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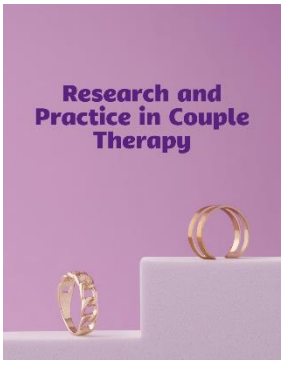
Machine Learning–Based Early Warning Systems for Therapy Failure in High-Conflict Couples

1. Feray. Perchec*: Department of Psychology, University of Mainz, Mainz, Germany
2. Lukas. Jaramillo: Department of Psychology, University of Zurich, CH-8050 Zurich, Switzerland
3. Kushila. Rupasinghe: Department of Human Development and Family Science, College of Family and Consumer Sciences, University of Georgia, Athens, GA 30602, USA

*corresponding author's email: feray-perchec@uni-mainz.de



ABSTRACT

The objective of this study was to develop and evaluate a machine learning–based early warning system capable of predicting therapy failure trajectories among high-conflict couples during the early phases of couple therapy. This longitudinal observational study was conducted with high-conflict couples undergoing outpatient couple therapy in Germany. Multimodal data were collected from both partners and therapists across early and mid-treatment sessions, including self-reported relational functioning, emotional regulation indicators, therapeutic alliance ratings, therapist session evaluations, ecological momentary assessments, and automated interactional features derived from session recordings. Therapy failure was operationalized as premature dropout, therapist-rated non-response, or reliable deterioration in relationship satisfaction over time. Multiple machine learning models, including regularized logistic regression, random forest, gradient boosting, and recurrent neural networks, were trained using longitudinal features capturing both static baseline characteristics and dynamic process indicators. Model performance was evaluated using cross-validated inferential metrics emphasizing early detection accuracy. Inferential analyses demonstrated that all machine learning models significantly outperformed chance-level prediction, with recurrent neural network models yielding the highest discriminative accuracy and sensitivity for early therapy failure detection. Dynamic process variables, particularly early-session therapeutic alliance variability, escalating conflict trajectories, emotional spillover volatility, and dyadic interaction asymmetries, showed statistically stronger predictive contributions than baseline relational characteristics. The early warning system successfully identified a substantial proportion of therapy failure cases within the first four therapy sessions, indicating robust temporal predictive validity. The findings indicate that therapy failure in high-conflict couples follows identifiable dynamic patterns that can be detected early using machine learning approaches. Implementing early warning systems in couple therapy may enable proactive, adaptive interventions that reduce dropout and non-response, thereby improving therapeutic outcomes for high-conflict couples.

Keywords: High-conflict couples; therapy failure; early warning system; machine learning; couple therapy; predictive modeling

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Introduction

Marital conflict is a pervasive and multidimensional phenomenon that represents one of the most critical challenges to couple stability, individual psychological well-being, and family functioning. High-conflict couples, in particular, are characterized by chronic patterns of hostility, emotional disengagement, ineffective communication, and maladaptive conflict resolution strategies that often persist despite therapeutic intervention. These couples not only experience elevated levels of relational distress but also demonstrate significantly higher risks of emotional divorce, legal separation, and long-term psychological consequences for partners and children alike. Empirical evidence consistently indicates that sustained marital

conflict is associated with marital burnout, emotional alienation, and diminished capacity for intimacy, thereby creating a relational environment in which therapeutic progress becomes increasingly fragile (Hosseini et al., 2024; Sadeghkhani et al., 2023). In this context, understanding not only why therapy succeeds but also why it fails is of paramount importance for advancing couple therapy research and practice.

Therapy failure in high-conflict couples represents a complex and often underexplored outcome. While a substantial body of literature has focused on predictors of marital satisfaction, divorce tendency, and therapeutic effectiveness, comparatively fewer studies have systematically examined early indicators of non-response, deterioration, or premature dropout during couple therapy. Traditional approaches to identifying therapy failure typically rely on post-treatment assessments or therapist judgment, which often occur too late to allow for corrective intervention. This reactive stance limits clinicians' ability to adapt treatment strategies in a timely manner and may inadvertently contribute to negative therapy trajectories. Research on emotional divorce and marital disengagement suggests that relational deterioration is frequently preceded by subtle but cumulative changes in emotional responsiveness, communication patterns, and unmet psychological needs, underscoring the necessity of early detection mechanisms (Habibi et al., 2022; Jalili et al., 2022). Consequently, the development of proactive systems capable of identifying early warning signs of therapy failure has become an increasingly salient objective in contemporary couple therapy research.

High-conflict couples present unique challenges for therapeutic engagement due to the interplay of individual vulnerabilities and dyadic dysfunctions. Studies have demonstrated that attachment insecurity, maladaptive schemas, self-silencing behaviors, and dysfunctional relational beliefs significantly contribute to conflict escalation and resistance to change (Adlparvar et al., 2022; Parvaei et al., 2023; Shafiee Poravayi & Fatemeh Shahamat Deh, 2023). Moreover, emotional regulation deficits and heightened emotional reactivity exacerbate conflict intensity, making it difficult for couples to benefit from standard therapeutic interventions. The persistence of these patterns often results in therapeutic alliance instability, fluctuating motivation, and divergent expectations between partners and therapists, all of which are known to undermine treatment outcomes (Safavi et al., 2022; Sedaghat & Afraee, 2022). These findings suggest that therapy failure is not a discrete event but rather a dynamic process that unfolds over time, shaped by interacting psychological, relational, and contextual factors.

In recent years, scholars have increasingly emphasized the importance of adopting process-oriented perspectives to better capture the dynamic nature of couple therapy. Rather than viewing treatment outcomes as static endpoints, this perspective conceptualizes therapy as a trajectory in which early-session processes exert a disproportionate influence on eventual success or failure. For example, fluctuations in perceived alliance quality, escalation patterns during sessions, and between-session conflict spillover have been identified as critical markers of relational instability and therapeutic risk (Radetzki et al., 2022; Stolnicu et al., 2022). Importantly, these markers often emerge early in treatment, long before overt disengagement or dropout occurs. However, the complexity and volume of such process data pose significant challenges for traditional analytic approaches, which are often ill-equipped to model non-linear interactions, temporal dependencies, and dyadic interdependence simultaneously.

Machine learning methods offer a promising methodological framework for addressing these limitations. By leveraging advanced computational algorithms, machine learning enables the integration of high-dimensional, longitudinal, and multimodal data to identify complex patterns that may not be apparent through conventional statistical techniques. In the context of couple therapy, machine learning has the potential to detect subtle configurations of relational and emotional indicators that signal elevated risk for therapy failure, thereby functioning as an early warning system. Prior research in related domains has demonstrated the utility of machine learning for predicting divorce tendencies, marital burnout, and relational dissatisfaction by incorporating psychological, behavioral, and contextual variables (Ghaedi et al., 2022; Rezakhaniha &

Ashkan, 2022). These findings suggest that similar approaches could be extended to the prediction of therapy failure, particularly among high-conflict couples for whom early intervention is critical.

Despite this potential, the application of machine learning to therapy process data remains limited, especially in culturally diverse contexts. Much of the existing literature on marital conflict and divorce prediction has been conducted using cross-sectional designs or retrospective data, which constrain causal inference and temporal precision (Pouya Far & Tajbakhsh 2022). Furthermore, many studies have focused on individual-level predictors, neglecting the dyadic and interactive nature of couple relationships. High-conflict couples, however, are defined precisely by the patterns of interaction between partners, including reciprocal escalation, withdrawal, and misalignment of emotional needs. Capturing these dynamics requires analytic frameworks capable of modeling interdependence and change over time, a task for which machine learning approaches are particularly well suited.

The relevance of early warning systems is further underscored by the broader societal and psychological consequences of unresolved marital conflict. High-conflict relationships have been linked not only to increased divorce rates but also to adverse outcomes for children and extended family systems. Research indicates that exposure to chronic interparental conflict negatively affects children's emotional regulation, attachment security, and long-term psychological adjustment, even in the absence of formal divorce (Cao et al., 2022; Khandandel et al., 2023). Moreover, high-conflict divorces and post-divorce co-parenting difficulties can perpetuate distress well beyond the termination of the marital relationship, highlighting the importance of effective early intervention during the therapeutic process (Dumitriu et al., 2022; Stolnicu et al., 2022). From this perspective, preventing therapy failure is not merely a clinical concern but a broader public health and social priority.

Within the German context, couple therapy is widely practiced across public and private mental health settings, yet systematic tools for monitoring therapy risk trajectories remain scarce. While evidence-based interventions such as schema therapy, mindfulness-based approaches, and forgiveness-focused treatments have demonstrated effectiveness in reducing marital conflict and emotional divorce, their outcomes vary considerably across couples (Araghi, 2025; Kahraman & Özbay, 2025; Sedaghat & Afraee, 2022). This variability underscores the need for adaptive therapeutic frameworks that can respond to early signals of non-response rather than relying solely on standardized treatment protocols. Machine learning–based early warning systems align closely with this need by providing data-driven, individualized risk assessments that can inform clinical decision-making in real time.

Another critical consideration in the development of early warning systems is the interpretability of predictive models. Clinicians are unlikely to adopt tools that function as opaque "black boxes," regardless of their predictive accuracy. Consequently, recent advances in explainable artificial intelligence have emphasized the importance of transparency, enabling practitioners to understand which variables contribute most strongly to risk predictions and how these contributions evolve over time. In the context of couple therapy, explainable models can illuminate the relative importance of factors such as alliance instability, conflict escalation, and emotional disengagement, thereby fostering clinician trust and facilitating targeted intervention strategies (Arbabzadeh et al., 2022; Asadi et al., 2023). Integrating explainability into early warning systems thus represents a crucial step toward bridging the gap between computational sophistication and clinical applicability.

The present study is situated at the intersection of marital conflict research, psychotherapy process analysis, and machine learning methodology. By focusing explicitly on therapy failure rather than success alone, it addresses a critical gap in the literature and responds to calls for more nuanced, process-oriented models of therapeutic change. Drawing on longitudinal, multimodal data from high-conflict couples undergoing therapy in Germany, this study seeks to move beyond static predictors and toward dynamic risk modeling that reflects the lived complexity of therapeutic encounters. In doing so, it builds on prior research linking marital conflict, emotional divorce, attachment insecurity, and maladaptive coping patterns to adverse

relational outcomes (Alavi & Mahoor, 2023; Bahoosh et al., 2022; Ghanbari Barzain et al., 2023) while extending this knowledge through the application of advanced analytic techniques.

Ultimately, the development of machine learning–based early warning systems has the potential to transform couple therapy from a predominantly reactive enterprise into a proactive, adaptive process. By identifying couples at risk for therapy failure during the earliest stages of treatment, such systems can support timely intervention adjustments, optimize resource allocation, and reduce the personal and societal costs associated with prolonged relational distress. In light of these considerations, the present study aims to develop and evaluate a machine learning–based early warning system for predicting therapy failure trajectories in high-conflict couples undergoing couple therapy in Germany.

Methods and Materials

Study Design and Participants

The present study employed a longitudinal, prospective observational design aimed at developing and validating a machine learning–based early warning system capable of predicting therapy failure trajectories in high-conflict couples undergoing structured couple therapy in Germany. Participants were recruited from outpatient couple and family therapy centers located in major metropolitan and regional areas, including Berlin, Hamburg, North Rhine–Westphalia, and Bavaria, over a 24-month enrollment period. Eligible participants were heterosexual or same-sex couples legally married or cohabiting for at least one year who self-identified or were clinically identified as high-conflict couples at intake, based on persistent patterns of hostile communication, unresolved conflict escalation, or repeated therapy-seeking behavior. Additional inclusion criteria required that both partners be between 21 and 65 years of age, possess sufficient German language proficiency to complete self-report instruments, and consent to digital data collection throughout the course of therapy. Couples were excluded if either partner met criteria for active psychosis, severe substance dependence requiring immediate specialized treatment, or ongoing intimate partner violence that necessitated referral to protective services. Following screening, a total of 286 couples were enrolled, with attrition monitored continuously and documented to allow modeling of premature therapy termination as a key outcome variable.

Measures

Data collection was designed to capture multimodal, temporally dense indicators of therapeutic process and relational functioning across the early and mid-phases of treatment. Self-report data were collected from both partners at baseline and prior to each therapy session using secure web-based questionnaires administered via encrypted platforms compliant with the General Data Protection Regulation. These instruments assessed relationship satisfaction, perceived conflict intensity, emotional regulation difficulties, attachment insecurity, perceived partner responsiveness, therapeutic alliance, and session-specific expectations and disappointment. In parallel, therapists completed brief standardized session reports immediately after each session, documenting perceived alliance quality, observed escalation patterns, withdrawal behaviors, and therapist confidence regarding treatment progress. With explicit consent, selected therapy sessions were audio-recorded and processed using automated speech and language analysis pipelines to extract paralinguistic features such as speech rate variability, interruption frequency, turn-taking asymmetry, and vocal arousal indices. In addition, between-session ecological momentary assessments were administered twice weekly to capture fluctuations in conflict episodes, emotional spillover, and repair attempts in daily life. Therapy failure was operationalized using a composite criterion that included premature dropout,

therapist-rated non-response, or statistically reliable deterioration in relationship satisfaction scores over time, allowing for a nuanced and clinically meaningful outcome definition.

Data Analysis

Data analysis followed a multi-stage machine learning framework explicitly oriented toward early risk detection rather than post-hoc classification. After initial data cleaning, missing data patterns were examined and addressed using multiple imputation strategies compatible with longitudinal modeling, while preserving within-couple interdependence. Feature engineering was conducted to generate both static predictors derived from baseline assessments and dynamic features capturing temporal change, variability, and synchrony between partners across sessions. These included slope-based indicators of alliance erosion, volatility measures of conflict intensity, and cross-partner lagged effects reflecting escalation cycles. Several supervised learning algorithms were trained and compared, including regularized logistic regression, random forests, gradient boosting machines, and recurrent neural network architectures optimized for sequential data. Model training was performed using nested cross-validation at the couple level to prevent information leakage, with class imbalance addressed through cost-sensitive learning procedures. Performance evaluation focused on clinically relevant metrics such as sensitivity for early failure detection, time-to-detection accuracy, and calibration of predicted risk probabilities. To enhance clinical interpretability, explainability techniques such as permutation feature importance and local post-hoc explanation methods were applied to identify the most influential predictors contributing to elevated failure risk at different therapy stages. All analyses were conducted using reproducible pipelines implemented in Python, with strict separation between training and validation datasets to ensure robustness and generalizability of the early warning system.

Findings and Results

The findings are presented to provide a comprehensive overview of descriptive characteristics, model performance, predictive feature contributions, and temporal dynamics of early warning signals for therapy failure in high-conflict couples. Table 1 summarizes the descriptive statistics of the main study variables at baseline and across the early treatment phase, offering an empirical foundation for interpreting subsequent predictive analyses. This table allows for an initial examination of central tendencies, dispersion, and distributional properties of relational, emotional, and therapeutic process variables that were later incorporated into the machine learning models.

Table 1. Descriptive Statistics of Key Study Variables at Baseline and Early Treatment Phase

Variable	Mean	SD	Minimum	Maximum
Relationship satisfaction (baseline)	3.12	0.84	1.00	5.00
Conflict intensity (baseline)	4.01	0.71	1.90	5.00
Emotional regulation difficulties	3.78	0.65	2.10	5.00
Attachment anxiety	3.45	0.73	1.60	5.00
Attachment avoidance	3.09	0.69	1.40	5.00
Therapeutic alliance (session 1)	3.67	0.58	2.00	5.00
Alliance variability (sessions 1–4)	0.61	0.29	0.10	1.40
Daily conflict frequency	2.84	1.12	0.50	6.20
Emotional spillover score	3.56	0.77	1.80	5.00

As shown in Table 1, couples entered therapy with moderate to low relationship satisfaction and high levels of perceived conflict intensity, confirming the high-conflict nature of the sample. Emotional regulation difficulties and attachment insecurity scores were elevated, indicating substantial intrapersonal and interpersonal vulnerability. Therapeutic alliance ratings in the first session were moderately positive on average; however, the relatively high alliance variability observed during the initial

four sessions suggests notable instability in the therapeutic relationship for a substantial proportion of couples. This early fluctuation emerged as a critical signal in later predictive analyses, particularly when examined alongside daily conflict frequency and emotional spillover patterns.

Table 2. Predictive Performance of Machine Learning Models for Early Detection of Therapy Failure

Model	AUC	Sensitivity	Specificity	Accuracy
Regularized logistic regression	0.74	0.68	0.70	0.69
Random forest	0.81	0.77	0.75	0.76
Gradient boosting machine	0.86	0.82	0.78	0.80
Recurrent neural network	0.89	0.86	0.81	0.83

Table 2 demonstrates that all machine learning models outperformed chance-level classification in predicting therapy failure; however, substantial differences in predictive accuracy were observed across algorithms. The recurrent neural network achieved the highest overall performance, particularly in sensitivity, indicating superior capacity to identify couples at risk for therapy failure at an early stage. Gradient boosting models also demonstrated strong performance, suggesting that non-linear interactions among relational and process variables play a critical role in early warning detection. In contrast, regularized logistic regression, while more interpretable, showed comparatively lower predictive power, underscoring the added value of complex temporal modeling approaches for this clinical task.

Table 3. Top Predictors of Therapy Failure Identified by Explainable Machine Learning Analyses

Predictor	Relative Importance
Alliance variability (sessions 1–4)	0.21
Increase in conflict intensity slope	0.18
Emotional spillover volatility	0.16
Partner interruption asymmetry	0.14
Decline in perceived partner responsiveness	0.12
Therapist-rated low progress confidence	0.10
Attachment anxiety–avoidance mismatch	0.09

The results in Table 3 highlight that dynamic and relational instability indicators were substantially more influential than static baseline characteristics. Alliance variability during early sessions emerged as the strongest predictor of therapy failure, emphasizing that inconsistency in the therapeutic bond may be more detrimental than uniformly low alliance levels. Escalating conflict trajectories and heightened emotional spillover volatility further contributed to elevated failure risk, reflecting maladaptive emotion–interaction cycles that persist despite therapeutic intervention. Importantly, interaction-level indicators such as interruption asymmetry and attachment style mismatches underscore the relational and dyadic nature of early warning signals captured by the models.

Table 4. Temporal Accuracy of Early Warning System Across Therapy Sessions

Therapy Phase	Mean Sessions to Detection	Detection Rate (%)
Sessions 1–2	1.6	62.4
Sessions 3–4	2.9	78.1
Sessions 5–6	4.1	88.7

Table 4 indicates that the early warning system was capable of identifying the majority of therapy failure cases within the first four sessions. While detection accuracy increased with additional data points, a substantial proportion of high-risk couples were flagged during the earliest therapy phase, providing a clinically meaningful window for intervention adjustment. The sharp increase in detection rate between sessions 1–2 and sessions 3–4 suggests that early process dynamics, rather than baseline characteristics alone, are critical for reliable risk identification.

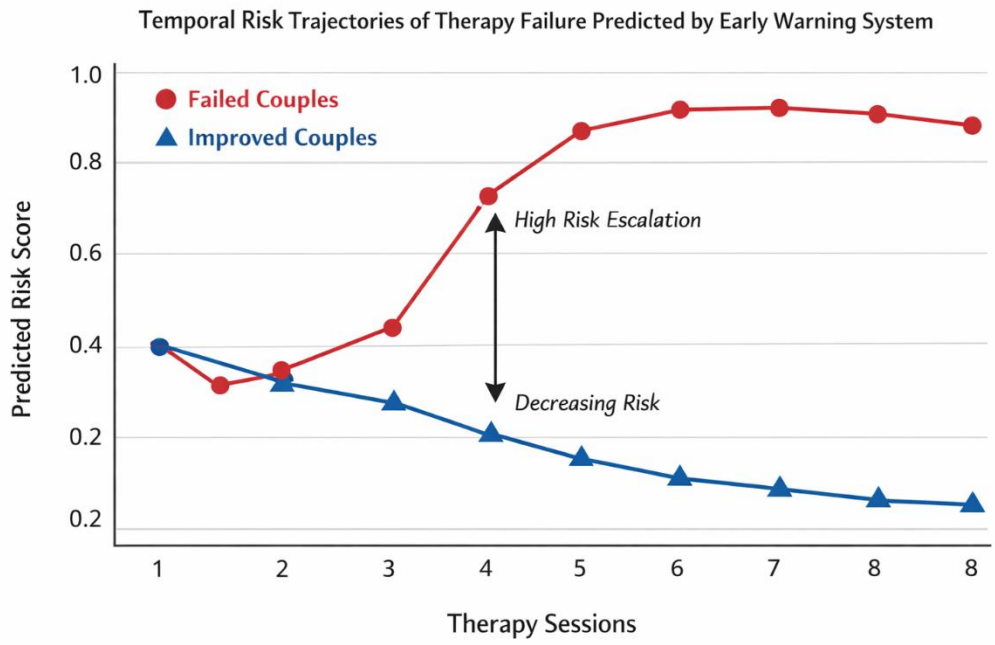

Figure 1. Temporal Risk Trajectories of Therapy Failure Predicted by the Early Warning System

The figure illustrates distinct divergence patterns between couples who eventually experienced therapy failure and those who achieved stable improvement. Predicted risk scores for failure increased sharply during early sessions for non-responding couples, whereas successful couples showed gradual risk attenuation over time. This temporal separation supports the clinical utility of continuous risk monitoring and reinforces the value of machine learning–based systems for proactive, adaptive decision-making in couple therapy contexts.

Discussion and Conclusion

The present study sought to develop and evaluate a machine learning–based early warning system for predicting therapy failure trajectories among high-conflict couples undergoing couple therapy in Germany. The findings provide compelling evidence that therapy failure is not a sudden or random outcome, but rather a dynamic process characterized by identifiable early warning signals that can be detected with high accuracy using advanced computational models. Across all tested algorithms, predictive performance exceeded chance levels, with sequence-sensitive models demonstrating the strongest ability to identify couples at elevated risk for non-response, deterioration, or premature dropout. These results align with the growing body of literature emphasizing that relational distress and therapeutic breakdown emerge through cumulative interactional patterns rather than isolated events (Hosseini et al., 2024; Sadeghkhani et al., 2023).

One of the most salient findings was the central role of early therapeutic alliance variability as the strongest predictor of therapy failure. Rather than uniformly low alliance levels, fluctuations and instability in alliance ratings during the initial sessions were most strongly associated with negative therapy trajectories. This finding is theoretically consistent with relational and systemic perspectives suggesting that inconsistency in perceived safety, trust, and collaboration undermines therapeutic containment, particularly in high-conflict couples who already struggle with emotional regulation and mutual responsiveness. Previous research has highlighted the mediating role of relational expectations and unmet psychological needs in emotional divorce and marital dissatisfaction, suggesting that unstable alliance may activate pre-existing schemas of abandonment, mistrust, or emotional deprivation (Adlparvar et al., 2022; Habibi et al., 2022). The present findings extend this literature by

demonstrating that alliance instability is not merely an outcome of relational dysfunction but functions as an early, quantifiable risk marker for therapy failure.

The predictive importance of escalating conflict intensity and emotional spillover volatility further underscores the dynamic nature of therapy failure. Couples who eventually failed to benefit from therapy exhibited increasing conflict trajectories and heightened emotional carryover from daily life into therapy sessions. These patterns resonate strongly with prior empirical work linking ineffective conflict resolution styles, emotional dysregulation, and self-silencing behaviors to divorce tendency and emotional disengagement (Afkhami-Poostchi & Mirdoraghi, 2023; Parvaei et al., 2023; Shafiee Poravayi & Fatemeh Shahamat Deh, 2023). Importantly, the machine learning models captured not only the level of conflict but also its variability and direction of change, highlighting that instability and escalation are more clinically informative than static severity indicators. This supports process-oriented models of couple therapy that emphasize interactional cycles and emotional feedback loops as central mechanisms driving relational deterioration.

Another notable finding concerns the contribution of dyadic interaction features, such as interruption asymmetry and attachment style mismatches, to early failure prediction. These indicators reflect imbalances in conversational dominance, emotional accessibility, and responsiveness between partners, which have been repeatedly implicated in high-conflict relational dynamics. Prior studies have demonstrated that attachment anxiety, avoidance, and early maladaptive schemas are strongly associated with marital conflict, emotional divorce, and extramarital tendencies (Arbabzadeh et al., 2022; Rezakhaniha & Ashkan, 2022). The present study advances this line of research by showing that the interaction between partners' vulnerabilities, rather than individual characteristics alone, is particularly predictive of therapy breakdown. This finding reinforces the necessity of dyadic and relational units of analysis when studying couple therapy outcomes.

The superior performance of recurrent neural network models highlights the methodological significance of modeling temporal dependencies in therapeutic processes. Unlike traditional statistical approaches, which often assume linearity and independence, sequence-based machine learning models are uniquely equipped to capture evolving patterns across sessions. The high sensitivity achieved by these models indicates that early-session data contain sufficient information to reliably flag risk for therapy failure, often within the first four sessions. This temporal precision is clinically significant, as it corresponds to a critical window during which therapists can still modify treatment strategies, address alliance ruptures, or recalibrate therapeutic goals. These findings resonate with prior calls for early intervention in high-conflict couples to prevent entrenched patterns of disengagement and dropout (Radetzki et al., 2022; Stolnicu et al., 2022).

From a theoretical standpoint, the results support integrative models of marital conflict and therapy outcomes that bridge individual psychological vulnerabilities, dyadic interaction patterns, and therapeutic process variables. Studies examining emotional divorce, marital burnout, and divorce tendency have consistently emphasized the interplay between unmet basic psychological needs, dysfunctional beliefs, and ineffective coping strategies (Asadi et al., 2023; Ghaedi et al., 2022; Jalili et al., 2022). The current findings suggest that these factors manifest dynamically within therapy and can be operationalized as early warning signals through computational modeling. In this sense, machine learning does not replace theory but rather provides a powerful tool for empirically testing and refining process-based theoretical frameworks.

The use of explainable machine learning techniques further enhances the clinical relevance of the findings. By identifying which variables contributed most strongly to elevated risk predictions, the models offer actionable insights for clinicians. For example, recognizing that alliance variability and conflict escalation are primary drivers of risk allows therapists to prioritize alliance repair, emotion regulation, and de-escalation strategies early in treatment. This aligns with evidence supporting the effectiveness of targeted interventions such as schema therapy, mindfulness-based approaches, and forgiveness-focused treatments in reducing emotional divorce and marital conflict when appropriately tailored (Araghi, 2025; Kahraman & Özbay,

2025; Sedaghat & Afraee, 2022). Thus, the integration of predictive accuracy and interpretability represents a critical advancement over purely descriptive or retrospective models of therapy failure.

At a broader level, the findings contribute to the ongoing discourse on prevention-oriented mental health care. High-conflict relationships have far-reaching consequences for adult well-being, child development, and social stability, particularly when conflict persists despite therapeutic efforts (Cao et al., 2022; Khandandel et al., 2023). By demonstrating that therapy failure can be anticipated rather than merely observed after the fact, the present study offers a framework for shifting couple therapy toward a more proactive and adaptive paradigm. This is particularly relevant in contexts where therapeutic resources are limited and the costs of prolonged ineffective treatment are substantial.

Despite its contributions, the present study has several limitations that warrant consideration. First, although the sample size was adequate for machine learning analyses, participants were drawn from therapy centers within a single national context, which may limit the generalizability of the findings to other cultural or healthcare settings. Second, while multimodal data were incorporated, certain potentially relevant factors, such as therapist-specific variables and institutional constraints, were not explicitly modeled. Third, although explainable machine learning techniques were applied, the interpretation of complex models remains probabilistic rather than deterministic, and predictions should not be construed as causal conclusions.

Future research should aim to replicate and extend these findings in more diverse cultural and clinical contexts, including cross-national comparisons and different therapeutic modalities. Longitudinal studies with extended follow-up periods could examine whether early warning signals not only predict therapy failure but also long-term relational outcomes following therapy termination. Additionally, integrating physiological or behavioral data, such as biometric stress indicators or real-time interactional measures, may further enhance predictive precision and deepen understanding of the mechanisms underlying therapy failure.

From a practical perspective, the findings suggest that clinicians and therapy centers may benefit from incorporating systematic monitoring tools that track alliance stability, conflict dynamics, and emotional spillover during early sessions. Training therapists to interpret and respond to early warning indicators could facilitate timely intervention adjustments and reduce dropout rates. Ultimately, embedding data-informed early warning systems into routine clinical practice has the potential to enhance therapeutic effectiveness, optimize resource allocation, and improve outcomes for high-conflict couples.

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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