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Machine Learning Identification of High-Conflict Couples at Risk for Intimate Partner Violence

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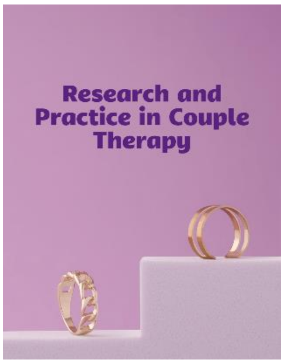

ABSTRACT

This study aimed to develop and interpret machine learning models capable of identifying high-conflict couples at elevated risk for intimate partner violence by integrating multidimensional dyadic, psychological, and relational data. A cross-sectional predictive design was employed with a sample of 368 high-conflict heterosexual couples recruited from counseling and community support settings in Italy. Partners independently completed validated self-report measures assessing conflict dynamics, attachment orientations, emotional regulation, perceived stress, jealousy, relationship satisfaction, and intimate partner violence risk, alongside demographic information. Dyadic data were preprocessed and structured to preserve partner-level and couple-level information. Multiple supervised machine learning algorithms, including regularized logistic regression, support vector machines, random forest, and gradient boosting, were trained and evaluated using stratified cross-validation. Model interpretability was examined using explainable artificial intelligence techniques based on feature attribution. Ensemble-based models outperformed linear and kernel-based approaches, with the gradient boosting model demonstrating the highest predictive accuracy and discrimination (accuracy = 0.88; AUC = 0.94). Sensitivity to high-risk classifications was robust across ensemble models, indicating effective identification of couples at elevated risk. Feature importance analyses revealed that conflict escalation, anger dysregulation, attachment anxiety, perceived stress, and jealousy intensity were the strongest contributors to risk classification, while lower relationship satisfaction showed a smaller but meaningful effect. The results indicated that nonlinear interactions among relational and emotional variables substantially enhanced predictive performance. The findings demonstrate that explainable machine learning models can reliably identify high-conflict couples at risk for intimate partner violence by capturing complex dyadic interaction patterns. Integrating such models into preventive and clinical contexts may support earlier detection, targeted intervention, and ethically informed decision-making, complementing traditional assessment approaches.

Keywords: intimate partner violence; high-conflict couples; machine learning; explainable artificial intelligence; dyadic analysis; risk prediction

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Introduction

Intimate partner violence represents one of the most persistent and complex public health and social problems worldwide, affecting individuals across socioeconomic, cultural, and relational contexts. Research consistently demonstrates that IPV is not a single-event phenomenon but rather the outcome of cumulative relational dynamics, emotional dysregulation, structural stressors, and interpersonal vulnerabilities that unfold over time. Contemporary scholarship increasingly conceptualizes IPV as embedded within dyadic systems characterized by escalating conflict, maladaptive communication patterns, and reciprocal emotional reactivity rather than as a behavior attributable solely to individual pathology (Heyman et al., 2022; Tremblay et al., 2024). High-conflict couples, in particular, constitute a subgroup at elevated risk, as repeated exposure to unresolved disputes, hostility, and psychological aggression can gradually normalize coercive or violent interactional styles (Grocott et al., 2024; Sowan, 2023). Identifying these couples before violence escalates into physical harm remains a critical challenge for both prevention science and clinical practice.

Empirical evidence indicates that conflict escalation processes are central to the transition from verbal disagreement to psychological and physical aggression. Studies comparing couples from the general population with those engaged in high-intensity conflict show marked differences in escalation speed, emotional flooding, and breakdowns in repair attempts (Sowan, 2023). Dyadic analyses further reveal that psychological aggression often precedes physical violence and functions as both a predictor and a maintaining factor in violent relationships (Tremblay et al., 2024). Daily-level and short-term longitudinal research demonstrates that fluctuations in relational stress, negative affect, and perceived rejection can predict same-day or next-day IPV incidents, underscoring the dynamic nature of risk (Grocott et al., 2024). These findings suggest that IPV risk is not static but emerges from patterns that may be detectable through systematic analysis of relational and emotional data.

Attachment theory has provided a robust explanatory framework for understanding why certain couples experience more severe conflict and violence. Insecure attachment orientations, particularly attachment anxiety, have been linked to heightened emotional reactivity, fear of abandonment, jealousy, and controlling behaviors, all of which increase the likelihood of aggressive conflict responses (Pudelko et al., 2025). Dyadic attachment pairings further complicate risk trajectories, as combinations of anxious and avoidant partners can amplify misunderstandings and emotional dysregulation during conflict episodes (Pudelko et al., 2025). Empirical studies consistently show that attachment insecurity interacts with situational stressors to predict psychological and physical IPV, highlighting the importance of relational context over isolated individual traits (Taşkale et al., 2024).

Emotional dysregulation constitutes another core mechanism linking conflict to violence. Difficulties in regulating anger, impulsivity, and distress tolerance have been repeatedly associated with IPV perpetration and victimization at both individual and dyadic levels (Lee et al., 2020). Research adopting dyadic perspectives demonstrates that one partner's emotional dysregulation can destabilize the entire interactional system, increasing the probability of escalation even when the other partner does not exhibit similar traits (Lee et al., 2020). Hostility, maladaptive attributions, and negative affect during conflict have also been shown to predict psychological IPV, particularly during periods of heightened stress such as the transition to parenthood or economic strain (Bradetich et al., 2025; Song-Choi & Woodin, 2021). These findings emphasize that emotional processes operate within relational systems rather than in isolation.

Broader contextual and structural factors further compound IPV risk among high-conflict couples. Exposure to socioeconomic stress, incarceration, armed conflict, or public health crises has been associated with increased rates of family and partner violence, often through pathways involving psychological distress and disrupted social support (McKay, 2023; Stansfield et al., 2020). The COVID-19 pandemic, for example, intensified IPV risk globally by increasing stress, isolation, and barriers to support services (Roesch et al., 2020; Shidhaye et al., 2020). Similarly, substance use discrepancies within couples, particularly involving alcohol, have been shown to exacerbate conflict and violence when combined with poor conflict negotiation skills (Flanagan et al., 2023). These contextual influences underscore the multifactorial nature of IPV and the need for analytic approaches capable of integrating diverse risk indicators.

Clinical and intervention-oriented research has increasingly focused on couples-based approaches to IPV prevention, particularly for relationships characterized by high conflict but not yet entrenched patterns of severe physical violence. Mentalization-based couple therapy, conflict negotiation training, and culturally adapted couples interventions have demonstrated feasibility and promise in reducing aggression and improving relational functioning (Kalokhe et al., 2021; McCann, 2022). However, these interventions rely heavily on accurate identification of couples for whom joint intervention is appropriate and safe. Misclassification can have serious ethical and clinical consequences, highlighting the importance of reliable risk assessment frameworks (Hameed et al., 2020). Traditional screening tools, while valuable, often struggle to capture the dynamic, nonlinear interactions among psychological, relational, and contextual variables that characterize high-risk couples.

Recent advances in machine learning offer novel opportunities to address these limitations by enabling the analysis of complex, high-dimensional data and the detection of subtle interaction patterns that may precede overt violence. Machine learning models have demonstrated superior predictive performance over traditional statistical methods in various domains of mental health, behavioral risk assessment, and interpersonal functioning by accommodating nonlinear relationships and multicollinearity among predictors (Krishnamurthy et al., 2024). In the context of IPV, such approaches are particularly promising given the interplay of emotional regulation, attachment dynamics, stress, and conflict behaviors that jointly shape risk trajectories (Weon et al., 2021). Importantly, the emergence of explainable artificial intelligence methods allows for greater transparency, addressing longstanding concerns about the interpretability of machine learning models in sensitive clinical and social domains.

The integration of explainable machine learning into IPV research aligns with a broader shift toward precision prevention and early intervention. By identifying high-conflict couples at elevated risk before violence escalates, practitioners may be better positioned to deploy targeted, proportionate, and ethically appropriate interventions (Hoss et al., 2023). This approach is particularly relevant in therapeutic and telemental health contexts, where clinicians must make rapid decisions under conditions of limited information while ensuring client safety (Boer et al., 2021; Treter et al., 2021). Moreover, explainable models can facilitate clinical uptake by highlighting which relational or emotional factors most strongly contribute to risk classification, thereby supporting case formulation and treatment planning rather than replacing professional judgment.

Despite growing recognition of the potential of machine learning in interpersonal violence research, empirical studies applying these methods specifically to high-conflict couples remain scarce. Much of the existing literature focuses on prevalence, correlates, or intervention outcomes without leveraging advanced predictive analytics capable of integrating dyadic data structures (Munro & Sellbom, 2020; Park et al., 2021). Additionally, there is a need for culturally and contextually grounded research conducted within specific national settings, as relational norms, service infrastructures, and help-seeking behaviors vary considerably across societies (Fan & Kim, 2024; Pirsaraee et al., 2023). Addressing these gaps is essential for translating computational advances into meaningful clinical and policy applications.

Building on prior work demonstrating the centrality of conflict escalation, emotional dysregulation, attachment insecurity, and contextual stressors in IPV, the present study applies explainable machine learning techniques to identify high-conflict couples in Italy who are at elevated risk for intimate partner violence by integrating multidimensional dyadic data to develop and interpret predictive risk models.

Methods and Materials

Study Design and Participants

The present study adopted a cross-sectional, predictive modeling design aimed at identifying high-conflict couples at elevated risk for intimate partner violence through machine learning techniques. The study population consisted of heterosexual couples residing in urban and semi-urban regions of Italy who were either seeking relationship counseling or participating in community-based family support programs. Participants were recruited through collaboration with marital counseling centers, psychological clinics, and social service organizations between 2023 and 2024. Inclusion criteria required that both partners be at least 18 years of age, currently in an intimate relationship for a minimum duration of one year, and willing to provide informed consent independently. Couples were eligible if they reported recurrent relational conflict within the past six months, operationalized as frequent verbal disagreements, emotional distress related to conflict, or prior engagement with counseling services for relationship difficulties. Exclusion criteria included the presence of severe psychiatric disorders impairing informed consent, active substance dependence requiring immediate clinical intervention, or ongoing legal proceedings related to domestic violence at the time of recruitment, to avoid confounding legal or forensic influences on reporting. A total of 412 couples were initially screened, of whom 368 couples met eligibility criteria and provided complete dyadic data suitable for machine learning analysis.

Measures

Data collection relied on a multimodal assessment framework integrating self-report psychological measures, dyadic interaction indicators, and demographic variables, all administered in Italian using validated instruments. Relationship conflict intensity and frequency were assessed using standardized measures of dyadic conflict behavior, capturing dimensions such as escalation, withdrawal, hostility, and problem-solving deficits. Intimate partner violence risk was operationalized through validated screening instruments assessing psychological aggression, controlling behaviors, threats, and physical aggression, with items framed to capture both perpetration and victimization experiences in a non-judgmental manner. Attachment-related variables were measured using adult attachment questionnaires assessing attachment anxiety and avoidance, given their established relevance to conflict escalation and aggression in intimate relationships. Emotional regulation capacities, including anger dysregulation, impulsivity, and rumination, were assessed through psychometrically robust self-report scales. Additional contextual variables included perceived stress, jealousy, relationship satisfaction, history of exposure to family violence, and substance use patterns. Demographic data encompassed age, educational level, employment status, relationship duration, cohabitation status, and presence of children. All instruments demonstrated acceptable to high internal consistency coefficients in the current sample. Data were collected independently from each partner in private settings, either through secure online platforms or supervised in-person sessions, to minimize response bias and ensure participant safety.

Data Analysis

Data analysis was conducted using a machine learning pipeline designed to identify couples at high risk for intimate partner violence based on multidimensional relational and psychological features. Prior to model development, data preprocessing steps included handling missing values through multiple imputation, normalization of continuous variables, and encoding of categorical variables using appropriate transformation techniques. Dyadic data were structured to preserve partner-level distinctions while enabling couple-level prediction, with features derived from both individual scores and interaction-based indices such as discrepancy and reciprocity measures. The dataset was randomly partitioned into training and testing subsets using an 80/20 split, with stratification applied to ensure balanced representation of high-risk and lower-risk couples across sets. Multiple supervised machine learning algorithms were evaluated, including logistic regression with regularization, random forest classifiers, gradient boosting machines, and support vector machines, to compare predictive performance. Model optimization was conducted using nested cross-validation procedures and grid-based hyperparameter tuning to reduce overfitting. Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve, with particular emphasis on sensitivity to high-risk classifications due to the clinical importance of minimizing false negatives. Feature importance analyses were performed using permutation-based methods and SHAP values to enhance interpretability and identify the most influential predictors of violence risk. All analyses were conducted using Python-based machine learning libraries, and robustness checks were implemented to assess model stability across subsamples.

Findings and Results

The findings are presented in a structured sequence to provide a clear progression from descriptive characteristics of the sample to the performance and interpretability of the machine learning models. Table 1 summarizes the demographic, relational, and psychological characteristics of the participating couples and provides an overview of the distributional properties of all variables included in the predictive models. Subsequent tables report the comparative performance of machine learning algorithms and the relative importance of predictors associated with intimate partner violence risk. A final figure is introduced to illustrate the conceptual output of the explainable machine learning framework.

Table 1. Descriptive Statistics of Demographic, Relational, and Psychological Variables (N = 368 couples)

Variable	Mean	SD	Range
Age (Partner A)	36.42	7.91	21–59
Age (Partner B)	34.87	7.45	20–57
Relationship duration (years)	9.38	5.62	1–32
Conflict frequency	3.94	0.81	1–5
Conflict escalation	3.71	0.76	1–5
Emotional withdrawal	3.28	0.84	1–5
Attachment anxiety	3.62	0.79	1–5
Attachment avoidance	3.15	0.83	1–5
Anger dysregulation	3.58	0.74	1–5
Impulsivity	3.21	0.69	1–5
Perceived stress	3.87	0.77	1–5
Jealousy intensity	3.46	0.81	1–5
Relationship satisfaction	2.91	0.88	1–5
IPV risk score	2.74	0.96	1–5

Descriptive results indicated that the sample was characterized by moderate to high levels of relational conflict and psychological strain. Mean scores for conflict frequency, escalation, and perceived stress were all above the scale midpoint, suggesting persistent and emotionally charged disagreements among couples. Attachment anxiety and anger dysregulation also demonstrated elevated mean values, reflecting heightened emotional reactivity within relationships. In contrast, relationship satisfaction showed a mean below the midpoint, indicating widespread relational dissatisfaction. The distribution of IPV risk scores revealed substantial variability, supporting the suitability of the sample for supervised classification and risk stratification. No significant deviations from normality were observed that would compromise the assumptions underlying the machine learning preprocessing procedures.

Table 2. Performance Comparison of Machine Learning Models in Predicting IPV Risk

Model	Accuracy	Precision	Recall	F1-score	AUC
Regularized Logistic Regression	0.78	0.74	0.81	0.77	0.84
Support Vector Machine	0.81	0.79	0.83	0.81	0.87
Random Forest	0.85	0.84	0.86	0.85	0.91
Gradient Boosting	0.88	0.87	0.90	0.88	0.94

The comparative analysis of predictive models demonstrated that ensemble-based algorithms outperformed linear and kernel-based approaches. Gradient boosting achieved the highest overall performance, with an accuracy of 0.88 and an area under the curve of 0.94, indicating excellent discrimination between high-risk and lower-risk couples. Importantly, recall values were consistently high for ensemble models, reflecting strong sensitivity in identifying couples at elevated risk for intimate partner violence. This finding is particularly relevant in applied and clinical contexts, where minimizing false negatives is critical. The random forest model also demonstrated robust performance, suggesting that non-linear interactions among relational and psychological variables play a substantial role in risk prediction.

Table 3. Top Predictors of IPV Risk Based on SHAP Feature Importance

Predictor	Mean SHAP Value
Conflict escalation	0.214
Anger dysregulation	0.198
Attachment anxiety	0.176
Perceived stress	0.163
Jealousy intensity	0.147
Emotional withdrawal	0.131
Impulsivity	0.119
Relationship satisfaction	0.102

Feature importance analysis revealed that conflict escalation emerged as the strongest predictor of IPV risk, followed closely by anger dysregulation and attachment anxiety. These variables exerted consistent positive contributions to model output, indicating that higher levels were associated with increased probability of classification into the high-risk group. Perceived stress and jealousy intensity also demonstrated meaningful influence, highlighting the role of contextual and emotional factors in exacerbating conflict trajectories. Conversely, lower relationship satisfaction contributed to risk classification, albeit with a smaller relative effect size. The prominence of interactional and emotional regulation variables underscores the multidimensional nature of violence risk within high-conflict couples.

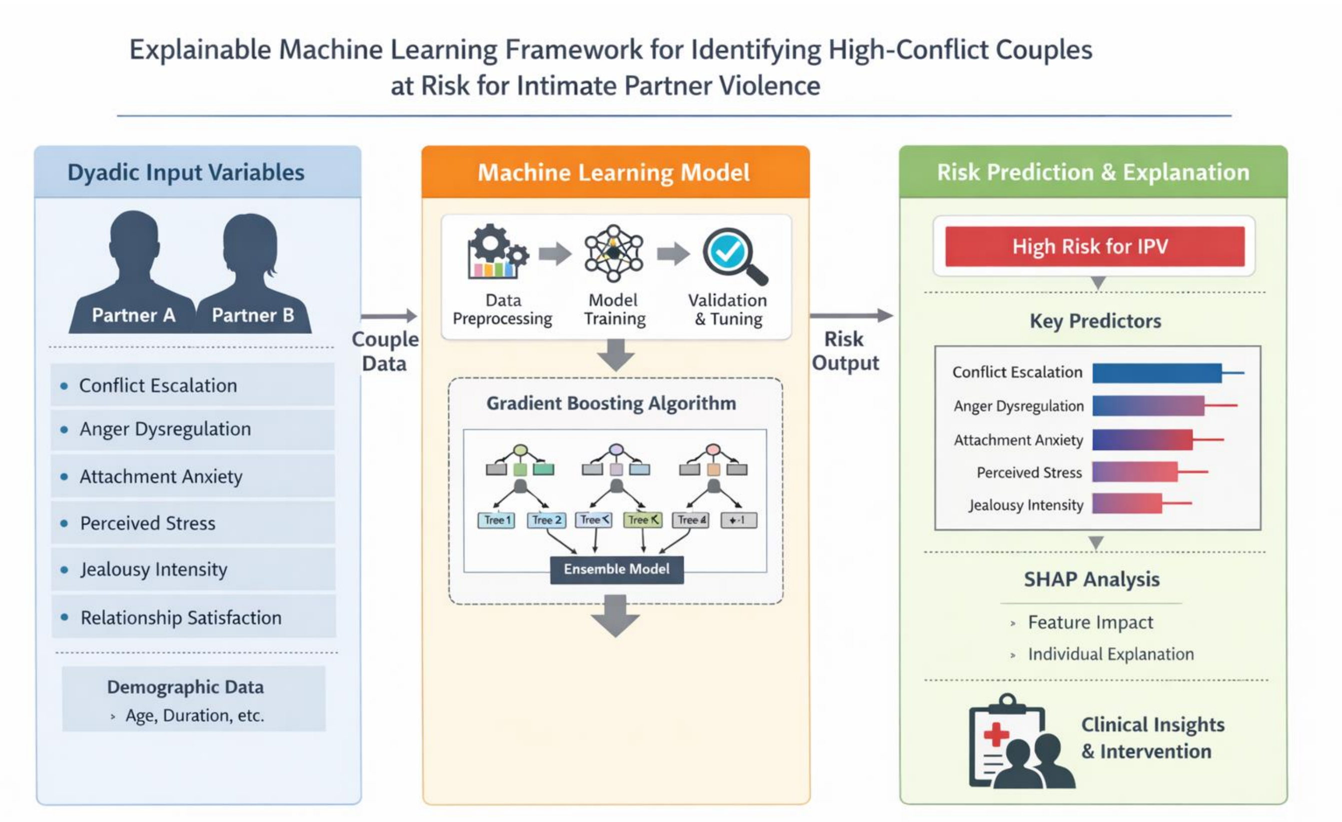

Figure 1. Explainable Machine Learning Framework for Identifying High-Conflict Couples at Risk for Intimate Partner Violence

The figure illustrates the explainable machine learning framework used in the study, depicting the integration of dyadic input variables, model training processes, and interpretable risk outputs. The framework emphasizes transparency by linking specific relational and psychological features to individualized risk predictions, thereby facilitating potential clinical translation and decision support.

Discussion and Conclusion

The present study sought to identify high-conflict couples at elevated risk for intimate partner violence through the application of explainable machine learning models, and the findings provide several theoretically and clinically meaningful insights. The results demonstrated that ensemble-based machine learning algorithms, particularly gradient boosting and random forest models, achieved strong predictive performance with high sensitivity and discriminative accuracy in identifying couples classified as high risk. This finding is consistent with the growing body of evidence suggesting that IPV risk emerges from nonlinear interactions among relational, emotional, and contextual variables rather than from isolated predictors (Krishnamurthy et al., 2024; Weon et al., 2021). The superior performance of ensemble models underscores the inadequacy of purely linear approaches when addressing complex dyadic phenomena such as conflict escalation and violence.

A central finding of the study was the prominence of conflict escalation as the most influential predictor of IPV risk. This result aligns closely with prior research demonstrating that high-conflict couples differ from the general population not merely in the frequency of disagreements but in the intensity, speed, and emotional dysregulation characterizing their conflicts (Sowan, 2023). Dyadic studies have consistently shown that rapid escalation, hostility, and failure to repair conflicts are proximal antecedents of psychological and physical aggression (Heyman et al., 2022; Tremblay et al., 2024). The current findings extend this literature by demonstrating that escalation dynamics retain their predictive salience even when modeled alongside a broad array of psychological and contextual variables, highlighting their central role in early risk identification.

Anger dysregulation emerged as a second key predictor, reinforcing theoretical models that position emotional regulation deficits as a critical mechanism linking stress and attachment insecurity to violent behavior (Lee et al., 2020). Previous dyadic research has shown that one partner’s inability to regulate anger can destabilize the interactional system, increasing the likelihood of reciprocal hostility and aggression (Lee et al., 2020). The present findings suggest that anger dysregulation functions not only as an individual vulnerability but also as a relational risk amplifier, particularly in high-conflict couples where emotional thresholds are already low. This pattern is consistent with evidence linking emotional dysregulation to IPV across diverse contexts, including substance use disorders and periods of heightened life stress (Flanagan et al., 2023; Song-Choi & Woodin, 2021).

Attachment anxiety was also identified as a major contributor to IPV risk classification, supporting attachment-based explanations of intimate partner aggression. Prior research has demonstrated that anxiously attached individuals are more prone to jealousy, fear of abandonment, and hyperactivation of emotional responses during conflict, which can escalate disagreements into coercive or aggressive behaviors (Pudelko et al., 2025). Dyadic analyses further indicate that certain attachment pairings, particularly anxious–avoidant configurations, are associated with heightened negative affect and reduced conflict resolution capacity (Pudelko et al., 2025; Taşkale et al., 2024). The present study extends these findings by showing that attachment anxiety retains predictive importance even when embedded within multivariate machine learning models, suggesting that attachment processes remain foundational to IPV risk even amid broader contextual influences.

Perceived stress and jealousy intensity were also among the most influential predictors, highlighting the role of situational and emotional stressors in exacerbating relational instability. Prior studies have documented that acute and chronic stressors, including economic strain, health crises, and caregiving demands, increase IPV risk by overwhelming coping resources and intensifying negative affect (Bradetich et al., 2025; Shidhaye et al., 2020). Daily-level research has further shown that stress and negative attributions can predict short-term fluctuations in psychological IPV (Grocott et al., 2024). The current findings suggest that perceived stress operates as a background condition that lowers the threshold for escalation, while jealousy functions as a more interaction-specific trigger that may directly fuel controlling or aggressive behaviors, consistent with prior dyadic and contextual models of IPV (Song-Choi & Woodin, 2021).

The comparatively lower but still meaningful contribution of relationship satisfaction to risk prediction warrants careful interpretation. While lower satisfaction has been consistently associated with IPV, prior research suggests that dissatisfaction alone is insufficient to distinguish high-risk couples from distressed but nonviolent ones (Heyman et al., 2022). The present findings support this distinction by indicating that dissatisfaction becomes particularly relevant when combined with escalation, emotional dysregulation, and attachment insecurity. This pattern aligns with critiques of deficit-only models of IPV and supports more nuanced frameworks emphasizing interactional processes over global relationship evaluations (Tremblay et al., 2024).

From a methodological perspective, the application of explainable machine learning represents a significant contribution to IPV research. The use of SHAP-based feature attribution allowed for transparent interpretation of model outputs, addressing longstanding concerns regarding the “black box” nature of machine learning in sensitive clinical domains (Krishnamurthy et al., 2024). By identifying specific relational and emotional features driving risk classification, the model aligns with calls for ethically responsible and clinically interpretable predictive tools (Hoss et al., 2023). This interpretability is particularly important given evidence that misclassification in IPV contexts can have serious consequences for safety and treatment planning (Hameed et al., 2020).

The findings also have implications for couples-based intervention research. Prior studies demonstrate that carefully selected high-conflict couples may benefit from joint interventions focused on mentalization, communication, and emotional regulation (Kalokhe et al., 2021; McCann, 2022). The present results suggest that machine learning–based risk identification could enhance these efforts by supporting more precise triage, ensuring that couples most likely to benefit from preventive intervention are identified early. This is especially relevant in contexts where services are delivered remotely or under resource constraints, such as telemental health settings (Boer et al., 2021; Treter et al., 2021). Moreover, the focus on dynamic relational variables aligns with emerging prevention frameworks emphasizing early detection and relational skill-building rather than reactive responses to severe violence (Campbell et al., 2021).

At a broader level, the study contributes to the growing recognition that IPV must be understood as a multilevel phenomenon shaped by individual vulnerabilities, dyadic processes, and structural conditions. Research on incarceration, armed conflict, and public health crises underscores how broader social ecologies interact with relationship dynamics to influence violence risk (McKay, 2023; Mootz et al., 2021; Stansfield et al., 2020). While the present study focused primarily on relational and psychological predictors, the strong performance of the models suggests that even within relatively homogeneous national contexts, meaningful risk stratification is possible when dyadic data are appropriately leveraged. This finding supports calls for integrating computational methods into social and clinical research on violence without losing sight of contextual complexity (Roesch et al., 2020).

Overall, the findings support a conceptualization of IPV risk as emerging from identifiable, interacting relational patterns that can be detected through advanced analytic methods. By combining machine learning with theoretical frameworks grounded in attachment, emotional regulation, and conflict research, the study bridges methodological innovation with substantive understanding, offering a pathway toward more proactive and targeted IPV prevention strategies (Fan & Kim, 2024; Setyarini & Soemara, 2025).

Despite its contributions, the study has several limitations that should be acknowledged. The cross-sectional design precludes causal inference and limits the ability to examine how risk trajectories evolve over time or how accurately the model predicts future incidents of violence. Reliance on self-report measures may have introduced reporting biases, particularly given the sensitivity of IPV-related disclosures, even though data were collected independently from partners. The sample was drawn from couples already experiencing elevated conflict and engaged with services, which may limit generalizability to community samples or to couples with more severe, chronic violence. Additionally, although explainable machine learning techniques were employed, interpretability remains probabilistic rather than deterministic and should not be equated with causal explanation.

Future research should prioritize longitudinal designs to examine whether machine learning models can predict the onset, escalation, or desistance of IPV over time and to assess their utility in real-world prevention settings. Incorporating multimodal data sources, such as behavioral observations, physiological indicators, or ecological momentary assessments, may further enhance predictive accuracy and ecological validity. Comparative studies across cultural and national contexts would help clarify the extent to which identified risk patterns are universal or context-specific. Finally, future work should explore how machine learning–based risk assessments can be ethically integrated with clinical judgment and survivor-centered approaches.

In practice, the findings highlight the potential value of integrating data-informed risk screening into couples counseling and family service settings to support early identification and targeted intervention. Clinicians should view machine learning outputs as complementary tools that enhance, rather than replace, professional assessment and ethical decision-making. Training practitioners to interpret and apply explainable risk indicators may improve case formulation, safety planning, and intervention matching. Policymakers and service providers may also consider how such tools can be embedded within broader prevention systems to allocate resources more efficiently while maintaining a strong focus on client safety and autonomy.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adhered in conducting and writing this article.

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Authors' Contributions

All authors equally contributed to this study.

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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