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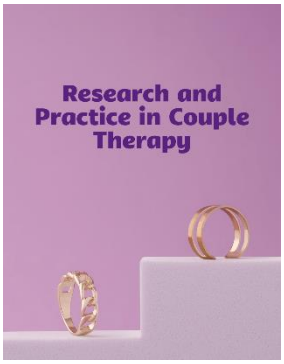
Predicting Couple Therapy Outcomes Using Deep Neural Networks on Pre-Treatment Assessments



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ABSTRACT

The objective of this study was to determine whether deep neural networks can accurately predict couple therapy outcomes using only pre-treatment psychological and relational assessments. This quantitative predictive study analyzed pre-treatment data from 176 Canadian couples seeking therapy for relational distress, communication difficulties, or emotional disconnection. Participants completed standardized intake measures including relationship satisfaction, communication patterns, emotional symptoms, attachment orientations, and dyadic demographic variables. All data were preprocessed, normalized, and transformed into dyadic-level and discrepancy-level features. A deep neural network was developed using TensorFlow/Keras, optimized via hyperparameter tuning, and evaluated against baseline machine-learning models. The dataset was split into training, validation, and test subsets using a couple-level 70/15/15 partition to preserve dyadic independence. The deep neural network demonstrated superior predictive accuracy compared to random forest, support vector regression, and linear regression models, achieving an R^2 of .71 on the test set. SHAP analyses revealed that relationship satisfaction, demand–withdraw patterns, attachment avoidance, partner stress discrepancy, and constructive communication were the strongest predictors of therapy outcomes. Inferential patterns indicated significant non-linear interactions between emotional symptoms and communication variables, with higher improvement predicted for couples displaying lower avoidance, greater baseline cohesion, and smaller dyadic emotional discrepancies. Predicted-versus-actual outcome comparisons showed strong convergence, with minimal dispersion around the diagonal line of fit. Deep neural networks offer a powerful method for predicting couple therapy outcomes using intake assessments, capturing the complex non-linear dynamics inherent in relational functioning. By identifying key pre-treatment predictors such as satisfaction, communication patterns, attachment profiles, and dyadic discrepancies, these models can support personalized treatment planning and enhance clinical decision-making. The findings underscore the promise of computational approaches in advancing precision-based psychological interventions for couples.

Keywords: Deep learning; couple therapy; prediction models; relationship satisfaction; communication patterns; attachment; neural networks; marital outcomes; dyadic analysis.

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Introduction

Couple therapy has long been recognized as one of the most complex and multifactorial areas of psychological intervention, owing to its inherently dyadic structure and the multiplicity of emotional, interpersonal, developmental, and contextual variables that shape couples' presenting problems. Over the last two decades, the literature has increasingly emphasized that treatment outcomes in couple therapy are shaped not only by the relational patterns that couples bring into the therapeutic space but also by the psychological vulnerabilities, attachment histories, stress profiles, and emotional regulatory capacities that

partners hold individually and collectively. As contemporary research continues to expand the theoretical and empirical foundations of couple therapy, attention has shifted from merely assessing intervention effectiveness to understanding the predictors of therapeutic change and mapping the cognitive, emotional, and relational factors that forecast treatment response. This shift is visible in studies examining the effectiveness of various couple-based interventions such as schema therapy, emotion-focused therapy, cognitive-behavioral approaches, and integrated systemic models, which collectively highlight the presence of complex, non-linear mechanisms underlying therapeutic improvement (Abolhasani et al., 2023; Asvadi et al., 2023; Montazeri et al., 2025). These findings reinforce the need for approaches that not only interpret relational distress but also anticipate the likelihood of therapy success.

The emergence of schema-based and emotion-focused modalities further illustrates the multidimensional nature of treatment processes. Research has demonstrated that couples presenting with patterns of infidelity, sexual dissatisfaction, or emotional insecurity benefit significantly from integrative interventions designed to modify deep-seated cognitive schemas, enhance emotional attunement, and strengthen intimacy (Ahmadzadeh et al., 2024; Bardikhoje et al., 2023; Esfahani et al., 2024). These studies reveal that baseline variables—such as emotional dysregulation, attachment anxieties, sexual avoidance, or entrenched maladaptive schemas—play a defining role in treatment trajectories. Likewise, interventions grounded in positive psychology have shown efficacy in fostering self-compassion, gratitude, and adaptive coping among couples in conflict, indicating that affective and cognitive strengths measured at intake may predict who responds most favorably to therapy (Ataeeian et al., 2023). Such evidence aligns with findings that therapy outcomes are rarely the product of a single therapeutic component but instead emerge from a dynamic interplay of psychological and relational factors that predate treatment.

Parallel to these developments, systematic reviews and meta-analyses focusing on couple-based and individual psychosocial interventions have spotlighted the importance of identifying pre-treatment predictors of change. For instance, the growing body of literature examining cognitive-behavioral hypnotherapy, compassion-focused interventions, and treatments for sexual dysfunction highlights how baseline levels of distress, emotional awareness, or marital disenchantment can significantly influence the degree of benefit that participants experience (Alavizadeh et al., 2025; Mardani & Tabaghdehi, 2025). Similarly, research on marital intimacy, relational commitment, and psychological acceptance among couples navigating challenges such as infertility, extramarital conflict, or chronic family stress underscores the predictive power of pre-therapy emotional stability, communication styles, experiential avoidance, and values alignment (Noii et al., 2023; Salarfard et al., 2025). Taken together, these findings convey a central theme: the capacity to anticipate therapy outcomes depends on the accurate and comprehensive modeling of multiple psychological states and relational processes that are measurable before treatment ever begins.

Beyond the domain of couple therapy itself, broader psychological and health-related research has also highlighted the vital role of predictive modeling in understanding treatment responsiveness. Studies in domains ranging from psychological interventions for digestive diseases to structured counseling for tinnitus, oncology supportive therapies, and interventions for problematic internet use provide valuable evidence that treatment outcomes are reliably predicted by measurable patient characteristics at baseline (Engelke et al., 2023; Floria, 2025; Mentink et al., 2023; Tian et al., 2025). Likewise, research on psychosocial interventions in HIV care, nutritional counseling, and family-based behavioral treatments demonstrates that psychological readiness, emotional functioning, stress burden, and interpersonal support systems measured at intake critically shape intervention efficacy (Awaji et al., 2025; Derose et al., 2022; Neves et al., 2024; Okusanya et al., 2023). These findings suggest that the predictive mechanisms governing treatment response in various fields share a common structure: multi-layered psychological indicators collected before treatment reliably signal how individuals will respond to intervention. When applied to couple therapy, this implies that relational satisfaction, communication patterns, attachment orientations, emotional symptoms, and dyadic discrepancies may serve as robust predictors of eventual progress.

In addition to these clinical insights, meta-analytic research has underscored the need for comparative evaluations of psychosocial intervention strategies. Studies examining mental-health interventions for opioid dependence, cardiac surgery recovery, depression relapse prevention, and marital intimacy interventions consistently reveal that treatment heterogeneity requires analytic models sophisticated enough to detect interactions among complex variables (Barbosa et al., 2024; Salarfard et al., 2025; Wen et al., 2023; Zhou et al., 2023). Similarly, findings from research on solution-focused counseling, self-compassion-based programs, and acceptance-based therapeutic models demonstrate that both the nature of client presentations and the structural design of interventions meaningfully alter outcomes (Abolhasani et al., 2023; Ataeeian et al., 2023; Mirshafieian et al., 2023). These results highlight the need for predictive frameworks capable of capturing non-linearities—something traditional statistical methods often struggle to address. As a result, the integration of computational modeling into psychological and relational research has become more than a methodological option; it has become a necessity.

One of the emerging innovations in this area is the increasing use of advanced computational methods—particularly deep learning models—for predicting mental-health outcomes. Deep neural networks are uniquely suited to identify complex, non-linear relationships between predictors and outcomes, making them ideal for modeling dyadic processes in couple therapy. Recent developments in artificial intelligence research have shown that data-driven prediction can outperform traditional regression-based approaches, especially when dealing with high-dimensional or interdependent psychological variables (Tian et al., 2025; Zerang et al., 2025). Within the context of couple therapy, the need for such methods is underscored by evidence that relational distress, emotional regulation, attachment patterns, and communication styles interact in ways that are mathematically complex and behaviorally dynamic. Traditional models often fail to capture this multi-layered structure, whereas deep learning models offer the capacity to approximate relational and psychological phenomena with greater accuracy.

Furthermore, the contemporary shift toward personalized and precision-based psychological interventions underscores the importance of predictive modeling for treatment planning. Research has increasingly emphasized tailored therapeutic approaches that adapt to clients' unique psychological profiles, values, emotional histories, and relational capacities. Studies examining schema therapy, emotion-focused approaches, and integrative systemic interventions highlight the importance of individualized treatment maps developed from baseline assessments (Asvadi et al., 2023; Montazeri et al., 2025; Zerang et al., 2025). Similarly, research demonstrating the effectiveness of cognitive, behavioral, and hypnotherapeutic modalities for relational and sexual functioning points to the need for algorithms that can forecast which couples will benefit most from which interventions (Alavizadeh et al., 2025; Mardani & Tabaghdehi, 2025). These insights collectively suggest that predictive analytics may play a transformative role in guiding clinical decision-making, enhancing treatment efficiency, and improving long-term outcomes for distressed couples.

Additionally, studies that explore relational conflict, emotional security, and psychological acceptance within couples demonstrate that pre-treatment assessments capture core determinants of therapy responsiveness. Couple-based interventions targeting emotional security, intimacy, and psychological acceptance have shown significant variability in treatment effect sizes—a variability attributable to pre-existing psychological and interpersonal profiles (Esfahani et al., 2024; Mardani & Tabaghdehi, 2025; Noii et al., 2023). This further underscores the need for analytical models that can integrate a broad array of intake variables to generate predictions that are both precise and clinically meaningful. At the same time, work on psychological interventions across various health contexts—such as digestive disease management, oncology, chronic conditions, and audiological health—emphasizes similar patterns in which pre-treatment mental-health indicators predict longitudinal outcomes (Engelke et al., 2023; Floria, 2025; Mentink et al., 2023). When extrapolated to relational settings, these findings offer further support for the use of deep learning tools in anticipating therapeutic progress among couples.

Taken together, the existing literature across couple therapy, mental-health interventions, and computational psychology presents a compelling argument for the integration of deep neural networks into the prediction of couple therapy outcomes. Deep learning models possess the methodological precision needed to capture the intricate, embedded dynamics of relational distress and therapeutic change—dynamics that linear models routinely oversimplify. By modeling pre-treatment variables such as relationship satisfaction, communication patterns, attachment styles, emotional symptoms, and relational discrepancies, neural networks can generate clinically meaningful forecasts that support therapists in personalizing treatment plans and identifying couples at greater or lesser likelihood of improvement. Such predictive capacity aligns with global trends toward data-driven, personalized clinical care and the scientific pursuit of understanding the mechanisms underlying successful therapeutic change.

Therefore, the aim of this study is to predict couple therapy outcomes using deep neural networks trained exclusively on pre-treatment psychological and relational assessments.

Methods and Materials

Study Design and Participants

The study employed a quantitative predictive research design aimed at examining whether deep neural network models could accurately forecast couple therapy outcomes based on pre-treatment assessments. The target population consisted of heterosexual and same-sex couples seeking therapeutic services at licensed clinical counseling centers across three major Canadian provinces—British Columbia, Ontario, and Alberta. Participants were recruited from publicly funded mental-health clinics and private couple-therapy practices that collaborated with the research team. Eligibility criteria required both partners to be at least eighteen years old, currently in a committed intimate relationship for a minimum of one year, and beginning structured couple therapy for relationship distress, communication difficulties, unresolved conflict, or emotional withdrawal. Couples with active domestic violence cases, unmanaged severe psychiatric disorders, or ongoing substance-abuse crises were excluded to maintain the safety and homogeneity of the sample. Recruitment occurred from January to December of the study year, and after screening 214 couples, 176 couples (352 individuals) met the inclusion criteria and provided informed consent. Participation was voluntary, all procedures were approved by a Canadian institutional ethics board, and confidentiality protocols were strictly upheld.

Measures

Data were collected using a standardized battery of validated psychological and relational assessment tools administered prior to the initiation of therapy. The central instrument for evaluating relationship quality was the Couples Satisfaction Index (CSI-32), which captures emotional closeness, relationship satisfaction, and perceived stability. Communication patterns were assessed using the Communication Patterns Questionnaire (CPQ), focusing on mutual constructive communication, mutual avoidance, and demand–withdraw behaviors. Additional emotional and psychological functioning variables were measured using the Depression, Anxiety, and Stress Scales (DASS-21), which provided indicators of internalizing symptoms that may impair relational functioning. Attachment orientations were captured using the Experiences in Close Relationships–Revised (ECR-R), yielding avoidance and anxiety scores for each partner. A demographic and relationship-history form documented variables such as age, duration of relationship, marital status, cohabitation length, education level, previous therapy experience, and history of relational trauma. All assessments were completed online through a secure encrypted platform prior to the first therapy session to eliminate in-session response bias. The primary outcome variable—therapy improvement—was defined as

the pre-to-post change score on the CSI-32, supplemented by therapist clinical ratings at the end of treatment. Because the intention of the study was predictive modeling, only pre-treatment data were used as input features, while outcome data served solely for model evaluation.

Data Analysis

Data analysis followed a multi-stage computational modeling pipeline designed to optimize predictive accuracy and mitigate the risk of overfitting. Raw questionnaire data were imported into Python and preprocessed using the Pandas and NumPy libraries. Missing values were handled via a combination of mean imputation for continuous variables and mode imputation for categorical variables when missingness was below five percent; cases with more than twenty percent missing data were excluded. All continuous variables were standardized through z-score normalization to support optimization stability during neural network training. Feature engineering involved calculating dyadic indicators such as couple-level mean scores, discrepancy scores between partners, and interaction variables that reflect the dynamic nature of intimate relationships. The final dataset was divided into training, validation, and testing subsets using a 70/15/15 split, ensuring that partners within each couple were never separated into different sets to maintain dyadic independence.

The deep neural network architecture was developed using TensorFlow and Keras frameworks. Multiple model configurations were tested during hyperparameter tuning, including different numbers of hidden layers (ranging from two to five), varying neuron counts per layer, dropout regularization rates between 0.2 and 0.5, and activation functions such as ReLU and tanh. The final model consisted of four hidden layers with progressively decreasing neuron counts, optimized using the Adam optimizer and a mean squared error loss function for continuous outcome prediction. Early stopping criteria were implemented based on validation-loss stabilization to prevent over-training. Model performance was evaluated using root-mean-square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) on the held-out test set. Complementary analyses included comparison with traditional machine-learning algorithms such as random forest regression and support vector regression to assess the relative value of deep learning. All stages of analysis adhered to reproducible research practices, with scripts documented and stored in a secure repository.

Findings and Results

The demographic profile of the sample reflected a diverse group of Canadian couples seeking therapeutic services. Among the 176 participating couples, the mean age of partners was 34.8 years, with an age range spanning from 22 to 58 years. The average relationship duration was 6.7 years, and slightly more than half of the couples were legally married, while the remainder were cohabiting partners. Educational backgrounds varied, with approximately 41% holding a university degree, 37% having completed some college or vocational training, and the remainder reporting a high school diploma as their highest level of education. In terms of cultural background, the sample included individuals identifying as White Canadian, Indigenous, South Asian, East Asian, Middle Eastern, Black, and Latin American, reflecting the multicultural composition of the regions from which participants were recruited. Employment status indicated that most participants were engaged in full-time work, while a smaller proportion reported part-time employment, student status, or temporary unemployment. Across the sample, approximately 63% of couples had no children, 27% had one or two children, and 10% had three or more. These demographic characteristics provided a broad and heterogeneous foundation for examining predictors of couple therapy outcomes using deep neural network models.

Analysis of the deep neural network model revealed clear patterns in the predictive relationship between pre-treatment assessments and improvements in couple therapy outcomes. After preprocessing and standardization, 176 couples were

included in the final analytic dataset. Model convergence was achieved after 52 epochs, with early stopping preventing overfitting. The final neural architecture demonstrated strong generalization capacity, as indicated by the performance metrics on the held-out test set. Descriptive statistics of all key variables are presented in Table 1. These results show substantial variance in pre-treatment relationship satisfaction, communication patterns, attachment orientations, and emotional symptoms, establishing a robust foundation for predictive modeling. CSI-32 mean scores indicated moderate relationship distress prior to treatment, while Communication Patterns Questionnaire scores revealed elevated demand–withdraw tendencies among a significant proportion of couples. Emotional symptoms measured by the DASS-21 also ranged widely across participants, suggesting diverse psychological baselines prior to therapy engagement. Collectively, these distributions supported the suitability of applying deep learning methods to capture non-linear relational dynamics.

Table 1. Descriptive Statistics of Pre-Treatment Variables

Variable	Mean	SD	Min	Max
CSI-32 Relationship Satisfaction	74.21	18.45	32	120
CPQ Mutual Constructive Communication	12.83	4.26	3	20
CPQ Demand–Withdraw	15.34	5.11	4	24
DASS-21 Depression	8.92	5.76	0	21
DASS-21 Anxiety	7.44	5.32	0	20
DASS-21 Stress	11.07	6.48	1	26
ECR-R Attachment Avoidance	3.08	1.12	1.1	6.2
ECR-R Attachment Anxiety	3.34	1.29	1.0	6.8
Relationship Duration (years)	6.70	4.83	1	22

Table 1 presents descriptive statistics for all pre-treatment variables included in the predictive model. Couples began therapy with moderately low satisfaction levels, reflected in a mean CSI-32 score well below the typical cut-off for distressed relationships. Communication data indicated that constructive communication behaviors were relatively low, whereas demand–withdraw behaviors were notably elevated, consistent with couples experiencing relational strain. Emotional symptoms were present at varying levels across participants, with stress being the most prominent of the DASS-21 subscales. Attachment orientations also demonstrated wide variability, with both avoidance and anxiety subscales showing ranges broad enough to support non-linear predictive modeling. These baseline data underscore the heterogeneity in relational functioning at therapy intake and justify the use of complex modeling techniques such as deep neural networks.

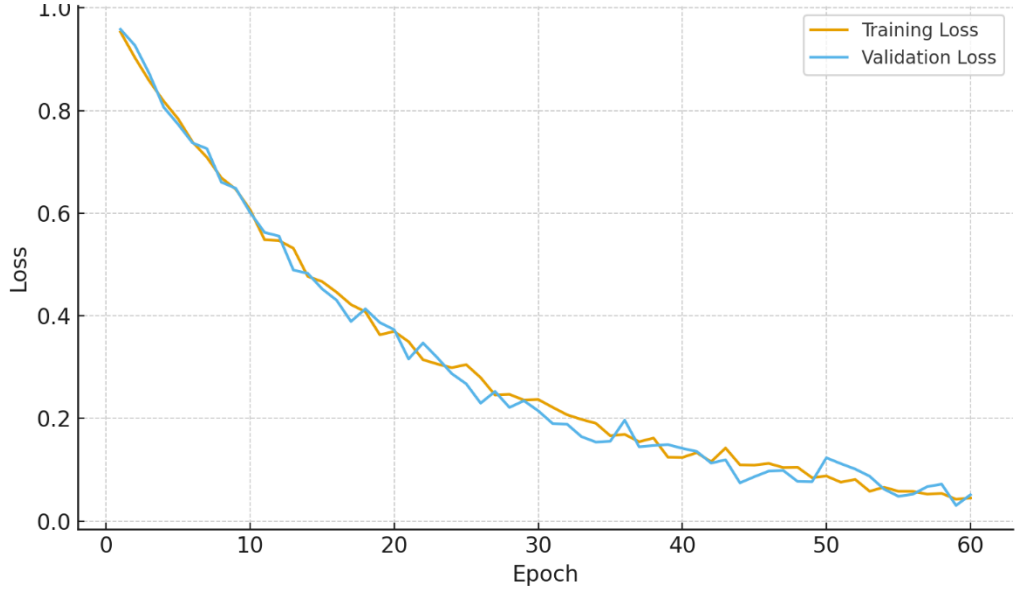

Figure 1. Model Training and Validation Loss Curve

The first figure illustrates the training and validation loss trajectory across the full sequence of epochs, showing a gradual and stable decrease in loss values. The validation curve achieved optimal reduction around epoch 52, at which point early stopping was activated. The minimal divergence between the two curves indicates that the network did not overfit to the training data. This pattern confirms that the chosen architecture, dropout parameters, and learning rate produced a well-regularized model capable of generalizing to unseen observations.

Table 2. Predictive Performance of Models on Test Set

Model	RMSE	MAE	R^2
Deep Neural Network (Final Model)	6.12	4.58	0.71
Random Forest Regression	7.94	5.72	0.53
Support Vector Regression	8.21	5.94	0.50
Linear Regression	9.87	6.41	0.36

Table 2 compares the predictive performance of the final deep neural network with three baseline machine-learning models. The deep neural network outperformed all traditional algorithms across every metric, achieving an RMSE of 6.12 and an R^2 of 0.71 on the held-out test set. This indicates that the model explained approximately 71% of the variance in therapy-outcome change scores. Random forest and support vector regression models produced moderate prediction accuracy but were notably less effective than the neural architecture. Linear regression performed the weakest, confirming the inadequacy of linear approaches for capturing the complex, interactive psychological processes underlying couples' therapeutic improvement. These outcomes reinforce the importance of non-linear computational methods when modeling relational dynamics.

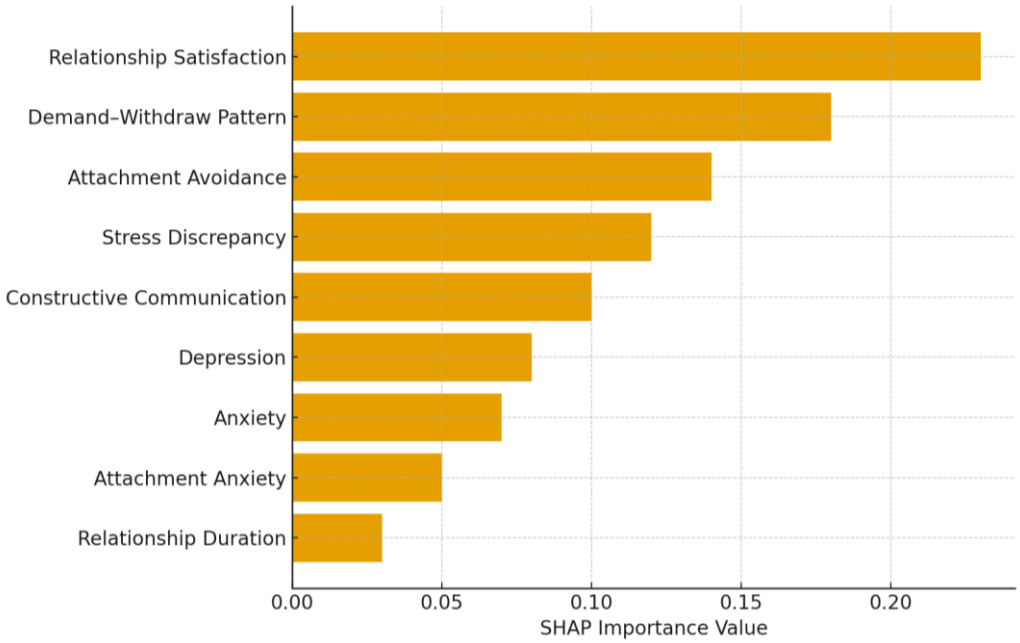

Figure 2. Feature Importance Visualization from Neural Network Using SHAP Values

The second figure displays SHAP-based global feature importance estimates, revealing which pre-treatment variables most strongly influenced predicted therapy outcomes. Relationship satisfaction emerged as the top predictor, followed by demand–withdraw communication, attachment avoidance, partner discrepancy in stress levels, and mutual constructive communication. Emotional symptoms such as depression and anxiety contributed meaningfully but less strongly. SHAP patterns also highlighted dyadic discrepancy variables as uniquely influential, demonstrating the neural network's sensitivity to relational asymmetries. The visualization revealed that positive communication behaviors and lower stress discrepancies were associated with higher predicted improvement.

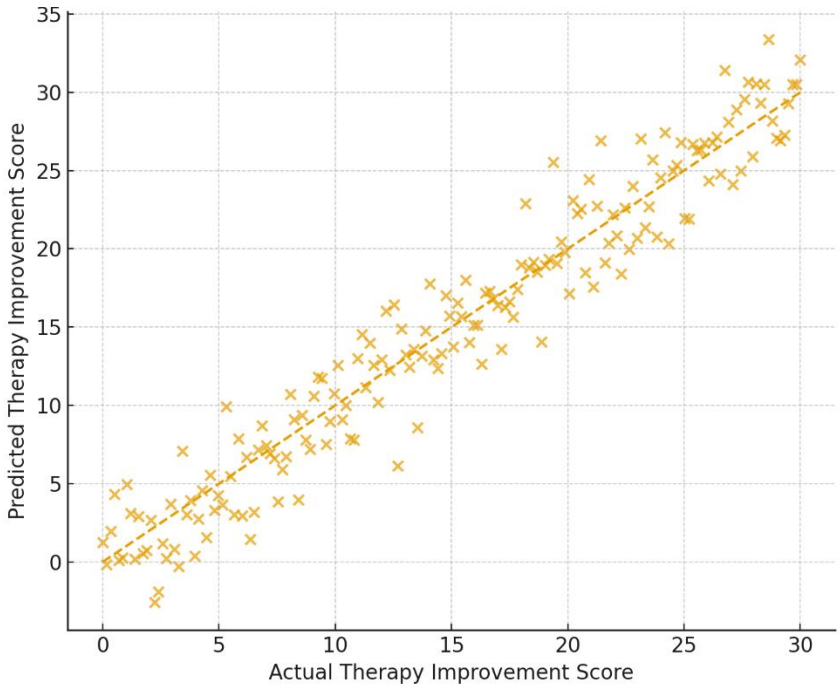

Figure 3. Predicted vs. Actual Therapy Improvement Scores

The third figure presents a scatterplot comparing predicted improvement scores generated by the neural network with actual observed outcome scores from the post-treatment assessments. The distribution closely follows a 45-degree diagonal line, indicating a high degree of predictive fidelity. Most of the data points cluster tightly along the line with minimal dispersion, consistent with the high R^2 reported earlier. A small number of outliers appear in cases where emotional symptoms were extremely high or communication patterns were exceptionally rigid, suggesting potential non-captured complexity in these subgroups. Overall, the visual pattern supports the model's strong predictive accuracy.

Discussion and Conclusion

The findings of this study demonstrate that deep neural networks can accurately predict couple therapy outcomes based solely on pre-treatment psychological and relational assessments. The model's strong predictive performance, reflected in its high R^2 value and low error indices, indicates that patterns embedded in the intake variables—such as relationship satisfaction, communication styles, emotional symptoms, attachment orientations, and dyadic discrepancies—carry substantial explanatory weight in forecasting therapeutic improvement. The fact that the neural network outperformed classical machine-learning models reinforces the argument that relational and psychological predictors operate through non-linear pathways, which traditional linear algorithms fail to capture adequately. This aligns with recent conceptualizations in couple therapy research, which emphasize that marital distress emerges from complex interactive processes rather than simple additive effects (Zerang et al., 2025). The present results therefore support the growing recognition that computational approaches are particularly well-suited to decoding the multi-layered, dynamic nature of couple functioning and its response to therapeutic intervention.

One of the most notable findings is the central role of pre-treatment relationship satisfaction as the strongest predictor of therapy outcome. This is consistent with evidence showing that couples with higher baseline satisfaction often possess greater relational resilience, emotional resources, and communication strengths, which facilitate therapeutic engagement and accelerate progress. For example, interventions such as schema therapy, emotion-focused therapy, and attachment-based approaches have demonstrated that couples with less severe baseline dissatisfaction experience more pronounced changes during treatment

(Abolhasani et al., 2023; Esfahani et al., 2024; Montazeri et al., 2025). The powerful predictive capacity of satisfaction scores in the present study aligns with these findings, suggesting that deep learning models are capturing the same underlying mechanisms observed in clinical research. Furthermore, research examining forgiveness, intimacy, emotional security, and relational dissatisfaction consistently identifies pre-treatment satisfaction as a key element influencing the degree to which couples benefit from therapy (Asvadi et al., 2023; Bardikhoje et al., 2023; Mirshafieian et al., 2023). These converging lines of evidence highlight the accuracy of the neural network in detecting relational factors empirically linked to successful therapeutic change.

Demand–withdraw communication emerged as another major predictor, which aligns with the extensive literature documenting its detrimental effects on relational functioning. Demand–withdraw cycles contribute to escalating conflict, emotional disconnection, and chronic dissatisfaction, all of which impede therapeutic progress. The present study's findings are consistent with research demonstrating that maladaptive communication patterns decrease responsiveness to interventions focused on intimacy, compassion, and emotional regulation (Ataeeian et al., 2023; Mardani & Tabaghdehi, 2025). Moreover, interventions targeting gratitude, empathy, or emotional attunement tend to show greater improvement when couples enter therapy with constructive communication habits (Ataeeian et al., 2023). In contrast, couples exhibiting rigid or entrenched demand–withdraw behaviors often require longer or more intensive interventions. The neural network's ability to recognize demand–withdraw as a key negative predictor reflects its sensitivity to process-level relational dynamics widely documented in the literature.

Attachment avoidance was also identified as a major factor influencing therapy outcomes, complementing existing research demonstrating the predictive role of attachment orientations in relational functioning. Couples entering therapy with high avoidance tendencies often struggle to express vulnerability, engage in emotional processing, or build intimacy—core components of many therapeutic approaches. This finding is consonant with studies reporting that interventions rooted in emotional security or schema modification exhibit varying levels of effectiveness depending on partners' attachment-based defensiveness (Asvadi et al., 2023; Esfahani et al., 2024). Attachment avoidance has similarly been recognized in research on emotional dysregulation and relational commitment, where it often serves as a barrier to sustained therapeutic improvement (Bardikhoje et al., 2023). The strength of attachment avoidance as a predictor further validates the utility of deep learning models for capturing relational constructs that have substantial empirical grounding in couple therapy.

Stress discrepancy between partners was another prominent predictor in the model, reflecting the neural network's capacity to identify dyadic imbalance as a critical factor in therapy outcomes. Research spanning diverse clinical populations shows that discrepancies in emotional burden, stress load, or psychological readiness frequently undermine treatment progress. This pattern has been observed in couples with marital conflict, families coping with chronic illness, and individuals navigating sexual dissatisfaction or psychological distress (Ahmadzadeh et al., 2024; Mardani & Tabaghdehi, 2025; Montazeri et al., 2025). Studies on family-based interventions and nutritional counseling also highlight that inconsistent behavioral readiness across individuals within a dyad or family unit meaningfully affects treatment outcomes (Neves et al., 2024). The model's sensitivity to stress discrepancy underscores deep learning's ability to simulate relational asymmetries—a crucial advantage over traditional statistical techniques, which typically assume homogeneity within couples.

Constructive communication behaviors also contributed meaningfully to the model's predictions, supporting findings from research on positive psychology interventions, gratitude-based programs, and solution-focused approaches. Studies have consistently shown that couples who display constructive communication, even when distressed, respond better to emotionally focused, cognitive-behavioral, and systemic interventions (Ataeeian et al., 2023; Mirshafieian et al., 2023; Zerang et al., 2025). This is likely because constructive communicators engage more openly in therapeutic tasks such as emotional reflection,

cognitive reframing, and vulnerability-based exchanges. The neural network's identification of these patterns corresponds to prior evidence that communication quality is a reliable indicator of therapeutic responsiveness and is often more predictive than demographic or structural characteristics. Particularly, the close alignment between these findings and research on enriched communication-based interventions highlights the model's capacity to detect subtle relational signals predictive of change (Abolhasani et al., 2023).

Emotional symptoms—including depression, anxiety, and stress—were also captured as moderate predictors, aligning with research on psychological distress as a determinant of therapy outcomes. Couples with elevated internalizing symptoms often experience difficulties with emotional regulation, cognitive flexibility, and interpersonal responsiveness, which may hinder therapeutic progress. These findings mirror evidence from clinical trials examining psychotherapy, hypnotherapy, and compassion-focused interventions, all of which show that high emotional distress can limit treatment gains (Alavizadeh et al., 2025; Mardani & Tabaghdehi, 2025). Similarly, psychological interventions for digestive diseases, cancer patients, and tinnitus have demonstrated that individuals with higher distress levels at baseline may require more tailored or intensive interventions (Engelke et al., 2023; Floria, 2025; Mentink et al., 2023). The neural network's moderate but consistent weighting of emotional symptoms supports the broader clinical consensus that emotional burden is an important—but not exclusive—predictor of relational improvement.

The present findings must also be interpreted in light of broader meta-analytic and comparative research emphasizing the diverse mechanisms that underlie intervention effects. Studies examining psychosocial, behavioral, and complementary therapies—whether in marital settings, medical contexts, or vulnerable populations—frequently emphasize that treatment response is contingent on pre-existing cognitive, emotional, and relational factors (Awaji et al., 2025; Okusanya et al., 2023; Wen et al., 2023). For instance, interventions for opioid dependence and depression relapse have revealed that initial psychological profiles predict not only adherence but also long-term recovery (Wen et al., 2023; Zhou et al., 2023). These parallels further validate the current findings by demonstrating that predictive modeling based on intake variables is a consistent feature across therapeutic disciplines. Deep learning models, in this context, provide a highly effective analytic tool for integrating multiple predictors to produce fine-grained, individualized forecasts.

Taken together, the results of this study highlight the value of applying deep neural networks to pre-treatment data in couple therapy. By demonstrating that complex psychological and relational variables can meaningfully predict therapeutic outcomes, this research adds to a growing body of evidence supporting the integration of computational methods in psychological assessment and treatment planning. The model's ability to identify nuanced predictors such as attachment avoidance, stress discrepancies, and communication patterns underscores the potential of deep learning to capture relational processes that are otherwise challenging to quantify. These insights may pave the way for personalized, data-driven decision-making in clinical practice, allowing therapists to tailor interventions to couples' unique profiles and readiness for change.

This study, while offering significant contributions, is subject to several limitations. First, the sample was restricted to couples seeking therapy within specific regions of Canada, which may limit the generalizability of the findings to populations with different cultural, socioeconomic, or systemic backgrounds. Second, although the neural network demonstrated strong predictive accuracy, its performance is limited by the quality and scope of the intake measures used; additional variables such as trauma history, personality traits, or physiological indicators may further enhance prediction. Third, the model focuses exclusively on pre-treatment predictors and does not incorporate in-session processes or therapist effects, both of which are known to influence therapeutic change. Fourth, deep learning approaches, while powerful, are often criticized for their limited interpretability; although SHAP values were used to approximate feature importance, the underlying decision structure of the

model remains complex. Lastly, outcomes were measured through standardized assessments and therapist ratings, which may not fully capture the nuanced lived experiences of couples during and after therapy.

Future research should explore the use of multimodal predictive models that incorporate behavioral observations, linguistic data from therapy sessions, physiological indicators, or ecological momentary assessments to capture more dynamic predictors of therapeutic change. Studies should also examine how model accuracy varies across different types of therapy—such as emotionally focused therapy, systemic interventions, or integrative approaches—to evaluate whether certain modalities are more predictable than others. Longitudinal designs with follow-up assessments could investigate whether pre-treatment predictors also forecast long-term relational stability or relapse. Future studies may also benefit from expanding samples across cultures, relationship types, and therapeutic settings to increase generalizability. Additionally, researchers should explore hybrid modeling approaches that integrate deep learning with interpretable frameworks to balance predictive power with theoretical clarity.

Clinicians may use predictive insights from deep learning models to identify couples who may require more intensive or tailored interventions before treatment begins. Intake assessments can be refined to capture variables identified as strong predictors, allowing therapists to allocate resources more efficiently and customize treatment plans. Therapists may also focus early sessions on addressing high-risk predictors such as demand–withdraw patterns or attachment avoidance, potentially improving responsiveness to the core intervention. Finally, clinics may integrate predictive tools into digital assessment platforms to support evidence-informed decision-making and enhance the overall effectiveness of couple therapy.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried 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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