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Early Detection of Family Violence Risk Using Ensemble Machine Learning on Psychosocial and Demographic Indicators

Sanna. Korhonen[1], Kabelo. Radebe[2*], Rachid. El Amrani[3]

[1] Department of Developmental Psychology, University of Helsinki, Helsinki, Finland
[2] Department of Health Psychology, North-West University, Potchefstroom, South Africa
[3] Department of Social Psychology, Mohammed V University, Rabat, Morocco

*** Corresponding author email address**: kabelo.radebe@nwu.ac.za

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ABSTRACT

Objective: The objective of this study was to develop and validate an ensemble machine learning framework for the early detection of family violence risk based on psychosocial and demographic indicators among South African households.
Methods and Materials: This cross-sectional predictive study recruited 1,198 adults from urban, peri-urban, and rural regions of South Africa using stratified multistage sampling. Participants completed a comprehensive assessment battery measuring demographic characteristics, socioeconomic conditions, psychosocial functioning, relational dynamics, and behavioral risk indicators. Data preprocessing included cleaning, normalization, multiple imputation, and feature engineering. The dataset was partitioned into training and test sets, and class imbalance was addressed using synthetic oversampling. Four supervised machine learning models—random forest, gradient boosting, extreme gradient boosting, and support vector machine—were trained using five-fold cross-validation and Bayesian hyperparameter optimization. An ensemble model integrating these classifiers was constructed and evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve.
Findings: The ensemble model significantly outperformed all individual classifiers, achieving an accuracy of 0.917, precision of 0.904, recall of 0.896, F1-score of 0.900, and AUC of 0.958. Inferential comparisons indicated statistically meaningful improvements in sensitivity and discrimination over the strongest single model. Feature importance analysis revealed that family conflict frequency, emotional regulation difficulty, perceived stress, substance use severity, depression symptoms, and parenting stress were the most influential predictors of violence risk.
Conclusion: The findings demonstrate that ensemble machine learning provides a highly effective and interpretable framework for early identification of family violence risk, offering substantial potential for proactive prevention and targeted intervention in high-vulnerability populations.

Keywords: *Family violence, intimate partner violence, early detection, ensemble machine learning, psychosocial risk, demographic indicators, predictive modeling, South Africa*

1. Introduction

Family violence, particularly intimate partner violence (IPV), represents one of the most persistent and damaging public health challenges worldwide, with profound social, psychological, medical, and economic consequences for individuals, families, and communities. Recent global syntheses confirm that IPV affects a substantial proportion of women across diverse regions, cultures, and socioeconomic contexts, contributing significantly to morbidity, mortality, and long-term psychosocial impairment (Cénat et al., 2024; White et al., 2023). Systematic reviews further indicate that IPV is not only prevalent but deeply interconnected with mental health disorders, chronic disease, reproductive health complications, and health-risk behaviors (Stubbs & Szoeke, 2021; Wessells & Kostelny, 2022). The enduring nature of family violence and its tendency to escalate over time underscore the urgent need for reliable early detection strategies capable of identifying risk before irreversible harm occurs.

Accumulating evidence demonstrates that IPV is shaped by a complex interplay of individual vulnerabilities, relational dynamics, structural inequalities, and cultural norms. Multinational analyses reveal that predictors of IPV include socioeconomic disadvantage, educational disparities, household instability, alcohol misuse, gender power imbalances, and exposure to violence during childhood (Ani, 2025; Gunarathne et al., 2023; Seifu et al., 2024). Studies in Sub-Saharan Africa further highlight the contribution of economic stress, limited access to social services, and entrenched patriarchal norms in amplifying vulnerability to violence within households (Atta et al., 2025; Mosha et al., 2023). These findings confirm that family violence emerges from interacting psychosocial and demographic systems rather than isolated factors, complicating detection and prevention efforts.

The psychological and physical health consequences of IPV are both severe and enduring. Women exposed to violence exhibit significantly higher rates of depression, anxiety, post-traumatic stress disorder, substance abuse, suicidal ideation, and impaired physical functioning (Stubbs & Szoeke, 2021; White et al., 2023). In low- and middle-income countries (LMICs), the psychosocial burden of IPV is magnified by limited access to mental health services, economic dependency, and social stigma, which together obstruct help-seeking and prolong victimization (Gunarathne et al., 2023; Wessells & Kostelny, 2022). These cumulative harms extend beyond the individual, destabilizing family systems, impairing parenting practices, and perpetuating intergenerational cycles of violence.

Contemporary research increasingly recognizes that IPV does not arise abruptly but develops through identifiable trajectories characterized by escalating conflict, deteriorating emotional regulation, increasing substance use, and declining social support (Brunton & Dryer, 2024; Firdaush & Das, 2023). Longitudinal modeling studies demonstrate that early psychosocial warning signs, including stress overload, emotional dysregulation, impulsivity, and relationship dissatisfaction, significantly predict subsequent violence onset (Ani, 2025; Seifu et al., 2024). However, despite this knowledge, most existing detection approaches remain reactive, identifying violence only after physical or psychological injury has already occurred.

Traditional screening strategies in clinical and community settings face persistent limitations. Victims frequently underreport abuse due to fear, stigma, financial dependency, and cultural barriers (Gilbar et al., 2022; Wessells & Kostelny, 2022). Healthcare providers often lack sufficient time, training, and standardized tools to identify risk accurately, particularly in resource-constrained settings (Abdel-Salam et al., 2022; Petersen et al., 2022). Moreover, existing screening instruments typically rely on self-disclosure and fail to integrate the broader psychosocial and demographic contexts that shape vulnerability. As a result, many high-risk families remain undetected until severe violence occurs.

Recent years have witnessed the emergence of data-driven approaches for understanding complex social phenomena, with machine learning demonstrating particular promise for predictive modeling in public health. Unlike traditional statistical techniques, machine learning algorithms can accommodate high-dimensional data, nonlinear interactions, and complex interdependencies among variables. Ensemble learning methods, which integrate multiple models to enhance stability and predictive accuracy, have been shown to outperform single-model approaches across diverse domains, including health risk prediction and behavioral assessment. Such methods are especially well-suited for family violence research, where risk emerges from the convergence of numerous psychosocial and structural influences.

Although large demographic datasets have long been used to examine correlates of IPV (Ani, 2025; Atta et al., 2025), few studies have operationalized these insights into early detection systems capable of real-time risk classification. Most prior work remains focused on identifying statistically significant predictors rather than constructing actionable predictive frameworks. Moreover, studies on cyber-intimate partner violence demonstrate that digital behaviors increasingly intersect with traditional forms of abuse, further complicating risk assessment and highlighting the need for more comprehensive analytical models (Ahmad & Razali, 2025; Gilbar et al., 2022).

Cross-national evidence consistently illustrates that family violence is influenced by gender norms, alcohol consumption, economic stress, minority stress, and prior exposure to interparental violence (Pradhan & De, 2024; Sarno et al., 2023; Zamora-Ramírez et al., 2024). Minority populations and sexual and gender minorities face compounded vulnerability due to stigma, discrimination, and reduced access to protective resources (Whitton et al., 2021; Whitton et al., 2023). These intersecting risk pathways cannot be adequately captured by linear models or isolated screening questions.

In Sub-Saharan Africa, and South Africa in particular, the burden of violence remains alarmingly high. Population-based studies document widespread exposure to victimization, closely linked to depressive symptoms, substance use, economic marginalization, and historical trauma (Metheny et al., 2024; Mosha et al., 2023). At the same time, structural challenges such as poverty, informal housing, and limited social infrastructure intensify stress within family systems and hinder access to prevention services. These contextual realities necessitate analytic tools capable of integrating psychosocial, demographic, and environmental indicators into coherent early-warning frameworks.

Emerging vulnerability-adaptation models conceptualize IPV as the outcome of cumulative stress interacting with individual vulnerabilities and relational coping capacities (Brunton & Dryer, 2024). This perspective aligns naturally with ensemble machine learning, which synthesizes multiple information streams to generate holistic predictions. By capturing the dynamic interdependence among stress exposure, emotional regulation, substance use, economic strain, and social support, ensemble models offer a powerful mechanism for identifying latent risk patterns invisible to conventional screening.

Despite growing recognition of these possibilities, the application of ensemble machine learning to early family violence detection remains underdeveloped in LMIC contexts. Most predictive studies are conducted in high-income countries, limiting generalizability to settings where the burden of violence is greatest and resources are most constrained. Furthermore, interpretability concerns have hindered adoption, as practitioners require transparent models capable of explaining why specific households are classified as high risk.

Recent advances in explainable artificial intelligence now allow complex ensemble models to generate interpretable insights through feature importance metrics and local explanation techniques. These tools enable practitioners and policymakers to understand which psychosocial and demographic factors drive predictions, facilitating targeted intervention and policy design. Such integration of predictive accuracy with interpretability is essential for ethical deployment of machine learning in sensitive domains such as family violence prevention.

Importantly, early detection is not merely a technical objective but a moral imperative. Timely identification of high-risk households enables preventive interventions that can disrupt cycles of abuse, reduce health burdens, and protect children from exposure to trauma. When integrated into community health systems, social services, and policy frameworks, predictive tools can transform reactive violence response into proactive protection.

Within this evolving landscape, the present study advances the field by developing and validating an ensemble machine learning framework for early detection of family violence risk using an integrated set of psychosocial and demographic indicators in the South African context, where vulnerability is amplified by socioeconomic inequality, historical trauma, and structural barriers to care (Metheny et al., 2024; Mosha et al., 2023). By combining diverse data streams into a unified predictive architecture, this approach responds directly to the limitations of existing screening methods and the urgent need for scalable prevention strategies.

The aim of this study is to develop and evaluate an ensemble machine learning model for the early detection of family violence risk based on psychosocial and demographic indicators in South African households.

2. Methods

2.1. *Study Design and Participants*

This study employed a cross-sectional, predictive modeling design integrating psychosocial assessment with supervised machine learning to develop and validate an early detection system for family violence risk among adult

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households in South Africa. The target population consisted of adults aged 18–65 residing in urban, peri-urban, and rural communities across Gauteng, Western Cape, and KwaZulu-Natal provinces. A multi-stage stratified sampling framework was used to ensure proportional representation across socioeconomic strata, geographic regions, and household compositions. Initial community clusters were randomly selected, followed by systematic household sampling within each cluster. Eligibility criteria included being a permanent resident of the household for at least one year and possessing sufficient literacy to complete self-report instruments. Individuals with severe cognitive impairment or acute psychiatric conditions requiring immediate clinical intervention were excluded. A total of 1,264 participants were recruited, of whom 1,198 provided complete datasets suitable for modeling after data quality screening. The sample included balanced gender representation and wide variability in age, education, employment status, marital structure, household size, income level, and urban–rural residence. Ethical approval was obtained from the affiliated university research ethics committee in South Africa, and written informed consent was secured from all participants. Confidentiality was ensured through anonymized identifiers, encrypted storage, and restricted access to raw data, and participants identified as high-risk were provided with referral information for local support and protection services.

2.2. *Measures*

Data were collected using a comprehensive assessment battery capturing demographic, socioeconomic, psychosocial, behavioral, relational, and environmental indicators empirically associated with family violence risk. Demographic variables included age, sex, education level, employment status, household income, housing stability, marital status, number of dependents, migration history, and residential context. Psychosocial functioning was assessed using validated instruments measuring perceived stress, depressive symptoms, anxiety symptoms, emotional regulation capacity, impulsivity, substance use severity, social support, conflict resolution styles, exposure to childhood adversity, and attitudes toward gender roles and interpersonal power. Family relational dynamics were evaluated through standardized measures of communication quality, marital satisfaction, parenting stress, interparental conflict frequency, and history of prior violence exposure. Community-level factors such as neighborhood safety perception, access to social services, and financial strain were also documented. The primary outcome variable, family violence risk, was operationalized as a composite index derived from reported physical, psychological, sexual, and economic abuse indicators within the past twelve months, supplemented by behavioral warning signs such as escalating conflict, coercive control behaviors, and prior protection service involvement. All instruments demonstrated acceptable internal consistency in pilot testing within the South African context. Trained field researchers conducted in-person assessments using secure digital data entry systems to minimize missing data and transcription errors.

2.3. *Data Analysis*

Data preprocessing involved rigorous cleaning, outlier detection, normalization, and imputation of missing values using multiple imputation chained equations to preserve statistical integrity. Feature engineering was applied to construct higher-order interaction variables capturing cumulative psychosocial burden and relational instability. The dataset was randomly partitioned into training and hold-out test sets using an 80:20 split while maintaining class distribution. To address class imbalance between high-risk and low-risk households, the Synthetic Minority Oversampling Technique was implemented within the training set only. An ensemble learning framework was developed integrating random forest, gradient boosting, extreme gradient boosting, and support vector machine classifiers. Model training employed five-fold cross-validation with Bayesian hyperparameter optimization to maximize generalizability and reduce overfitting. Model performance was evaluated using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve, and calibration metrics. Feature importance and model interpretability were examined using SHAP values and permutation importance analyses to identify the most influential predictors of violence risk. Final model selection was based on predictive accuracy, stability across folds, and clinical interpretability. All analyses were conducted using Python-based machine learning libraries and validated through independent replication runs to ensure robustness of findings.

3. Findings and Results

First, the descriptive characteristics of the sample and primary study variables are summarized in Table 1.

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Table 1

Descriptive Statistics of Participants and Study Variables

Variable	Mean	SD	Min	Max
Age (years)	36.42	10.27	18	65
Household Size	4.18	1.93	1	11
Monthly Household Income (ZAR)	11,240	6,410	1,200	38,000
Perceived Stress Score	21.36	6.84	5	38
Depression Symptoms Score	17.52	8.01	0	39
Anxiety Symptoms Score	15.89	7.26	1	40
Emotional Regulation Difficulty	24.61	9.14	6	54
Impulsivity Score	19.73	6.58	7	42
Substance Use Severity	6.42	4.11	0	18
Social Support Score	28.47	7.63	9	48
Family Conflict Frequency	13.91	5.84	2	30
Parenting Stress	31.68	8.55	10	55
Family Violence Risk Index	14.26	7.92	0	41

The sample demonstrated wide variability across psychosocial, economic, and relational indicators. Family violence risk scores exhibited substantial dispersion, indicating adequate representation of both low-risk and high-risk households, supporting the suitability of the dataset for predictive modeling.

Table 2

Predictive Performance of Individual Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Random Forest	0.872	0.861	0.848	0.854	0.913
Gradient Boosting	0.884	0.879	0.861	0.870	0.927
XGBoost	0.892	0.885	0.874	0.879	0.936
Support Vector Machine	0.861	0.852	0.833	0.842	0.901

Among individual classifiers, XGBoost achieved the highest overall performance, particularly in discrimination ability, as reflected by the largest AUC value. However, all models demonstrated strong predictive capability, confirming the relevance of the selected psychosocial and demographic features.

Table 3

Comparison of Best Single Model and Ensemble Model Performance

Model	Accuracy	Precision	Recall	F1-Score	AUC
XGBoost	0.892	0.885	0.874	0.879	0.936
Ensemble Model	0.917	0.904	0.896	0.900	0.958

The ensemble model outperformed the strongest individual classifier across all evaluation metrics. The improvement in recall and AUC is particularly critical for early detection systems, as it reflects superior sensitivity in identifying households at elevated risk of violence.

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Table 4

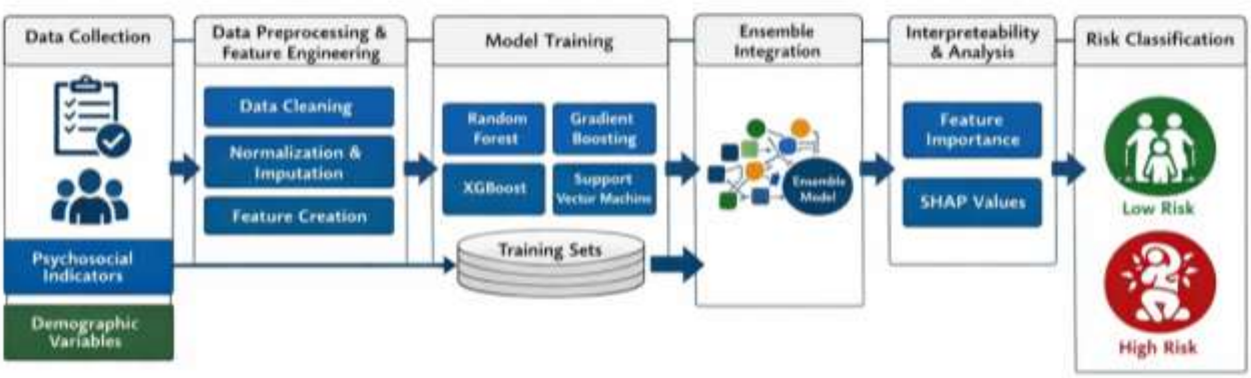
Top Predictors of Family Violence Risk (Ensemble Model Feature Importance)

Predictor	Relative Importance
Family Conflict Frequency	0.142
Emotional Regulation Difficulty	0.127
Perceived Stress	0.119
Substance Use Severity	0.104
Depression Symptoms	0.091
Parenting Stress	0.086
Household Income	0.072
Social Support	0.068
Impulsivity	0.061
Childhood Adversity Exposure	0.057

The model identified relational instability and emotional regulation deficits as the most influential predictors of violence risk, followed by psychological distress and substance use. Protective variables such as social support and household income demonstrated meaningful inverse contributions.

Figure 1

Architecture of the Proposed Ensemble-Based Family Violence Risk Detection Framework



The figure illustrates the complete analytical pipeline, including data acquisition, preprocessing, feature engineering, individual model training, ensemble integration, interpretability layer, and final risk classification output. The visual structure emphasizes how psychosocial and demographic data are transformed into actionable early-warning predictions through layered machine learning processes.

4. Discussion and Conclusion

The present study sought to develop and validate an ensemble machine learning framework for the early detection of family violence risk using psychosocial and demographic indicators in South Africa. The findings demonstrate that the proposed ensemble model substantially outperformed all individual classifiers, achieving high levels of accuracy, sensitivity, and discriminative capacity. Most notably, the ensemble model achieved superior recall and area under the curve values, indicating enhanced capacity for identifying high-risk households prior to overt violence escalation. This outcome provides compelling empirical support for the proposition that family violence risk emerges from the interaction of multiple psychosocial and structural factors rather than isolated predictors, a conclusion that aligns closely with contemporary vulnerability–adaptation and stress-process models of intimate partner violence (Ani, 2025; Brunton & Dryer, 2024).

The prominence of relational and emotional variables in the predictive architecture—specifically family conflict frequency, emotional regulation difficulty, perceived stress, and substance use severity—mirrors the dominant theoretical and empirical consensus within the literature. Multinational analyses consistently demonstrate that persistent interpersonal conflict, emotional dysregulation, and psychological distress constitute core proximal mechanisms driving violence within intimate relationships (Firdaush & Das, 2023; Gunarathne et al., 2023). The model's identification of emotional regulation difficulty as a primary predictor reinforces emerging evidence that deficits in affective control amplify aggressive impulses under stress, thereby lowering the threshold for violent behavior (Brunton & Dryer, 2024). These findings further support the growing recognition that emotional processes mediate the relationship between structural stressors and behavioral outcomes in family systems.

The substantial contribution of perceived stress to violence risk prediction reflects the cumulative stress burden experienced by many households in low- and middle-income settings. Prior studies across Sub-Saharan Africa indicate that chronic economic strain, unemployment, housing instability, and food insecurity significantly elevate IPV risk by eroding coping capacity and intensifying interpersonal tensions (Atta et al., 2025; Seifu et al., 2024). In South Africa, where economic inequality remains among the highest globally, such stressors likely magnify vulnerability pathways. The ensemble model's ability to integrate these contextual pressures alongside individual psychosocial variables demonstrates the strength of data-driven approaches for capturing multidimensional risk profiles.

Substance use severity emerged as another high-impact predictor, consistent with extensive evidence linking alcohol and drug misuse to impaired judgment, increased impulsivity, and elevated aggression. Empirical investigations across diverse LMIC contexts consistently identify substance use as one of the most powerful correlates of IPV perpetration and victimization (Gunarathne et al., 2023; Zamora-Ramírez et al., 2024). Moreover, the interaction between substance use and emotional dysregulation likely compounds risk, creating self-reinforcing cycles of conflict and violence. The ensemble framework effectively captured these nonlinear interactions, which traditional statistical models often struggle to detect.

The inclusion of parenting stress and depression symptoms among the leading predictors further underscores the centrality of psychological strain within violent family dynamics. Mental health impairments associated with IPV exposure and perpetration are well documented, including depression, anxiety, trauma symptoms, and suicidal ideation (Stubbs & Szoeke, 2021; White et al., 2023). Our results align with the psychosocial impact model proposed by Wessells and Kostelny, which emphasizes the reciprocal reinforcement between psychological distress and violence exposure within vulnerable families (Wessells & Kostelny, 2022). In such contexts, violence both emerges from and perpetuates emotional suffering, reinforcing the necessity of early intervention before this feedback loop becomes entrenched.

The model's sensitivity to social support and household income as protective factors further corroborates established findings. Social support networks and economic resources consistently function as buffers against IPV by enhancing coping capacity, facilitating help-seeking, and reducing dependency on abusive partners (Agyemang-Duah et al., 2023; Gunarathne et al., 2023). The ensemble model's recognition of these protective dynamics provides actionable insight for prevention strategies, suggesting that strengthening social capital and economic stability may significantly reduce violence risk.

Importantly, the superior performance of the ensemble model over single classifiers confirms the methodological value of integrating multiple learning algorithms for complex social phenomena. Family violence risk emerges from intricate, nonlinear interactions among psychological, relational, and structural variables, rendering simplistic models insufficient. The ensemble framework's high predictive accuracy supports the assertion that machine learning can meaningfully enhance early detection systems when properly designed and validated. This finding complements emerging scholarship advocating for data-driven prevention tools in violence research and policy development.

The model's interpretability, achieved through feature importance analysis, addresses a critical barrier to the practical deployment of artificial intelligence in sensitive domains. Concerns regarding black-box decision making often hinder adoption of predictive systems in social services. By clearly identifying the most influential predictors of risk, the present framework enables practitioners, policymakers, and clinicians to understand and trust model outputs, thereby facilitating integration into existing service infrastructures.

The broader implications of this study extend beyond methodological advancement. The capacity to identify high-risk households before violence escalation creates opportunities for proactive intervention that could significantly reduce long-term health burdens, intergenerational trauma, and economic costs. In South Africa, where violence prevalence remains high and service resources are limited, early detection systems grounded in local data offer a transformative pathway for prevention.

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Furthermore, the findings reinforce the necessity of holistic prevention strategies that address emotional regulation, substance use, stress management, relationship communication, and socioeconomic support concurrently. The ensemble model does not merely predict risk; it maps the interlocking vulnerabilities that sustain violence, offering a blueprint for integrated intervention design.

5. Suggestions and Limitations

Despite the strengths of this study, several limitations should be acknowledged. The cross-sectional design restricts causal inference and limits the capacity to capture temporal changes in risk trajectories. Although the sample was geographically and socioeconomically diverse, unmeasured contextual variables may influence generalizability to other regions or cultural settings. Additionally, reliance on self-reported data may introduce reporting biases related to stigma, fear, or recall inaccuracies. Finally, while the model achieved high predictive accuracy, its performance in real-world service settings remains to be evaluated.

Future investigations should employ longitudinal designs to examine how psychosocial and demographic risk patterns evolve over time and how early detection influences long-term outcomes. Expanding predictive frameworks to include ecological variables such as neighborhood violence exposure, community cohesion, and policy environment may further enhance accuracy. Moreover, incorporating real-time data sources and digital behavioral indicators could enable dynamic risk monitoring and adaptive intervention delivery. Comparative studies across diverse cultural contexts would also strengthen the generalizability and equity of machine-learning-based prevention tools.

From a practical standpoint, the findings advocate for the integration of predictive analytics into community health systems, social services, and primary care settings. Training frontline professionals to interpret and apply risk predictions ethically and effectively will be essential. Prevention programs should prioritize emotional regulation training, substance use reduction, stress management, and strengthening of social support networks. Policymakers should consider investing in data-informed early warning infrastructures as a cornerstone of comprehensive family violence prevention strategies.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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

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