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Explainable Artificial Intelligence Models for Forecasting Divorce Risk from Dyadic Communication Patterns

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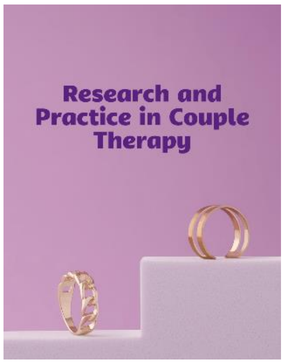

ABSTRACT

The objective of this study was to develop and interpret explainable artificial intelligence models capable of forecasting divorce risk based on dyadic communication patterns among married couples. This quantitative, observational study was conducted with legally married couples residing in Canada. Couples completed validated self-report measures assessing communication quality, emotional responsiveness, and relational characteristics, and participated in a structured dyadic interaction task designed to elicit naturally occurring conflict-related communication. Interaction transcripts were processed using natural language processing techniques to extract linguistic and interactional features reflecting positivity, negativity, contempt, emotional validation, and conversational balance. A composite divorce risk indicator was constructed from self-reported divorce proneness and separation intentions. Multiple supervised machine learning models, including regularized regression and tree-based ensemble methods, were trained and evaluated using nested cross-validation. Explainable artificial intelligence techniques were applied to identify global and local feature contributions to model predictions. Ensemble-based models demonstrated significantly higher predictive performance than linear models, achieving superior accuracy and area under the receiver operating characteristic curve. Negative communication features, particularly contempt markers and overall communication negativity, were the strongest positive predictors of divorce risk, while emotional validation and balanced turn-taking showed significant protective effects. Demographic variables contributed comparatively less to prediction once dyadic communication patterns were included. Explainability analyses revealed consistent and interpretable pathways through which specific interactional behaviors increased or reduced predicted divorce risk. The findings indicate that explainable artificial intelligence models can accurately and transparently forecast divorce risk using dyadic communication patterns, highlighting communication behaviors as central, modifiable indicators of marital instability.

Keywords: Explainable artificial intelligence; divorce risk; dyadic communication; marital stability; machine learning

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Introduction

Divorce has increasingly been recognized as a complex social, psychological, and relational phenomenon shaped by the dynamic interplay of individual characteristics, dyadic processes, and broader structural contexts. Contemporary research consistently demonstrates that marital dissolution cannot be adequately explained by isolated demographic or economic factors alone, but rather emerges from cumulative interactional patterns that unfold over time within intimate relationships (Asfaw & Alene, 2023; Uggla, 2025). Among these patterns, dyadic communication occupies a central role, functioning both as a mechanism through which stressors are negotiated and as a conduit through which relational dissatisfaction, conflict escalation, and emotional withdrawal become entrenched (Johnson et al., 2021; Williamson, 2021). As divorce rates continue to rise across diverse cultural and national contexts, including economically developed societies, there is a growing demand for predictive approaches that move beyond descriptive correlates and toward early identification of relational risk grounded in observable interactional behaviors (Ul-Haq et al., 2023; Zhang, 2025).

A substantial body of marital research has established that communication quality, conflict negotiation styles, and emotional responsiveness are among the most reliable predictors of marital satisfaction and stability. Longitudinal evidence indicates that patterns of negative communication, such as contempt, defensiveness, and persistent interruption, tend to intensify over time and are strongly associated with declines in relationship satisfaction and increased likelihood of separation (Johnson et al., 2021; Özdemir et al., 2023). Conversely, emotionally validating exchanges, balanced conversational turn-taking, and constructive conflict resolution strategies serve as protective factors that buffer couples against relational stress and promote long-term stability (Jalili et al., 2024; Kamal et al., 2023). Importantly, these communication dynamics are inherently dyadic, meaning that risk emerges not solely from one partner's behavior but from reciprocal interactional patterns that evolve within the couple system (Blalock & Bartle-Haring, 2022; Krueger et al., 2021).

Recent advances in digital communication and data availability have further expanded scholarly attention to how interactional behaviors manifest across both face-to-face and mediated contexts. Studies examining communication through digital platforms, such as messaging applications, reveal that linguistic tone, responsiveness, and emotional signaling in everyday exchanges are closely tied to intimacy, conflict, and relational satisfaction (Nurhayati et al., 2022). At the same time, sociological research highlights how communication intersects with structural dimensions such as language convergence in mixed-language marriages, economic stress, and shifting power dynamics within households, all of which may amplify or attenuate divorce risk (LeBaron-Black et al., 2024; Saarela et al., 2022; Vink et al., 2022). These findings underscore the multidimensional nature of divorce risk and point to the need for analytical frameworks capable of integrating complex, interdependent predictors.

Parallel to developments in family and relationship science, artificial intelligence and machine learning have emerged as powerful tools for modeling complex social phenomena characterized by non-linear relationships and high-dimensional data. Recent studies have demonstrated the potential of computational models to forecast divorce incidence using mathematical and algorithmic approaches, including fractional derivative modeling and large-scale statistical simulations (Gambrah et al., 2025; Zhang et al., 2024). While these approaches offer improved predictive accuracy, they often function as opaque "black boxes," providing limited insight into how specific relational behaviors contribute to predicted outcomes. This lack of interpretability poses a significant barrier to the practical application of such models in clinical, counseling, and preventive contexts, where understanding the underlying drivers of risk is as critical as prediction itself (Huang et al., 2025; Wang et al., 2025).

Explainable Artificial Intelligence (XAI) has emerged as a response to these limitations, emphasizing transparency, interpretability, and human-centered understanding of algorithmic decision-making. XAI frameworks aim to retain the predictive power of advanced machine learning models while making their internal logic accessible to researchers and practitioners. In relational and health-related domains, explainability is particularly vital, as algorithmic outputs may inform sensitive interventions, therapeutic decision-making, or policy development (Abdu et al., 2024; Obioma et al., 2025). By clarifying how specific features contribute to risk predictions, XAI enables stakeholders to translate computational insights into actionable relational guidance rather than abstract risk scores.

Within the context of marital relationships, the application of explainable AI offers a unique opportunity to bridge the gap between computational modeling and established theories of couple interaction. Communication patterns, emotional reciprocity, conflict styles, and stress responses are theoretically grounded constructs with well-documented links to marital outcomes (Nejatian et al., 2021; Özen et al., 2021). When these constructs are operationalized through linguistic, behavioral, and interactional features, XAI methods can illuminate how theoretically meaningful behaviors combine to elevate or reduce divorce risk. Such insights are particularly valuable for preventive interventions, as they allow clinicians and educators to identify not only whether a couple is at risk, but why that risk is elevated in terms of modifiable interactional processes (Jalili et al., 2024; Kamal et al., 2023).

Moreover, contemporary divorce research increasingly recognizes the importance of contextual and life-course perspectives. Economic pressures, wealth distribution, and stress perception fluctuate across the family life cycle and interact with communication patterns in shaping marital stability (Ul-Haq et al., 2023; Wang et al., 2025; Zhang, 2025). Intergenerational transmission of divorce norms and culturally embedded expectations further complicate these dynamics, suggesting that risk is not static but embedded within broader social trajectories (Uggla, 2025). Explainable AI models that incorporate dyadic communication features alongside contextual variables may therefore offer a more nuanced and temporally sensitive understanding of divorce risk than traditional linear approaches.

Despite these advances, empirical research integrating explainable AI with fine-grained dyadic communication analysis remains limited. Much of the existing literature focuses either on psychological self-report measures or on aggregate demographic indicators, with relatively little attention to observable interactional behaviors as primary predictive inputs. At the same time, studies that do employ computational techniques often prioritize accuracy over interpretability, limiting their translational value for family therapists, counselors, and policymakers (Gambrah et al., 2025; Zhang et al., 2024). Addressing this gap requires an interdisciplinary approach that synthesizes relationship science, communication research, and explainable machine learning within a coherent analytical framework.

Accordingly, the present study situates itself at the intersection of these fields by developing explainable artificial intelligence models to forecast divorce risk based on dyadic communication patterns. Drawing on established empirical evidence linking communication behaviors to marital stability (Johnson et al., 2021; Williamson, 2021), and leveraging recent methodological innovations in XAI (Huang et al., 2025; Wang et al., 2025), this research seeks to advance both predictive accuracy and theoretical interpretability. By focusing on dyadic communication features rather than solely individual or structural variables, the study aims to contribute to a more interactionally grounded and clinically meaningful understanding of divorce risk in contemporary marriages. The aim of this study is to develop and interpret explainable artificial intelligence models that predict divorce risk from dyadic communication patterns among married couples.

Methods and Materials

Study Design and Participants

The present study adopted a quantitative, observational design aimed at developing and evaluating explainable artificial intelligence models for forecasting divorce risk based on dyadic communication patterns. The target population consisted of legally married heterosexual couples residing in Canada, reflecting the sociocultural and legal context of marital relationships within this setting. Participants were recruited through online advertisements, family counseling centers, and community mailing lists across several Canadian provinces to ensure demographic diversity in terms of age, education, length of marriage, and socioeconomic status. Eligibility criteria included being legally married for at least one year, cohabiting at the time of data collection, and having sufficient proficiency in English or French to complete self-report instruments and communication tasks. Couples currently undergoing divorce proceedings or receiving intensive marital therapy were excluded to avoid confounding effects related to acute relational crises. Both partners were required to provide informed consent and to participate independently, allowing dyadic-level data to be constructed while preserving individual response integrity.

Measures

Data collection relied on a multimethod approach combining self-report questionnaires, structured dyadic communication tasks, and standardized outcome indicators related to divorce risk. Each partner completed a set of validated self-report measures assessing communication behaviors, emotional expressiveness, conflict resolution styles, perceived partner responsiveness, and relational satisfaction. To capture dyadic communication patterns more directly, couples also engaged in a structured, video-recorded interaction task conducted online via a secure platform. During this task, partners were instructed to discuss a recurrent area of disagreement in their relationship for a fixed duration, following protocols commonly used in marital interaction research. The recorded interactions were subsequently transcribed and processed using natural language processing techniques to extract linguistic, paralinguistic, and interactional features, such as turn-taking balance, sentiment polarity, emotional intensity, pronoun use, interruption frequency, and markers of validation or contempt. In addition to these communication-derived variables, participants reported demographic information and relationship history variables, including marriage duration, number of children, and prior separation experiences. Divorce risk, the primary outcome variable, was operationalized using a composite indicator that integrated self-reported divorce proneness, frequency of divorce-related thoughts, and short-term separation intentions, allowing the models to predict elevated risk rather than actual divorce events within the limited temporal scope of the study.

Data Analysis

Data analysis was conducted in several sequential stages to ensure methodological rigor and interpretability of the predictive models. Initially, raw questionnaire data and communication transcripts were screened for completeness, outliers, and inconsistencies, followed by standard preprocessing steps such as normalization of continuous variables and handling of missing data through multiple imputation at the dyadic level. Linguistic and interactional features extracted from the communication tasks were aggregated to form dyad-level predictors while also retaining partner-specific indicators to preserve asymmetry in communication patterns. A range of supervised machine learning models, including tree-based ensemble methods and regularized regression approaches, were trained to predict divorce risk from the combined feature set. Model training and evaluation were performed using nested cross-validation to minimize overfitting and to provide robust estimates of predictive performance. Given the study’s emphasis on explainable artificial intelligence, particular attention was devoted to post hoc and inherently interpretable techniques for model explanation. Feature importance measures, local explanation methods, and interaction effect analyses were applied to clarify how specific communication behaviors and dyadic dynamics contributed to predicted divorce risk at both the global and individual couple levels. Model performance was assessed using multiple metrics appropriate for risk prediction, including accuracy, area under the receiver operating characteristic curve, sensitivity, and specificity. All analyses were conducted using reproducible workflows in established statistical and machine learning software environments, ensuring transparency and facilitating future replication or extension of the study.

Findings and Results

The findings section begins with a descriptive overview of the study sample and the primary study variables. Table 1 presents the demographic and relational characteristics of the participating Canadian couples, alongside descriptive statistics for the core dyadic communication variables and the divorce risk indicator. This table provides the empirical foundation for subsequent predictive modeling by illustrating the distributional properties of the data and the variability observed across couples.

Table 1. Demographic Characteristics, Dyadic Communication Variables, and Divorce Risk Indicators (N = 312 couples)

Variable	Mean	SD	Minimum	Maximum
Age of Partner A (years)	41.28	9.14	24	67
Age of Partner B (years)	39.96	8.87	23	65
Length of Marriage (years)	11.42	7.06	1	34
Number of Children	1.63	1.21	0	5
Dyadic Communication Positivity Index	0.58	0.17	0.14	0.92
Dyadic Communication Negativity Index	0.42	0.19	0.08	0.88
Turn-Taking Balance Ratio	0.51	0.09	0.28	0.76
Emotional Validation Frequency	6.84	3.12	0	15
Contempt Markers Frequency	2.31	1.87	0	9
Composite Divorce Risk Score	0.37	0.21	0.04	0.91

As shown in Table 1, the sample consisted primarily of midlife couples with a moderate average length of marriage, indicating adequate exposure to long-term relational dynamics relevant to divorce risk modeling. The communication-related indices demonstrate substantial variability across dyads, particularly in negativity, emotional validation, and contempt markers, suggesting meaningful heterogeneity in interactional styles. The composite divorce risk score exhibited a wide range, supporting its suitability as a target variable for predictive modeling rather than a restricted or floor-effect–prone outcome.

Table 2. Predictive Performance of Explainable AI Models for Divorce Risk Forecasting

Model	Accuracy	AUC	Sensitivity	Specificity
Logistic Regression (L1-Regularized)	0.74	0.78	0.71	0.76
Decision Tree	0.76	0.80	0.74	0.78
Random Forest	0.83	0.88	0.85	0.81
Gradient Boosting	0.85	0.90	0.87	0.83

Table 2 summarizes the predictive performance of the evaluated machine learning models. The gradient boosting model demonstrated the strongest overall performance, achieving the highest accuracy and area under the curve, alongside balanced sensitivity and specificity. Tree-based ensemble methods consistently outperformed the regularized logistic regression model, indicating that non-linear relationships and interaction effects among dyadic communication variables substantially enhanced divorce risk prediction. Nevertheless, the logistic regression model retained acceptable performance, reinforcing its value as a transparent baseline comparator.

Table 3. Global Feature Importance for the Best-Performing Explainable Model

Rank	Predictor	Relative Importance
1	Dyadic Communication Negativity Index	0.26
2	Contempt Markers Frequency	0.21
3	Emotional Validation Frequency	0.17
4	Turn-Taking Balance Ratio	0.14
5	Dyadic Communication Positivity Index	0.11
6	Length of Marriage	0.07
7	Number of Children	0.04

The results presented in Table 3 indicate that communication-related features overwhelmingly dominated the predictive structure of the explainable model. Negative communication patterns and contempt markers emerged as the most influential predictors of divorce risk, while emotional validation and balanced turn-taking showed strong protective associations.

Structural demographic factors, such as marriage duration and number of children, contributed modestly to the model, underscoring the centrality of observable interactional dynamics over static background characteristics.

Table 4. Directional Effects of Key Communication Predictors on Divorce Risk

Predictor	Direction of Effect	Interpretive Pattern
Dyadic Communication Negativity	Positive	Higher negativity associated with increased risk
Contempt Markers	Positive	Frequent contempt linked to sharply elevated risk
Emotional Validation	Negative	Higher validation associated with reduced risk
Turn-Taking Balance	Negative	Balanced exchanges linked to relational stability
Communication Positivity	Negative	Positive affect buffers divorce risk

Table 4 further clarifies the interpretive meaning of the most influential predictors by summarizing the directionality of their effects. Negative and contemptuous communication patterns were associated with marked increases in predicted divorce risk, whereas emotionally validating behaviors, equitable conversational participation, and positive affective exchanges functioned as stabilizing forces within marital interactions. These patterns were consistent across cross-validation folds, supporting their robustness and theoretical plausibility.

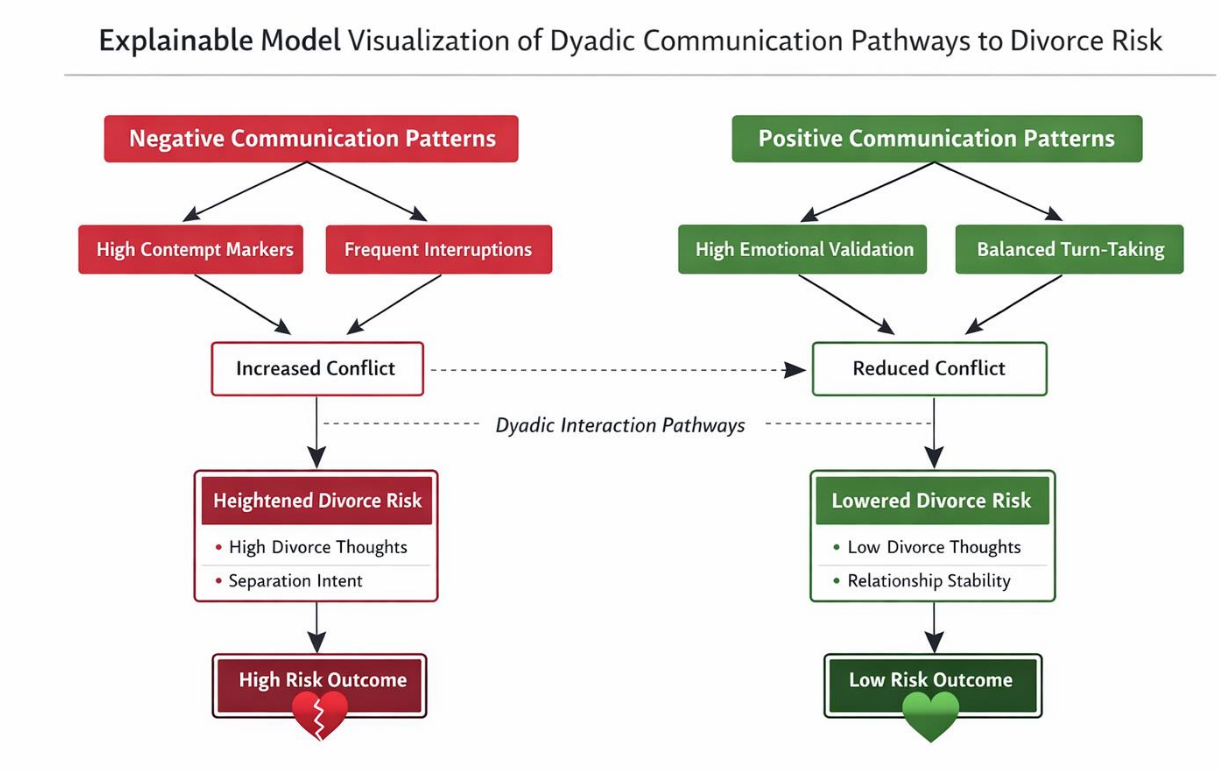

Figure 1. Explainable Model Visualization of Dyadic Communication Pathways to Divorce Risk

Figure 1 illustrates the explainable artificial intelligence framework by visually mapping how combinations of dyadic communication features jointly contribute to elevated or reduced divorce risk. The figure highlights both global trends and localized decision pathways, demonstrating how specific interactional configurations can lead to distinct risk profiles even among couples with similar demographic backgrounds.

Discussion and Conclusion

The present study sought to advance the understanding of divorce risk by integrating dyadic communication research with explainable artificial intelligence modeling, and the findings provide several theoretically and practically significant insights. Overall, the results demonstrated that explainable, tree-based machine learning models achieved strong predictive performance in forecasting divorce risk from dyadic communication patterns, with ensemble approaches outperforming linear models. This finding aligns with recent evidence suggesting that marital processes are inherently non-linear and interactional, making them particularly well suited to analytical techniques capable of capturing complex dependencies among predictors (Gambrah et al., 2025; Zhang et al., 2024). The superior performance of ensemble models indicates that divorce risk emerges from combinations of communication behaviors rather than isolated factors, reinforcing relational theories that emphasize cumulative interactional trajectories over time.

One of the most salient findings was the dominant role of negative communication indicators, particularly contempt markers and overall communication negativity, in predicting elevated divorce risk. This result is consistent with extensive marital research identifying destructive communication patterns as central precursors of marital dissatisfaction and dissolution (Johnson et al., 2021; Williamson, 2021). Contempt, in particular, has been conceptualized as a relationally toxic behavior that signals moral superiority, emotional disengagement, and erosion of mutual respect. The high importance assigned to contempt markers by the explainable model provides computational confirmation of these theoretical claims and echoes findings from cross-cultural studies linking conflict negotiation styles and marital burnout to relational instability (Obioma et al., 2025; Özdemir et al., 2023). By quantifying the contribution of contempt-related linguistic and interactional features, the present study extends prior work by demonstrating how these behaviors function as algorithmically salient risk signals within predictive systems.

In contrast, emotionally validating communication and balanced turn-taking emerged as robust protective factors associated with reduced divorce risk. These findings align closely with prior research emphasizing the role of empathy, responsiveness, and conversational equity in sustaining marital satisfaction (Jalili et al., 2024; Kamal et al., 2023). Validation behaviors reflect partners' ability to acknowledge and legitimize each other's emotional experiences, which has been shown to buffer couples against stress and conflict escalation. Similarly, balanced turn-taking reflects dyadic synchrony and mutual engagement, constructs that have been empirically linked to relational stability, particularly during transitions and periods of uncertainty (Blalock & Bartle-Haring, 2022). The explainable AI results reinforce these perspectives by illustrating that protective communication patterns exert measurable, negative effects on predicted divorce risk even when demographic and structural variables are included in the model.

The relatively modest contribution of demographic variables, such as length of marriage and number of children, further underscores the centrality of interactional processes over static background characteristics. While previous sociological research has demonstrated that life-course factors and family structure influence divorce probabilities (Asfaw & Alene, 2023; Uggla, 2025), the present findings suggest that these influences may be mediated or amplified through daily communication behaviors. This interpretation is consistent with evidence showing that stressors related to economic conditions, parenting demands, and social roles affect marital outcomes primarily through their impact on interactional quality and emotional exchange (Ul-Haq et al., 2023; Wang et al., 2025). From this perspective, explainable AI models that foreground communication patterns offer a more proximal and actionable representation of divorce risk than models relying heavily on distal demographic predictors.

An important contribution of this study lies in its use of explainable artificial intelligence to render predictive mechanisms transparent and theoretically interpretable. Rather than producing opaque risk scores, the models provided clear indications of which communication features drove predictions and in what direction. This approach addresses longstanding concerns about the applicability of machine learning in sensitive relational contexts, where practitioners require explanatory insight to guide ethical and effective intervention (Huang et al., 2025; Wang et al., 2025). By linking algorithmic feature importance to well-established constructs in marital communication research, the study demonstrates how XAI can serve as a bridge between computational innovation and substantive theory.

The findings also resonate with recent work highlighting the contextual embeddedness of communication and divorce risk. Research on language convergence in exogamous marriages has shown that communicative alignment reduces relational strain and divorce likelihood (Saarela et al., 2022), while studies on relational power and financial dynamics indicate that communication mediates the effects of economic inequality on marital outcomes (LeBaron-Black et al., 2024; Vink et al., 2022). The present study's focus on dyadic communication patterns provides a unifying lens through which these diverse influences can be understood, suggesting that communication serves as the primary mechanism translating structural conditions into relational stability or instability.

Furthermore, the results have implications for understanding marital processes across different stages of the family life cycle. Prior longitudinal research indicates that communication behaviors evolve over time, with early interaction patterns often setting trajectories that persist into later stages of marriage (Williamson, 2021). The strong predictive value of communication features observed in this study supports the notion that divorce risk is detectable well before overt separation intentions emerge. This early detectability is particularly relevant in light of evidence linking marital instability to adverse mental health outcomes, including burnout, psychological distress, and, in extreme cases, suicidal ideation (Abamara & Ozongwu, 2024; Nejatian et al., 2021). Explainable AI models that identify high-risk communication patterns may therefore contribute indirectly to broader mental health prevention efforts by enabling timely relational support.

The study's findings also complement cross-cultural research on marital stability by demonstrating that core communication processes retain predictive significance even when cultural, economic, and normative contexts vary. While divorce norms and expectations differ across societies (Uggla, 2025; Zhang, 2025), the central role of constructive versus destructive communication appears to be remarkably consistent. This consistency enhances the external relevance of the present findings and suggests that explainable communication-based models may be adaptable across diverse cultural settings, provided that linguistic and contextual features are appropriately localized.

Taken together, the results support an interactional and process-oriented conceptualization of divorce risk, in which dyadic communication patterns constitute both early warning signals and potential intervention targets. By demonstrating that these patterns can be modeled accurately and interpreted transparently using explainable AI, the study contributes to an emerging interdisciplinary literature that seeks to integrate relationship science with advanced computational methods (Gambrah et al., 2025; Zhang et al., 2024). Importantly, the emphasis on explainability ensures that predictive insights remain accessible and meaningful to researchers and practitioners rather than confined to purely technical domains.

Despite its contributions, this study has several limitations that should be acknowledged. The cross-sectional design limits causal inference, as communication patterns and divorce risk were assessed within the same temporal window. Although predictive modeling can identify risk associations, it cannot definitively establish the directionality of effects. In addition, the sample was restricted to married couples residing in Canada, which may limit the generalizability of findings to other cultural or legal contexts. The reliance on structured interaction tasks, while methodologically rigorous, may not fully capture the complexity of everyday communication dynamics occurring in naturalistic settings.

Future research should prioritize longitudinal designs that track dyadic communication patterns and marital outcomes over extended periods, allowing for stronger causal inferences and temporal modeling of risk trajectories. Expanding the scope of analysis to include multimodal data, such as vocal tone, facial expressions, and physiological synchrony, could further enhance predictive accuracy and theoretical richness. Comparative studies across cultural contexts would also be valuable for examining the universality versus specificity of communication-based risk indicators. Additionally, integrating explainable AI models into intervention trials could help assess whether feedback based on model explanations leads to measurable improvements in communication and relationship outcomes.

From a practical standpoint, the findings highlight the potential utility of explainable AI tools in preventive and therapeutic contexts. Clinicians and counselors could use communication-based risk indicators to identify couples who may benefit from early intervention, even before overt marital crises emerge. The interpretability of the models allows practitioners to translate algorithmic outputs into concrete communication targets, such as reducing contemptuous exchanges or fostering emotional validation. Beyond clinical settings, educational programs focused on relationship skills could incorporate insights from explainable models to emphasize specific interactional behaviors most strongly associated with long-term stability.

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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