

SIGNIFICANCE

In summary, this study was the first to explicitly study the different levels of impact these specific protective factors have on outcomes in children with exposure to violence. We expanded upon past research by examining the impacts of protective factors on exposed children's academic performance and self-motivation, in addition to the previously studied behavioral and emotional outcomes. Understanding how to address these various effects can inform future practices to help children escape cycles of violence. Broadening our sample size to include children exposed to all forms of violence also helped account for the children exposed to community-level violence who are usually left out of research studies in favor of children exposed to family-level violence (Valrie et al., 2024). Overall, our research has widened the scope of traditional studies of violence-exposed children, and our novel findings on effectiveness across multiple different protective factors can help direct the focus of intervention programs towards areas that will offer the most benefits to the children. In a world where the rate of childhood violence exposure is extremely high, it becomes crucial for social workers to quickly identify the best methods to target the protective factors that will yield the most positive results. Studying and comparing factors across outcomes can help optimize implementation.

IMPLEMENTATIONS AND FUTURE RESEARCH

The findings of this study suggest that interventions should prioritize strengthening family bonds and encouraging child involvement in activities. Implementing interventions like family-centered programs, anti-bullying initiatives, and structured extracurricular opportunities can strengthen resilience and improve outcomes across all domains. Additionally, expanding access to mental health services and family support programs at the policy level would address both immediate risks and long-term resilience.

Future research should monitor how the effects of protective factors evolve over a period of time. Our study utilized cross-sectional data, limiting our ability to determine the details of variable relationships. Employing the use of longitudinal studies in the future could be beneficial for establishing more causal pathways between the factors and the child outcomes. Rather than relying on reports by parents/guardians, future studies could also incorporate multi-informant data (teachers, peers, self-reports), which would effectively mitigate any existing biases. When modeling the results, logistic regressions, decision trees, and Random Forests performed modestly. Experimenting with deep learning architectures in the methodology could help capture more complex, non-linear relationships. Future research should also examine cross-cultural contexts, conduct intervention trials, and investigate how structural inequities interact with protective factors to shape developmental outcomes.

CONCLUSION

This study examined and compared the effects of multiple factors, including family support, community support, community involvement, and mentorship, in predicting outcomes like academic performance, emotional well-being, self-motivation, and behavioral outcomes among children with exposure to violence. Across multiple modeling approaches, family support was consistently found to be the strongest protective factor, promoting stronger academics and self-motivation, and buffering against emotional and behavioral problems. Bullying victimization was the strongest risk factor, with the strongest negative impact in behavioral and emotional outcomes. Community involvement displayed modest but meaningful protective effects for self-motivation and academic achievement. Mentorship and community support did not emerge as significant predictors, suggesting that their predictive influence may depend on contextual variation or indirect pathways not captured in the present models. Overall, this study demonstrates that resilience among children exposed to violence is not determined by any single factor but emerges from multiple protective and risk influences from multiple ecological levels, and that the individual and microsystem-level factors tend to yield the most significant results.

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