

Deep Neural Network Prediction of Couple Relationship Quality Using Multidimensional Relational and Psychological Features

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ABSTRACT

Objective: This study aimed to develop and evaluate a deep neural network model for predicting couple relationship quality using multidimensional relational, psychological, contextual, and demographic features.

Methods and Materials: This quantitative cross-sectional predictive study was conducted with 680 adults involved in committed romantic relationships and residing in Canada. Participants completed standardized assessments of relationship quality, relationship satisfaction, communication quality, conflict processes, perceived partner responsiveness, emotional intimacy, commitment, trust, attachment anxiety and avoidance, depressive symptoms, anxiety, perceived stress, emotion regulation, self-esteem, psychological well-being, and selected contextual characteristics. The dataset was divided into training ($n = 476$), validation ($n = 102$), and independent test ($n = 102$) subsets. A feedforward deep neural network with four hidden layers was trained using the Adam optimizer, dropout regularization, batch normalization, and early stopping. Predictive performance was evaluated using mean absolute error, mean squared error, root mean squared error, and coefficient of determination and was compared with multiple linear regression, ridge regression, random forest regression, and gradient-boosted regression. SHAP analysis was used to interpret feature importance.

Findings: The deep neural network demonstrated the strongest predictive performance on the independent test set, with MAE = 3.91, MSE = 26.63, RMSE = 5.16, and $R^2 = .84$. It outperformed multiple linear regression ($R^2 = .64$), ridge regression ($R^2 = .66$), random forest regression ($R^2 = .74$), and gradient-boosted regression ($R^2 = .78$). The most influential predictors were relationship satisfaction, perceived partner responsiveness, destructive conflict, communication quality, emotional intimacy, attachment anxiety, commitment, trust, perceived stress, and attachment avoidance. Sensitivity analysis showed that removing relationship satisfaction reduced model performance to $R^2 = .76$, while the multidimensional full model retained the highest accuracy.

Conclusion: Deep neural networks can accurately predict couple relationship quality by integrating relational and psychological features and may provide a useful framework for identifying complex nonlinear patterns relevant to relationship assessment and intervention.

Keywords: couple relationship quality; deep neural network; relationship satisfaction; attachment; communication; psychological features; machine learning.

1. Introduction

Romantic relationships constitute one of the most influential interpersonal contexts in adult life, shaping emotional security, psychological well-being, identity, health behaviors, coping processes, and broader life satisfaction. The perceived quality of an intimate relationship is therefore not simply a reflection of satisfaction with a partner but a multidimensional construct encompassing emotional closeness, communication, commitment, trust, conflict management, perceived responsiveness, mutual support, attachment security, and the ability of partners to maintain a stable sense of connection over time. Research has consistently shown that the quality of close relationships is associated with both psychological and physical health, suggesting that relational functioning should be considered a central component of adult well-being rather than a peripheral interpersonal outcome (Kanth, 2022). Relationship quality also appears to be connected to broader dimensions of psychological functioning, including the capacity to love, positive self-evaluation, emotional regulation, and subjective well-being (Fernandes et al., 2023; Glavač et al., 2024). Consequently, understanding why some individuals experience highly satisfying and resilient relationships while others report distress, disconnection, instability, or emotional exhaustion requires an integrative approach that incorporates multiple relational and psychological domains simultaneously.

A central methodological challenge in this field concerns the conceptualization and measurement of relationship quality. Relationship satisfaction has often been used as a primary indicator because it captures an individual's overall evaluation of the quality and fulfillment of a romantic partnership. Psychometric evidence supports the usefulness of established measures of relationship satisfaction across different populations, while also emphasizing the need to consider measurement invariance, external validity, and cultural context when interpreting such scores (Adamczyk et al., 2022). Yet relationship quality cannot be fully reduced to satisfaction alone. Emerging measurement approaches have highlighted other dimensions, including the sense of “we-ness,” perceived individuality within the couple, negative interaction patterns, and dehumanizing or deindividuating relational experiences (Brock & Gervais, 2025; Brock et al., 2023; Cruwys et al., 2022; Ventura-León et al., 2025). These developments indicate that contemporary relationship research is increasingly moving away from single-variable explanations and toward multidimensional

models capable of representing the complex architecture of intimate functioning.

Communication and conflict processes are among the most immediate relational mechanisms associated with relationship quality. Couples differ substantially in their ability to communicate needs, regulate disagreement, listen responsively, express vulnerability, and repair relational ruptures. Negative interactions characterized by criticism, defensiveness, emotional escalation, withdrawal, and unresolved conflict can gradually undermine relational security and satisfaction. Emotional flooding is particularly relevant because intense physiological and affective arousal during conflict may impair cognitive flexibility, perspective-taking, and constructive problem solving, thereby amplifying destructive interaction cycles (Castillo-López et al., 2024). Conversely, relational processes that preserve emotional connection during disagreement may reduce the harmful consequences of conflict. Relationship nostalgia, for example, has been proposed as a psychological resource that may offset the effects of romantic conflict and support commitment by restoring a positive shared relational narrative (Swets et al., 2024). Similarly, appreciation appears to function as an important relational mechanism, particularly when partners perceive sacrifice, investment, and support as recognized rather than taken for granted (Özdemir, 2025).

Perceived partner responsiveness represents another central predictor of relationship quality because it reflects whether individuals experience their partner as understanding, caring, validating, and attentive to important emotional needs. Need fulfillment and consensus within the relationship are closely tied to commitment and satisfaction, suggesting that relationship quality depends not only on the presence of interaction but on whether relational exchanges are experienced as supportive and psychologically meaningful (Park & Harris, 2025). The cooperative dimension of couple functioning may also matter in more subtle ways. Tacit coordination and the capacity to cooperate effectively without extensive explicit negotiation can influence satisfaction, with such effects potentially varying according to relationship stage and the type of coordination demand involved (Xu et al., 2026). These findings reinforce the view that relationship quality is generated through a dynamic system of interpersonal processes rather than any single behavior or trait.

Attachment theory provides an important psychological framework for understanding why individuals respond differently to the same relational conditions. Adult

attachment anxiety is typically associated with fear of rejection, heightened vigilance toward signs of abandonment, and an increased need for reassurance, whereas attachment avoidance is associated with discomfort with dependence, emotional distance, and reluctance to engage in vulnerability. Dyadic research indicates that attachment patterns can influence both one's own and a partner's marital adjustment through actor and partner pathways (Uluyol & Özen-Çıplak, 2024). Attachment matching and relational interaction patterns have also been examined in both same-sex and different-sex couples, further illustrating that attachment processes operate within dyadic systems rather than solely within individuals (Miscioscia et al., 2021). Recent evidence has additionally suggested that appreciation and perceived giving may help explain the association between adult attachment and intimate relationship satisfaction, indicating that attachment insecurity may influence relationship quality partly through daily relational interpretations and exchange processes (Zhu et al., 2026).

Attachment is also relevant to the long-term effects of adverse developmental experiences. Childhood trauma and maltreatment can shape internal working models of self and others, social-support expectations, emotion regulation, and patterns of closeness in adult romantic relationships. Evidence indicates that attachment and social support may mediate associations between childhood trauma and later relationship satisfaction (Quan et al., 2025). Self-compassion may also act as a protective mechanism linking earlier maltreatment experiences with marital quality, with possible effects extending across partners within a dyadic system (Lassri & Zamir, 2026). These findings demonstrate that contemporary relationship functioning may reflect not only current interaction patterns but also enduring psychological schemas and developmental histories that affect how individuals interpret closeness, conflict, dependence, rejection, and support.

Personality and broader dispositional characteristics also contribute to romantic relationship satisfaction. Neuroticism has received particular attention because individuals high in neuroticism may experience greater negative affectivity, interpersonal sensitivity, threat perception, and difficulty regulating emotional responses, all of which can influence relationship satisfaction through both intrapersonal and interpersonal mechanisms (Kreuzer & Gollwitzer, 2021). Other personality traits also show associations with romantic relationship satisfaction, although their relative predictive contributions can vary across samples and relational

contexts (Ricafronte et al., 2024). Personality-based selection into relationships may further complicate these associations because assortative mating can occur across stable characteristics, interaction tendencies, and more dynamic behavioral dispositions (Nguyen, 2023). This suggests that relational outcomes may emerge from combinations of partner characteristics rather than isolated individual attributes.

Psychological distress represents another important domain. Depression can diminish motivation, emotional availability, positive affect, and responsiveness, while also altering perceptions of partner behavior. Couple-level analyses have shown meaningful associations between different operationalizations of relationship quality and depression, with actor and partner effects indicating reciprocal relational influence (Aguilar-Raab et al., 2022). Experimental work also suggests that intentionally increasing appreciation within a partnership can improve momentary relationship satisfaction and mood among individuals experiencing depression, reinforcing the possibility that relational and psychological processes interact bidirectionally (Warth et al., 2020). Sleep is similarly associated with relationship satisfaction, particularly among young adults, highlighting the relevance of everyday physiological and behavioral functioning to relational well-being (Madsen et al., 2023). These findings collectively suggest that poor relationship quality and psychological distress can become mutually reinforcing, making it difficult to isolate simple one-directional pathways.

Emotion regulation is especially important within this context because intimate relationships routinely expose individuals to situations involving vulnerability, frustration, uncertainty, jealousy, disappointment, and perceived rejection. Adaptive regulation may allow individuals to remain responsive and constructive during emotionally charged interactions, whereas dysregulation may increase conflict escalation, impulsivity, avoidance, or withdrawal. Infidelity research has similarly emphasized the role of emotional and psychological factors in processes that threaten relationship stability (Shrestha et al., 2023). Obsessive-compulsive relationship symptoms may also contribute to marital instability, in part through mechanisms involving infidelity tendency and persistent doubt regarding the relationship or partner (Genç & Büyüka, 2026). Such findings underscore the value of incorporating cognitive, emotional, and behavioral features together when attempting to predict relationship outcomes.

Sexual and embodied dimensions also contribute to romantic relationship quality. Body appreciation, sexual esteem, and sexual assertiveness are associated with satisfaction in romantic relationships, indicating that relational quality partly depends on how individuals experience their bodies, sexuality, and communicative agency within intimate contexts (Rizzo et al., 2025). Sexual satisfaction itself may be influenced by psychological capacities such as resilience and thought control, illustrating the intersection between cognitive resources and intimate functioning (Rostami, 2024). Gender-role expectations may further shape the experience of satisfaction through culturally informed beliefs regarding intimacy, emotional expression, division of responsibility, sexuality, and interpersonal behavior (Arora & Chauhan, 2024). These findings suggest that any comprehensive predictive model of relationship quality should be broad enough to accommodate both interpersonal and intrapersonal dimensions.

Relationship quality is also embedded within social and structural contexts. Discrimination, racism, and colorism may affect psychosocial health and relationship satisfaction by increasing chronic stress, threatening identity, and reducing psychological resources available for close relationships (Brown et al., 2023). More recent work has similarly shown that multidimensional racism-related stress can undermine Black romantic relationships, illustrating how external social adversity can penetrate intimate relational systems (Rice et al., 2025). Financial strain, work pressure, and socioeconomic stress may operate through comparable pathways by increasing conflict exposure, reducing emotional resources, and intensifying perceived inequity or insecurity. Such findings caution against treating relationship quality exclusively as a private matter between two individuals and instead support models in which relational outcomes are partly shaped by broader contextual pressures.

Contemporary relationships are additionally influenced by technological environments. Excessive internet use and problematic online engagement may reduce shared time, increase perceived neglect, create opportunities for relational disconnection, and contribute to couple burnout (Bagheri et al., 2023). These patterns highlight the need to consider behavioral-contextual features alongside conventional psychological predictors, particularly because modern relational experiences are increasingly mediated by digital communication and online activity. At the same time, relational functioning may be affected by large-scale disruptions. Research conducted during the COVID-19

pandemic demonstrated that lockdowns, social restrictions, uncertainty, and changing household demands influenced perceived separation risk and romantic functioning (Baez et al., 2023). A systematic mapping of relationship research during the pandemic further showed substantial heterogeneity in how couples responded to shared adversity, with some experiencing deterioration and others demonstrating resilience or increased cohesion (Estlein et al., 2022).

Dyadic coping has been identified as one pathway through which couples manage shared stress. When partners respond collaboratively to adversity, communicate stress effectively, and support one another's coping efforts, relationship quality may be preserved even under difficult external circumstances. Evidence suggests that dyadic coping can mediate associations between perceived relationship quality and emotional representations of stressful collective events such as COVID-19 (Relvas et al., 2023). This is consistent with broader conceptualizations of romantic relationships as regulatory systems in which each partner affects the other's emotions, behaviors, and interpretations. Relationship quality is therefore likely to emerge from interactions among stress exposure, attachment, communication, coping, responsiveness, personality, and psychological functioning rather than from any single explanatory factor.

Biological influences have also begun to enter the relationship literature. Genetic and epigenetic mechanisms may contribute to individual differences in couple adjustment through pathways involving temperament, stress reactivity, emotional regulation, and social behavior (Khani et al., 2023). Although such biological factors are not typically included in applied predictive models, their existence reinforces the underlying complexity of relationship functioning and the likelihood that observable relational outcomes emerge from multiple interacting levels of influence. In practical terms, this complexity poses a challenge for conventional statistical models that rely heavily on linearity, additivity, and predefined interaction terms.

This challenge is particularly important because many previous studies have investigated relationship quality by examining a limited number of predictors or testing theoretically specified mediation and moderation pathways. Such approaches are essential for causal and explanatory theory development, but they may not fully capture the nonlinear and high-order interactions that exist among multidimensional psychological and relational features. For

example, high attachment anxiety may be especially detrimental when partner responsiveness is low but less harmful when communication and reassurance are strong; similarly, financial strain may predict poor relationship quality more strongly among individuals with low emotion-regulation capacity than among those with high resilience. Conventional regression models can test such interactions only when they are explicitly specified in advance, and model complexity increases rapidly as the number of predictors grows.

Machine-learning methods provide a complementary approach because they focus on out-of-sample prediction and can identify complex feature combinations without requiring all relationships to be specified beforehand. Deep neural networks are especially suitable for multidimensional prediction because multiple hidden layers allow them to model nonlinear transformations and interactions across large sets of features. In the context of couple relationship quality, this makes it possible to integrate proximal relational processes such as satisfaction, communication, intimacy, trust, commitment, responsiveness, and conflict with more distal psychological characteristics such as attachment insecurity, stress, depressive symptoms, anxiety, emotion regulation, self-esteem, and broader well-being. Such an approach does not replace theory-driven analysis; rather, it can reveal which combinations of features carry the greatest predictive information and whether nonlinear models substantially outperform conventional statistical approaches.

The need for such predictive integration is further supported by evidence showing that relationship functioning includes both protective and risk processes that may operate simultaneously. Appreciation, commitment, cooperative coordination, emotional intimacy, adaptive coping, and relational identity may protect relationship quality (Cruwys et al., 2022; Park & Harris, 2025; Xu et al., 2026), whereas destructive conflict, attachment insecurity, obsessive relational doubts, psychological distress, inequity, discrimination-related stress, and technological disconnection may increase relational vulnerability (Bagheri et al., 2023; Genç & Büyükkada, 2026; Özdemir, 2025; Rice et al., 2025). Moreover, recent advances in measurement have made it increasingly feasible to represent relationship functioning through distinct yet related constructs rather than relying on a single satisfaction score (Brock & Gervais, 2025; Brock et al., 2023; Ventura-León et al., 2025). This growing multidimensionality creates a strong methodological rationale for predictive models capable of

handling numerous correlated inputs while preserving complex interactions among them.

Despite this progress, relatively little relationship research has employed deep neural networks to predict overall couple relationship quality using an integrated set of relational, psychological, contextual, and demographic features. Most existing work remains primarily explanatory, cross-sectional, dyadic, or psychometric, with comparatively limited emphasis on independent test-set prediction, model comparison, nonlinear feature interactions, and interpretable machine learning. A predictive framework can therefore make an important contribution by evaluating not only whether particular variables are statistically associated with relationship quality but also how accurately a multidimensional feature set can estimate relationship quality in previously unseen individuals. Comparing deep learning with conventional linear and tree-based models can further determine whether increased computational flexibility yields meaningful improvements in generalization rather than merely improving fit to the observed sample.

Accordingly, the aim of the present study was to develop and evaluate a deep neural network for predicting couple relationship quality from multidimensional relational, psychological, contextual, and demographic features and to compare its predictive performance with conventional benchmark models while identifying the most influential predictors of relationship quality.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a quantitative, cross-sectional predictive design to develop and evaluate a deep neural network model for predicting couple relationship quality from multidimensional relational, interpersonal, emotional, cognitive, and psychological features. The target population consisted of adults involved in an ongoing romantic relationship and residing in Canada. A total of 742 individuals initially entered the study and completed the online screening procedure. After excluding 38 respondents because of substantial missing data, 11 because of duplicate or inconsistent response patterns, and 13 because they did not meet the predefined eligibility criteria, the final analytic sample consisted of exactly 680 participants. Participants were recruited from Ontario, British Columbia, Alberta, Quebec, Manitoba, Saskatchewan, Nova Scotia, New Brunswick, Newfoundland and Labrador, and Prince

Edward Island through community advertisements, university and public online notice boards, social-media announcements, and electronic research-participation platforms. Recruitment was designed to produce variation in age, relationship duration, marital status, educational attainment, employment status, and socioeconomic background so that the predictive model would not be restricted to a narrowly defined relational subgroup.

Eligibility criteria required participants to be at least 18 years of age, currently involved in a committed romantic relationship for a minimum of six months, residing in Canada at the time of data collection, able to read and understand English sufficiently to complete the questionnaires independently, and willing to provide informed consent. Both married and unmarried individuals in committed relationships were eligible. Participants were excluded if they were not currently involved in a romantic relationship, had been in their current relationship for less than six months, failed to complete the principal relationship-quality outcome measure, left more than 20% of the predictor items unanswered, or demonstrated response patterns indicative of inattentive participation, such as extremely short completion time or invariant responding across large questionnaire sections. Because the primary objective was individual-level prediction rather than dyadic interdependence analysis, the unit of analysis was the individual partner. When both members of a couple participated, responses were retained only when they could be treated as separate individual observations within the predictive framework, and no partner's responses were used to construct the outcome value of the other partner.

The participants ranged in age from 18 to 67 years, allowing the model to represent relationship experiences across early adulthood, middle adulthood, and later adulthood. Data collection was conducted entirely online through a secure electronic survey platform. Participants first viewed an information page describing the study objectives, voluntary nature of participation, confidentiality procedures, expected completion requirements, and their right to discontinue participation without penalty. After providing electronic informed consent, participants completed demographic and relationship-background questions followed by the standardized psychological and relational instruments. No directly identifying information was incorporated into the machine-learning dataset. Each record was assigned an anonymous numeric identifier before preprocessing and analysis. The study procedures were conducted in accordance with established ethical principles

for research involving human participants, including informed consent, confidentiality, voluntary participation, data minimization, and secure storage of research data.

2.2. Measures

Data were collected using a multidimensional assessment battery designed to represent both the direct interpersonal characteristics of the romantic relationship and psychological characteristics of the individual that could contribute to perceived relationship quality. The principal outcome variable was overall couple relationship quality. This construct was operationalized as a continuous composite score derived from participants' evaluations of relationship satisfaction, dyadic consensus, emotional cohesion, affectional connection, and perceived relationship stability. Higher scores indicated a more positive evaluation of the current romantic relationship. Treating relationship quality as a continuous outcome was selected because it preserved individual differences across the full distribution of relational functioning and permitted the neural network to learn nonlinear associations between predictor features and the criterion rather than forcing participants into arbitrary high- and low-quality categories.

Relationship satisfaction was assessed using a standardized multi-item measure addressing overall satisfaction with the romantic relationship, perceived fulfillment of relational expectations, positive evaluation of the partnership, and satisfaction with interactions between partners. Items were rated on ordered Likert-type response scales and were coded so that higher scores represented greater satisfaction. Dyadic adjustment was assessed through items measuring agreement between partners on important areas of shared life, emotional and behavioral cohesion, satisfaction with the relationship, and expression of affection. These indicators were used both as components of the broader relational feature space and, where conceptually appropriate, to support the construction of the overall relationship-quality criterion. Internal consistency coefficients were calculated in the present sample before model development, and scale scores were generated only when the minimum required proportion of items had been completed.

Communication quality was assessed through items examining openness of communication, clarity of emotional expression, active listening, responsiveness, mutual understanding, constructive discussion of needs, and the ability to discuss sensitive topics without escalation. Higher

scores reflected more adaptive couple communication. Conflict characteristics were assessed separately because constructive communication and destructive conflict are not conceptually identical dimensions. Conflict-related variables therefore included conflict frequency, conflict intensity, criticism, defensiveness, withdrawal, escalation, difficulty reaching resolution, and constructive problem-solving. Items were coded so that higher destructive-conflict scores represented more problematic interaction patterns, whereas higher constructive-resolution scores represented more adaptive conflict management. Maintaining these variables as distinct predictors allowed the neural network to identify potentially nonlinear or interactive effects, such as whether strong communication skills attenuated the negative association between conflict frequency and relationship quality.

Perceived partner responsiveness was evaluated by assessing the degree to which participants experienced their partner as understanding, validating, caring, available, and responsive to emotional needs. Emotional intimacy was assessed through items concerning closeness, emotional disclosure, perceived mutual understanding, trust in sharing vulnerable experiences, and feelings of interpersonal connectedness. Commitment was assessed in terms of intention to maintain the relationship, long-term orientation, psychological attachment to the partnership, and willingness to invest effort in preserving the relationship. Trust was measured through perceptions of partner reliability, honesty, dependability, and relational security. These constructs were retained as separate feature groups because conceptually similar relational resources may nevertheless contribute differently to the prediction of relationship quality.

Attachment-related characteristics were included to represent relatively stable interpersonal expectations and emotional responses within close relationships. Adult attachment anxiety was assessed through concerns regarding rejection, abandonment, insufficient partner availability, and excessive need for reassurance. Attachment avoidance was assessed through discomfort with emotional dependence, reluctance to rely on a partner, preference for emotional distance, and difficulty with interpersonal vulnerability. Higher scores indicated greater attachment insecurity in the respective dimension. Inclusion of both attachment dimensions allowed the prediction model to distinguish between hyperactivating and deactivating relational tendencies and to test whether their predictive contributions depended on other psychological or relational features.

Individual psychological functioning was represented by measures of depressive symptoms, anxiety symptoms, perceived stress, emotion regulation, self-esteem, and psychological well-being. Depressive symptoms were assessed using items addressing low mood, reduced interest or pleasure, fatigue, negative self-evaluation, concentration difficulty, and related affective experiences during a recent reference period. Anxiety was measured through symptoms of excessive worry, tension, nervousness, restlessness, and difficulty controlling anxious thoughts. Perceived stress reflected the extent to which recent life circumstances were experienced as unpredictable, uncontrollable, or overwhelming. These variables were included because psychological distress may influence both interpersonal behavior and the cognitive evaluation of relationship experiences.

Emotion-regulation variables assessed participants' typical ability to identify, understand, accept, and modify emotional responses, as well as tendencies toward maladaptive regulation when distressed. Particular attention was given to cognitive reappraisal, emotional suppression, difficulty controlling impulses under emotional distress, and perceived access to effective regulatory strategies. Self-esteem was operationalized through positive and negative evaluations of personal worth and competence. Psychological well-being included indicators of positive functioning, perceived purpose, autonomy, competence, and positive self-evaluation. These variables were retained separately rather than combined into a single general psychological-health score because deep neural networks can exploit differences in the predictive importance and interactions of individual features.

Additional relational and contextual variables included relationship duration, marital status, cohabitation status, presence of children, number of children, weekly time spent together, perceived division of household responsibilities, perceived social support, financial strain, work-related stress affecting the relationship, and major recent life stressors. Demographic variables included age, gender, educational attainment, employment status, and household income category. Relationship duration was represented continuously in months to retain greater information for the predictive model. Categorical variables were subsequently transformed into machine-readable representations during preprocessing. All instruments were administered in a fixed electronic format, with reverse-scored items recoded before scale computation. Scale and subscale scores were calculated according to their scoring structures, with higher

values consistently oriented toward the construct represented by the variable name whenever possible. Before modeling, the distributions, ranges, missingness patterns, internal consistency, and intercorrelations of all candidate predictors were examined to identify coding errors and potentially redundant variables.

2.3. Data Analysis

Data analysis was conducted as a multistage procedure consisting of preliminary statistical screening, feature preparation, deep neural network development, hyperparameter tuning, and independent evaluation of predictive performance. Initial data management and descriptive analyses included inspection of data completeness, response ranges, distributional properties, outliers, duplicate records, and internal consistency of the multi-item measures. Continuous variables were summarized using means, standard deviations, minimum and maximum values, whereas categorical participant characteristics were summarized using frequencies and percentages. Pearson correlations were calculated among the principal continuous relational and psychological variables as an exploratory description of their bivariate associations; however, variable inclusion in the neural network was not based solely on statistical significance in bivariate analyses because the purpose of the predictive approach was to identify multivariate and potentially nonlinear patterns.

Missing-data handling was undertaken before partitioning and modeling. Participants exceeding the predefined threshold of missing predictor data were removed. For the retained cases, small amounts of missing continuous data were imputed using values estimated from the training data, whereas categorical missing values were assigned using the most appropriate training-set category-based procedure. To prevent information leakage, all imputation parameters were estimated exclusively within the training portion of the data and subsequently applied unchanged to validation and test observations. Continuous input features were standardized to a mean of zero and a standard deviation of one using parameters derived from the training set. Nominal categorical predictors were transformed using one-hot encoding, whereas naturally ordered variables were represented using ordinal coding when their ordering was substantively meaningful. Preprocessing transformations were fitted to the training data only and then applied to the validation and test sets.

The final sample of 680 participants was randomly partitioned into mutually exclusive training, validation, and test subsets. Seventy percent of the observations were assigned to the training set, corresponding to 476 participants; 15% were assigned to the validation set, corresponding to 102 participants; and the remaining 15% were allocated to the independent test set, corresponding to 102 participants. The outcome distribution was examined across the three subsets to ensure that the random partition did not produce substantial differences in relationship-quality scores. The training set was used to estimate neural network weights, the validation set was used for architecture selection, hyperparameter adjustment, regularization decisions, and early stopping, and the test set remained completely unseen during model development and was used only for final estimation of generalization performance.

A feedforward deep neural network was constructed with an input layer corresponding to the complete set of preprocessed relational, psychological, contextual, and demographic features, followed by multiple fully connected hidden layers. The final architecture contained four hidden layers with 128, 64, 32, and 16 neurons, respectively. Rectified Linear Unit activation functions were used in the hidden layers because they provide efficient gradient propagation and are suitable for modeling complex nonlinear relationships in continuous multidimensional data. Batch normalization was applied to stabilize training and reduce sensitivity to scale differences in intermediate activations. Dropout regularization was incorporated between hidden layers, with dropout probabilities selected during validation, to reduce overfitting by preventing excessive dependence on specific hidden units. L2 weight regularization was additionally considered during model tuning to constrain overly large parameter estimates.

Because couple relationship quality was modeled as a continuous criterion, the network contained a single output neuron with a linear activation function. Mean squared error was specified as the primary loss function during training. Model parameters were optimized using the Adam optimization algorithm, which adaptively modifies learning rates during stochastic gradient-based estimation. Training was performed using mini-batches, and the initial learning rate, batch size, dropout rate, number of hidden units, regularization strength, and maximum number of epochs were adjusted according to validation performance. The maximum training duration was set sufficiently high to allow convergence, but early stopping was used to terminate training when validation loss failed to improve for a

predefined number of consecutive epochs. The network weights corresponding to the lowest validation loss were restored before final testing. This strategy minimized unnecessary training and reduced the likelihood of fitting idiosyncratic patterns in the training sample.

Hyperparameter selection was performed exclusively using the training and validation data. Candidate network configurations varied in depth, number of neurons per hidden layer, dropout probability, L2 regularization strength, batch size, and learning rate. Selection was based primarily on validation root mean squared error while also considering the stability of training and the difference between training and validation loss. A model was not selected simply because it produced the lowest training error; preference was given to architectures that demonstrated consistent generalization to the validation subset. Learning curves were examined to identify underfitting, overfitting, and unstable convergence. Random initialization was controlled through a fixed computational seed, and the final model was additionally trained across repeated initializations to evaluate whether predictive performance was highly dependent on a particular set of starting weights.

Final predictive accuracy was evaluated only after completion of model selection. Performance on the independent test set was quantified using the mean absolute error, root mean squared error, mean squared error, and coefficient of determination. Mean absolute error represented the average absolute difference between predicted and observed relationship-quality scores and provided an interpretable measure of typical prediction error. Root mean squared error imposed a greater penalty on larger predictive deviations, whereas the coefficient of determination represented the proportion of variance in relationship quality captured by the model in previously unseen observations. Predicted and observed values were also examined graphically and through residual diagnostics to determine whether prediction error varied systematically across low, moderate, and high levels of relationship quality.

To assess whether deep learning provided added predictive value beyond conventional approaches, supplementary benchmark models were fitted using the same training and test partitions. These included multiple linear regression, ridge regression, random forest regression, and gradient-boosted regression. All models were evaluated on the identical independent test set using the same error metrics. The deep neural network was considered to demonstrate superior predictive performance when it produced lower mean absolute and root mean squared errors

and a higher coefficient of determination than the benchmark models without evidence of substantial train-test performance divergence.

Model interpretation procedures were incorporated because predictive accuracy alone does not identify which relational and psychological characteristics contribute most strongly to predictions. Feature importance was therefore evaluated using model-agnostic and local explanation procedures suitable for nonlinear models. SHapley Additive exPlanations were calculated to estimate the direction and magnitude of each feature's contribution to individual predictions and to overall predictive performance. Global importance rankings were generated using mean absolute SHAP values, while dependence patterns were examined for the most influential predictors to identify nonlinear relationships and potential threshold effects. Particular attention was given to relationship satisfaction, communication quality, destructive conflict, perceived partner responsiveness, intimacy, commitment, attachment anxiety, attachment avoidance, depressive symptoms, anxiety, stress, emotion regulation, and self-esteem. Interaction patterns among influential predictors were also examined to determine whether the predictive contribution of one relational characteristic varied according to the level of another psychological or interpersonal characteristic.

Potential overfitting and model robustness were assessed through comparison of training, validation, and test errors, inspection of learning curves, and repeated model estimation under different random initializations. Sensitivity analyses were conducted to determine whether predictive performance changed substantially after removal of demographic predictors or after restricting the feature set to relational variables alone. A further model containing psychological variables without direct relationship-evaluation variables was evaluated to determine the extent to which relationship quality could be predicted from individual psychological functioning and interpersonal dispositions independently of conceptually proximal satisfaction indicators. These analyses were used to distinguish predictive performance attributable to broad multidimensional information from performance driven primarily by variables closely overlapping with the outcome construct. Statistical preprocessing and conventional analyses were performed using standard statistical and Python-based analytical environments, whereas neural network construction and model training were implemented using contemporary deep-learning libraries. All hypothesis-related statistical procedures used a two-sided significance

level of .05 where inferential testing was applicable, while evaluation of the primary predictive model emphasized out-of-sample error and generalization metrics rather than null-hypothesis significance testing.

3. Findings and Results

The final analytic sample consisted of 680 participants residing in Canada. Participants ranged in age from 18 to 67 years, with a mean age of 37.84 years ($SD = 10.96$). Of the participants, 378 (55.59%) identified as women, 286 (42.06%) as men, and 16 (2.35%) identified as non-binary, gender-diverse, or preferred another description. Regarding relationship status, 409 participants (60.15%) were married, 181 (26.62%) were cohabiting with a romantic partner but not legally married, and 90 (13.24%) were in a committed non-cohabiting relationship. Relationship duration ranged from 7 months to 38 years, with a mean duration of 8.73 years ($SD = 7.24$). A total of 391 participants (57.50%) reported having at least one child, whereas 289 (42.50%) reported having no children. In terms of education, 76 participants (11.18%) had completed high school or an equivalent credential, 181 (26.62%) had completed a college or technical diploma, 264 (38.82%) held a bachelor's degree, and 159 (23.38%) held a graduate or professional degree. With respect to employment, 493 participants (72.50%) were employed full-time, 91 (13.38%) were employed part-time, 42 (6.18%) were students, and 54 (7.94%) were unemployed, retired, on leave, or otherwise outside paid employment. Participants were recruited from multiple Canadian provinces, with the largest proportions residing in Ontario, British Columbia, Alberta, and Quebec. Examination of the demographic distribution indicated adequate variability in age, relationship duration, educational attainment, family structure, employment status,

and socioeconomic background, thereby supporting the intended use of the sample for multidimensional predictive modeling rather than prediction within a narrowly defined population subgroup.

Table 1 presents the descriptive statistics for the principal relational and psychological variables included in the predictive analysis. The variables demonstrated substantial variation across the sample, which was desirable for training a supervised nonlinear model. The mean overall relationship-quality score was 71.84 ($SD = 13.27$), indicating that the sample covered a broad range of relatively low to high relationship functioning rather than clustering exclusively at the upper end of the scale. Relationship satisfaction, communication quality, perceived partner responsiveness, intimacy, commitment, trust, constructive conflict resolution, self-esteem, psychological well-being, and adaptive emotion regulation were positively associated with relationship quality. Conversely, destructive conflict, attachment anxiety, attachment avoidance, depressive symptoms, anxiety symptoms, perceived stress, and financial strain were negatively associated with the outcome. The strongest zero-order positive correlations with relationship quality were observed for relationship satisfaction ($r = .78$), perceived partner responsiveness ($r = .70$), communication quality ($r = .68$), intimacy ($r = .66$), commitment ($r = .63$), and trust ($r = .62$). The strongest negative associations were observed for destructive conflict ($r = -.61$), attachment anxiety ($r = -.49$), perceived stress ($r = -.46$), attachment avoidance ($r = -.44$), and depressive symptoms ($r = -.43$). Although several predictors were moderately intercorrelated, no pairwise correlation among the principal input variables exceeded .85, indicating that the feature space retained sufficient multidimensional distinction for inclusion in the machine-learning analysis.

Table 1

Descriptive Statistics and Correlations of Principal Relational and Psychological Variables with Relationship Quality

Variable	Mean	SD	Minimum	Maximum	Correlation with Relationship Quality (r)
Relationship quality	71.84	13.27	31.20	96.40	1.00
Relationship satisfaction	36.72	7.18	14.00	49.00	.78
Communication quality	42.15	8.04	17.00	60.00	.68
Constructive conflict resolution	31.48	6.31	12.00	45.00	.55
Destructive conflict	24.91	7.46	8.00	47.00	-.61
Perceived partner responsiveness	35.67	6.74	13.00	49.00	.70
Emotional intimacy	39.06	7.93	16.00	56.00	.66
Commitment	38.72	6.81	17.00	49.00	.63
Trust	34.85	6.48	14.00	45.00	.62
Attachment anxiety	28.47	8.26	10.00	52.00	-.49
Attachment avoidance	25.63	7.91	9.00	49.00	-.44

Depressive symptoms	10.82	6.39	0.00	27.00	-.43
Anxiety symptoms	9.74	5.91	0.00	26.00	-.39
Perceived stress	18.66	6.72	4.00	37.00	-.46
Adaptive emotion regulation	31.97	6.58	13.00	46.00	.41
Self-esteem	30.82	5.67	13.00	40.00	.38
Psychological well-being	41.53	7.49	18.00	56.00	.40
Financial strain	13.74	5.08	5.00	28.00	-.29

As shown in Table 1, relationship quality was most strongly associated with variables that reflected participants' direct interpersonal experience of their current relationship. Relationship satisfaction demonstrated the largest bivariate association with the criterion ($r = .78$), followed by perceived partner responsiveness ($r = .70$), communication quality ($r = .68$), emotional intimacy ($r = .66$), commitment ($r = .63$), and trust ($r = .62$). These findings indicated that participants who perceived their relationships as satisfying, emotionally responsive, communicatively open, intimate, committed, and trustworthy tended to report higher overall relationship quality. Destructive conflict showed the strongest negative correlation with relationship quality ($r = -.61$), whereas constructive conflict resolution showed a positive association ($r = .55$), suggesting that the manner in which disagreements were managed was more informative than conflict occurrence alone. Attachment anxiety and avoidance were both negatively related to relationship quality, with anxiety showing a somewhat stronger association. Psychological distress variables were also meaningfully associated with the criterion, particularly perceived stress and depressive symptoms. However, their correlations were smaller than those of the strongest relational variables, supporting the conceptual expectation

that psychological functioning contributes to relationship quality but does not fully account for it. The simultaneous presence of moderate and strong associations across multiple relational and psychological domains provided empirical support for the use of a multidimensional nonlinear prediction model.

The deep neural network was trained using the 476-participant training subset and optimized on the 102-participant validation subset. Training loss declined rapidly during the initial epochs and then decreased more gradually. Validation loss reached its lowest value at epoch 86, after which no meaningful improvement occurred during the predefined early-stopping interval. Consequently, the parameters corresponding to epoch 86 were restored and used for final evaluation. There was no evidence of severe divergence between training and validation loss, indicating that dropout, batch normalization, L2 regularization, and early stopping adequately constrained overfitting. The final test evaluation was performed once on the 102 participants who had remained completely unseen during training and model selection. Table 2 compares the predictive accuracy of the deep neural network with four conventional benchmark algorithms fitted to the same input-feature structure and evaluated on the identical test set.

Table 2

Comparison of Predictive Performance Across the Deep Neural Network and Benchmark Models

Model	MAE	MSE	RMSE	R ²
Multiple linear regression	6.21	60.84	7.80	.64
Ridge regression	5.97	56.55	7.52	.66
Random forest regression	5.18	44.09	6.64	.74
Gradient-boosted regression	4.73	37.58	6.13	.78
Deep neural network	3.91	26.63	5.16	.84

The results presented in Table 2 demonstrate that the deep neural network achieved the strongest out-of-sample predictive performance among all evaluated models. On the independent test set, the neural network produced a mean absolute error of 3.91 relationship-quality points, indicating that its predictions differed from the observed values by approximately four scale points on average. The

corresponding root mean squared error was 5.16, while the coefficient of determination was .84, indicating that the model explained approximately 84% of the variability in relationship-quality scores among previously unseen participants. In comparison, multiple linear regression explained 64% of the test-set variance and produced an RMSE of 7.80, whereas ridge regression yielded only a

modest improvement with an R^2 of .66 and RMSE of 7.52. The tree-based models performed better than the linear models, with random forest regression achieving an R^2 of .74 and gradient-boosted regression reaching .78. Nevertheless, the deep neural network reduced RMSE by approximately 15.8% relative to the gradient-boosted model, which was the strongest conventional benchmark. The superiority of the nonlinear approaches over the linear models also suggested that the relationship between the multidimensional predictors and relationship quality was not adequately represented by a purely additive linear structure. The additional improvement obtained by the deep neural network was consistent with its capacity to capture higher-order interactions and nonlinear effects across psychological and relational features.

SHAP-based model interpretation was used to examine the relative contribution of individual features to the

predictions generated by the final deep neural network. Feature importance was calculated using the mean absolute SHAP value across participants in the independent evaluation data. Higher mean absolute values indicated that variation in the corresponding predictor produced larger changes in predicted relationship quality, irrespective of the direction of the effect. Table 3 presents the 15 most influential predictors identified by the final model. Relationship satisfaction emerged as the most influential feature, followed by perceived partner responsiveness, destructive conflict, communication quality, emotional intimacy, attachment anxiety, commitment, trust, perceived stress, attachment avoidance, depressive symptoms, adaptive emotion regulation, self-esteem, financial strain, and constructive conflict resolution.

Table 3

Most Influential Predictors of Couple Relationship Quality According to SHAP Analysis

Rank	Predictor	Mean Absolute SHAP Value	Predominant Direction of Association
1	Relationship satisfaction	6.84	Positive
2	Perceived partner responsiveness	5.71	Positive
3	Destructive conflict	5.08	Negative
4	Communication quality	4.82	Positive
5	Emotional intimacy	4.36	Positive
6	Attachment anxiety	3.74	Negative
7	Commitment	3.48	Positive
8	Trust	3.21	Positive
9	Perceived stress	2.88	Negative
10	Attachment avoidance	2.61	Negative
11	Depressive symptoms	2.35	Negative
12	Adaptive emotion regulation	2.14	Positive
13	Self-esteem	1.89	Positive
14	Financial strain	1.71	Negative
15	Constructive conflict resolution	1.58	Positive

As demonstrated in Table 3, the neural network relied most heavily on proximal relational characteristics when estimating relationship quality, but psychological variables also contributed meaningfully to prediction. Relationship satisfaction had the largest global contribution, with a mean absolute SHAP value of 6.84, followed by perceived partner responsiveness at 5.71. Higher levels of these variables generally shifted predictions toward higher relationship-quality scores. Destructive conflict was the strongest negative predictor, producing substantial downward shifts in predicted quality when participants reported frequent criticism, defensiveness, withdrawal, escalation, and unresolved disagreement. Communication quality and

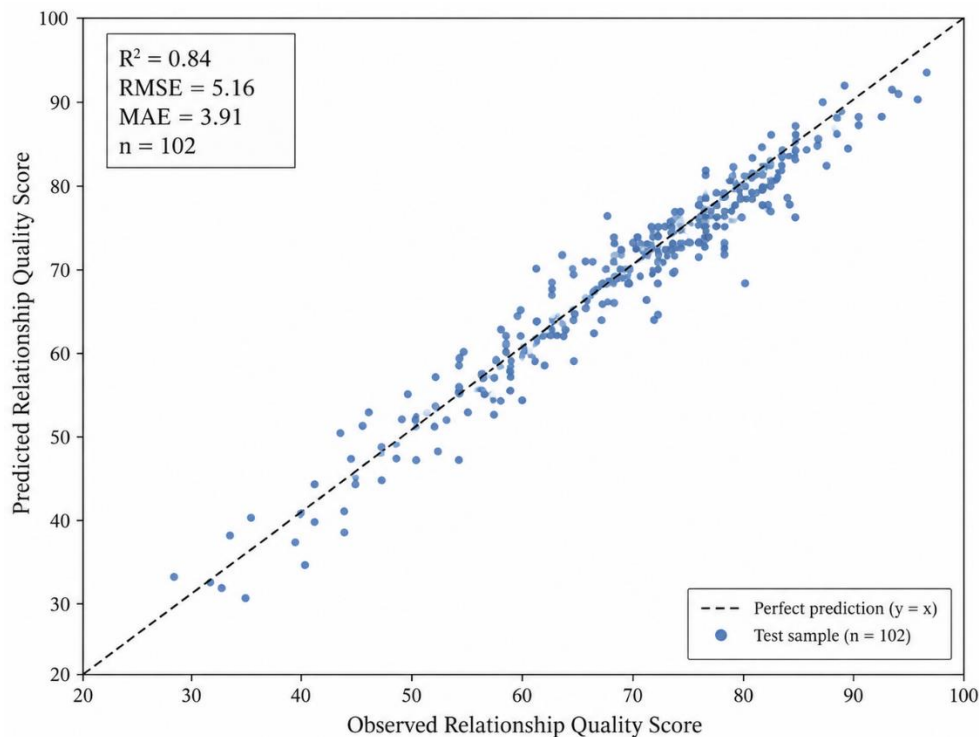
emotional intimacy also made large positive contributions, indicating that relational processes involving openness, understanding, disclosure, and emotional connectedness were central to the prediction function. Attachment anxiety represented the most influential individual-difference predictor and showed a predominantly negative contribution, particularly at higher values. Attachment avoidance demonstrated a similar but somewhat smaller negative contribution. Among psychological distress variables, perceived stress was more influential than either depressive or anxiety symptoms, suggesting that the subjective experience of being overwhelmed by ongoing demands may be particularly relevant to relationship

functioning. Emotion regulation and self-esteem were positively associated with predictions, whereas financial strain exerted a predominantly negative effect. Importantly, the SHAP distributions indicated that the influence of several predictors was nonlinear. For example, moderate increases in destructive conflict were associated with relatively small predicted reductions at lower levels of

conflict, but increasingly large negative shifts occurred once conflict severity passed the middle range of the distribution. Similarly, improvements in perceived partner responsiveness produced disproportionately larger positive changes among participants whose responsiveness scores moved from low to moderate levels, after which the incremental effect became smaller at the highest values.

Figure 1

Observed Versus Deep Neural Network-Predicted Couple Relationship Quality Scores in the Independent Test Sample



The observed-versus-predicted distribution shown in Figure 1 indicated close correspondence between actual relationship-quality scores and values generated by the final neural network. Most observations were concentrated near the line representing perfect agreement, with only a limited number of larger residuals. Prediction accuracy was strongest within the central and upper-middle portions of the relationship-quality distribution, where the majority of participants were located. Slightly greater prediction error was observed at the extreme lower end of the outcome distribution, reflecting the relatively smaller number of participants with very poor relationship quality and the consequent reduction in training examples representing these cases. Residual inspection did not reveal a strong systematic tendency toward either overprediction or underprediction across the overall score range. The mean residual was close to zero, supporting the absence of

substantial overall prediction bias. Examination of squared and absolute residuals also indicated that prediction variability increased only modestly at the extremes of the outcome distribution. These findings supported the adequacy of the final model for generalized prediction across a broad range of relationship-functioning levels rather than accuracy being restricted to participants close to the sample mean.

Additional robustness analyses supported the stability of the model. Across repeated random initializations, test-set R^2 values remained between .81 and .84, while RMSE values ranged from 5.16 to 5.48, suggesting that predictive performance was not dependent on a single favorable initialization of network weights. Removal of demographic variables produced only a small reduction in performance, with R^2 decreasing from .84 to .82, indicating that most of the model's predictive information was derived from

relational and psychological characteristics rather than age, gender, education, employment, or other demographic factors. When the network was trained using relational variables alone, test-set R^2 was .79, whereas a model containing psychological variables and contextual characteristics but excluding direct relational-evaluation variables produced an R^2 of .61. Thus, relational characteristics accounted for the largest proportion of predictive information, but the integration of individual psychological functioning improved performance beyond that obtainable from relationship-process variables alone. The full multidimensional model therefore showed the highest generalization accuracy, supporting the central premise that couple relationship quality can be predicted most effectively when interpersonal and individual psychological features are modeled jointly rather than in isolation.

Further sensitivity analysis was conducted to determine whether the high predictive performance of the full model could be attributed disproportionately to relationship satisfaction, which was conceptually close to the outcome variable. When relationship satisfaction was removed from the predictor set and the model was retrained using all remaining relational, psychological, contextual, and demographic features, the independent test-set R^2 decreased from .84 to .76 and RMSE increased from 5.16 to 6.39. Although this reduction confirmed that relationship satisfaction carried substantial predictive information, the remaining model still explained more than three quarters of the variance in relationship quality. In this restricted model, perceived partner responsiveness, destructive conflict, communication quality, emotional intimacy, attachment anxiety, commitment, trust, and perceived stress became the dominant predictors. This finding demonstrated that the predictive performance of the neural network was not solely the result of conceptual overlap between relationship satisfaction and overall relationship quality. Rather, the model retained substantial predictive capacity when relying on broader relational processes, attachment characteristics, psychological distress, and emotion-regulation features.

Inspection of SHAP interaction patterns further indicated that several predictors contributed jointly rather than independently. The negative effect of destructive conflict was particularly strong when perceived partner responsiveness was low, whereas elevated responsiveness partially attenuated the downward contribution associated with moderate conflict. Similarly, attachment anxiety was more strongly associated with reduced predicted relationship

quality among participants who simultaneously reported poor communication quality. Participants with relatively high attachment anxiety but high perceived responsiveness and adaptive communication tended to receive higher predicted relationship-quality values than participants with equivalent attachment-anxiety levels but weak relational resources. Perceived stress also interacted with emotional regulation: high stress was associated with more pronounced negative predictions among individuals with low adaptive emotion-regulation scores, whereas the negative contribution of stress was smaller among those with stronger regulatory capacities. These nonlinear interaction patterns provided additional evidence that couple relationship quality was best represented as the product of interdependent relational and psychological processes rather than as the simple additive sum of isolated risk and protective factors.

Overall, the findings demonstrated that the deep neural network successfully learned a stable multidimensional prediction function for couple relationship quality and generalized effectively to previously unseen participants. The final model substantially outperformed conventional linear regression, regularized regression, random forest, and gradient-boosting approaches, achieving an independent test-set R^2 of .84 and RMSE of 5.16. Relational satisfaction, perceived partner responsiveness, destructive conflict, communication quality, emotional intimacy, commitment, and trust constituted the strongest relationship-specific predictors, whereas attachment insecurity, perceived stress, depressive symptoms, emotion regulation, and self-esteem provided additional psychological information. The results therefore supported both the predictive value of deep learning and the substantive importance of integrating relational processes with individual psychological functioning when modeling differences in couple relationship quality.

4. Discussion

The present study developed and evaluated a deep neural network for predicting couple relationship quality using multidimensional relational, psychological, contextual, and demographic features. The principal finding was that the deep neural network demonstrated strong out-of-sample predictive performance, explaining 84% of the variance in relationship quality in the independent test sample, with a mean absolute error of 3.91 and a root mean squared error of 5.16. The model also outperformed multiple linear regression, ridge regression, random forest regression, and

gradient-boosted regression. In addition to the overall predictive performance, the feature-importance analysis showed that relationship satisfaction, perceived partner responsiveness, destructive conflict, communication quality, emotional intimacy, attachment anxiety, commitment, trust, perceived stress, attachment avoidance, depressive symptoms, adaptive emotion regulation, self-esteem, financial strain, and constructive conflict resolution were among the most influential predictors. These findings support the conceptualization of couple relationship quality as a multidimensional outcome that is better understood through the joint contribution of relational processes and individual psychological characteristics than through isolated variables.

The strong performance of the deep neural network suggests that couple relationship quality may be characterized by nonlinear and interactive relationships among multiple predictors. Conventional linear regression assumes that predictor effects are largely additive and linear unless interaction and nonlinear terms are specified explicitly. In contrast, deep neural networks can learn complex combinations among variables and therefore may be better suited to relational phenomena in which the effect of one characteristic depends on the presence or level of another. The higher accuracy of the neural network compared with both linear and tree-based benchmark models is consistent with the broader theoretical literature showing that relationship functioning reflects interdependent systems of communication, attachment, coping, emotional regulation, responsiveness, stress, and individual differences. The current findings therefore extend previous relationship research by demonstrating that these multiple domains can be integrated within a single predictive architecture capable of accurately estimating relationship quality in previously unseen cases.

Relationship satisfaction emerged as the strongest predictor in both the correlational and SHAP analyses. This finding is expected because satisfaction is conceptually proximal to broader relationship quality and captures an individual's overall evaluation of fulfillment, positivity, and functioning within the romantic partnership. Previous psychometric research has established the validity and external associations of relationship satisfaction measures and has shown that satisfaction is meaningfully related to a wide range of interpersonal and psychological outcomes (Adamczyk et al., 2022). At the same time, the sensitivity analysis showed that removal of relationship satisfaction reduced, but did not eliminate, predictive accuracy. The

restricted model still explained a substantial proportion of variance in relationship quality. This is important because it indicates that the neural network did not simply reproduce the outcome using a highly overlapping satisfaction measure; rather, it also captured meaningful predictive information from broader relationship and psychological processes.

Perceived partner responsiveness was the second most influential predictor and showed a strong positive association with relationship quality. This finding supports relational theories proposing that individuals experience greater satisfaction and security when they perceive their partner as understanding, caring, validating, and responsive to their needs. The results are consistent with evidence showing that need fulfillment, consensus, commitment, and satisfaction are closely interconnected within couple relationships (Park & Harris, 2025). Perceived responsiveness may strengthen relationship quality by increasing emotional safety and reducing uncertainty concerning a partner's availability during stress or conflict. It may also promote greater self-disclosure and cooperation, which can reinforce intimacy and trust. The importance of cooperative functioning is similarly supported by evidence that tacit coordination influences intimate relationship satisfaction and that the effect can vary across stages of relationship development (Xu et al., 2026). Together, these studies support the current finding that relationship quality depends not merely on the quantity of interaction but on whether interaction is experienced as emotionally responsive and coordinated.

Destructive conflict emerged as the strongest negative relational predictor. Participants reporting greater criticism, defensiveness, withdrawal, escalation, and unresolved disagreement tended to receive substantially lower predicted relationship-quality scores. This finding is consistent with research identifying negative interaction as a central indicator of couple dysfunction. Validation work on negative interaction measures has emphasized the importance of assessing harmful communication and conflict patterns as a distinct relational domain (Ventura-León et al., 2025). Emotional flooding may provide one mechanism explaining this result, because intense affective arousal during conflict can impair emotional regulation, perspective-taking, and constructive problem solving and may increase the probability of hostile or avoidant responses (Castillo-López et al., 2024). The nonlinear SHAP pattern observed in the present study is especially notable because the negative contribution of destructive conflict became

larger at higher levels. This suggests that relatively occasional conflict may not necessarily indicate poor relationship functioning, whereas recurrent and intense destructive conflict may produce disproportionately greater relational deterioration.

Communication quality and constructive conflict resolution also made important positive contributions. These findings reinforce the view that the effects of disagreement depend in part on how couples communicate during and after conflict. Constructive communication can enable partners to express needs, negotiate differences, and repair emotional disruption without transforming every disagreement into a threat to the relationship. The current findings are also compatible with evidence that relationship nostalgia may help couples offset conflict and preserve commitment (Swets et al., 2024). Positive shared memories may function as a relational resource that helps individuals maintain a favorable representation of the partnership during periods of disagreement. Likewise, appreciation may buffer negative consequences of sacrifice and imbalance by signaling that relational investments are recognized and valued (Özdemir, 2025). These processes illustrate how positive relational resources can coexist with conflict and potentially reduce its adverse consequences.

Emotional intimacy, commitment, and trust were also among the strongest predictors. Their contribution is consistent with multidimensional perspectives on relationship quality that emphasize the importance of emotional connectedness, shared identity, and relational security. The concept of “we-ness” captures the extent to which partners perceive themselves as members of a meaningful relational unit and has been proposed as an important dimension of couple functioning (Cruwys et al., 2022). At the same time, healthy relationships require sufficient space for individuality and authentic self-expression, as reflected in research on individuality within couples (Brock et al., 2023). The present findings therefore support a view of high-quality relationships as involving both connectedness and respect for individual identity. Conversely, dehumanizing or deindividuating experiences within relationships may undermine psychological security and mutual recognition (Brock & Gervais, 2025). Trust and commitment may be particularly important because they provide expectations of reliability, continuity, and mutual investment, all of which can stabilize relationships when couples encounter stress or disagreement.

Attachment anxiety was the most influential individual-difference predictor, and attachment avoidance was also

negatively associated with predicted relationship quality. These findings are strongly consistent with attachment-based research. Adult attachment patterns influence marital adjustment through both actor and partner processes, indicating that attachment insecurity can shape not only an individual's own relationship experience but also relational dynamics affecting the partner (Uluyol & Özen-Çıplak, 2024). Attachment matching and coparental interactions have similarly been studied across different couple configurations, demonstrating that attachment-related processes operate within the dyadic system (Miscioscia et al., 2021). The present study also found that attachment anxiety interacted with communication quality, such that high anxiety was associated with more negative predictions when communication was poor. This pattern is theoretically plausible because anxiously attached individuals may be particularly sensitive to ambiguity and perceived rejection, and ineffective communication may intensify uncertainty rather than provide reassurance.

Recent research further supports the association between attachment and relationship satisfaction through mediating processes such as appreciation and a sense of giving (Zhu et al., 2026). Attachment insecurity may therefore influence relationship quality partly by shaping how individuals interpret their partner's actions and their own relational contributions. The present findings are also consistent with evidence linking childhood trauma to romantic relationship satisfaction through attachment and social support (Quan et al., 2025). Earlier adverse experiences may contribute to enduring expectations concerning trust, rejection, or partner availability, thereby influencing later intimate functioning. Self-compassion may serve as an additional protective factor, particularly for individuals with histories of maltreatment, and dyadic evidence suggests that its influence may extend across partners (Lassri & Zamir, 2026). Collectively, these findings support the current model's inclusion of both current relationship processes and psychologically rooted attachment characteristics.

Perceived stress and depressive symptoms also contributed substantially to prediction. The negative influence of psychological distress is consistent with literature showing that depression and relationship quality are interconnected within couples. Actor-partner analyses demonstrate that depression is associated with multiple operationalizations of relationship quality and that one partner's psychological functioning can affect the other's relational experience (Aguilar-Raab et al., 2022). Experimental evidence also indicates that partnership

appreciation can improve mood and momentary relationship satisfaction among individuals experiencing depression (Warth et al., 2020). These findings suggest bidirectional mechanisms: psychological distress can reduce emotional availability, patience, and positive interaction, while low relationship quality can simultaneously contribute to distress.

The observed importance of perceived stress may be particularly relevant because stress often operates as a contextual amplifier of relational vulnerabilities. Under high stress, partners may have fewer emotional and cognitive resources for effective communication, responsiveness, and conflict regulation. The SHAP interaction analysis showed that the negative contribution of stress was smaller among individuals with stronger emotion-regulation capacities. This finding is consistent with the idea that emotion regulation can function as a resilience mechanism within intimate relationships. It also aligns with research showing that dyadic coping mediates associations between perceived relationship quality and emotional responses to shared stressors (Relvas et al., 2023). The COVID-19 literature similarly demonstrates that couples varied considerably in their responses to external disruption, with some relationships deteriorating and others showing resilience or increased cohesion (Estlein et al., 2022). Perceived risk of separation also changed under lockdown-related pressures, further illustrating how contextual stressors can affect intimate functioning (Baez et al., 2023).

Personality and broader dispositional characteristics provide another explanatory layer. The present study found that self-esteem and emotion regulation contributed positively to predictions, while psychological distress contributed negatively. These findings are compatible with research showing that personality traits are associated with romantic relationship satisfaction (Ricafronte et al., 2024). Neuroticism has been particularly strongly implicated in lower satisfaction through both intrapersonal and interpersonal pathways (Kreuzer & Gollwitzer, 2021). Individuals high in negative affectivity may perceive relational events more negatively, respond more intensely to conflict, and require greater regulatory effort during interpersonal stress. Assortative mating processes may further influence these patterns because partners are not randomly paired with respect to personality and behavioral tendencies (Nguyen, 2023). Thus, the neural network's capacity to represent complex combinations of relational and psychological features may be advantageous because such

characteristics likely influence one another rather than operating independently.

The findings also support the relevance of broader psychosocial and contextual variables. Financial strain was a negative predictor, although less influential than the principal relational and attachment variables. This pattern is consistent with the broader literature showing that external stressors can affect intimate relationships by increasing conflict exposure and reducing emotional resources. Discrimination and racism-related stress represent particularly important examples. Discrimination and colorism have been associated with psychosocial health and relationship satisfaction among Black and Latinx emerging adults (Brown et al., 2023), while multidimensional racism-related stress has been shown to undermine Black romantic relationships (Rice et al., 2025). These findings support the interpretation that relationship quality cannot be fully understood as an internal property of the couple because social environments can shape emotional resources, stress exposure, and patterns of interpersonal interaction.

Technology-related behavior may likewise contribute to relational functioning. Problematic internet use has been associated with couple burnout and marital disconnection, suggesting that digital engagement can interfere with shared attention, intimacy, and relational presence (Bagheri et al., 2023). Although technology-related variables were not among the strongest predictors in the present model, their potential role supports the broader multidimensional framework adopted in this study. Similarly, sexual and embodied factors may influence couple relationship quality. Body appreciation, sexual esteem, and sexual assertiveness have been linked to romantic relationship satisfaction (Rizzo et al., 2025), while resilience and thought control have been associated with sexual satisfaction (Rostami, 2024). Gender-role orientations may also shape expectations regarding emotional expression, intimacy, and relationship functioning (Arora & Chauhan, 2024). These domains were not the dominant features in the final model, but they remain relevant components of broader relational functioning.

The findings regarding individual psychological resources are also consistent with work on the capacity to love and well-being. The capacity to establish and sustain emotionally meaningful relationships has been associated with well-being across different adult developmental stages (Fernandes et al., 2023), while validation of the Capacity to Love Inventory has shown associations with clinical measures and mindfulness (Glavač et al., 2024). These results suggest that relational quality is supported by broader

psychological capacities involving emotional availability, self-regulation, and interpersonal engagement. Likewise, close relationships can influence both physical and mental health, further emphasizing the reciprocal relationship between intimate functioning and individual well-being (Kanth, 2022).

The sensitivity analyses strengthen the interpretation of the main findings. Removing demographic variables produced only a small decline in predictive performance, whereas restricting the model to psychological and contextual variables produced a considerably larger reduction. This suggests that direct relational processes carry the greatest predictive information, although psychological characteristics meaningfully enhance prediction. The model using relational variables alone performed relatively well, but the full multidimensional model performed best. This finding supports the argument that relationship quality cannot be adequately explained through either interpersonal or individual psychological features in isolation. Rather, the strongest predictive performance emerges when both domains are modeled simultaneously.

5. Conclusion

The interaction findings are particularly important. The adverse influence of destructive conflict was stronger when partner responsiveness was low, and the effect of attachment anxiety was more pronounced when communication quality was poor. These patterns illustrate why deep learning may offer an advantage in this field. Relationship processes rarely operate independently. A risk factor can be intensified or attenuated by another feature, and the resulting pattern may be nonlinear. For example, high conflict may not necessarily produce poor relationship quality when partners remain emotionally responsive, capable of repair, and strongly committed. Conversely, even moderate conflict may be damaging in relationships characterized by low trust and low responsiveness. The present findings therefore provide empirical support for a systems-oriented understanding of relationship quality in which relational and psychological variables function as interacting components of a broader dynamic structure.

6. Limitations & Suggestions

Several limitations should be considered when interpreting the findings. First, the study used a cross-sectional design, which prevents conclusions regarding causal direction or temporal ordering among the predictors

and relationship quality. Second, the data were primarily based on self-report measures, which may be affected by shared-method variance, social desirability, recall bias, and subjective interpretation. Third, although the sample included participants from multiple Canadian provinces and varied in age, relationship duration, and socioeconomic background, it cannot be assumed to represent all couples in Canada, particularly populations with limited internet access, linguistic minorities not comfortable completing English questionnaires, and underrepresented cultural groups. Fourth, the unit of analysis was the individual rather than the couple, which means that reciprocal partner effects and dyadic interdependence were not modeled directly. Fifth, deep neural networks can be sensitive to sample composition and model specification, and although independent testing, regularization, and repeated initialization were used, external validation in a separate sample remains necessary. Finally, the strong predictive role of relationship satisfaction reflects some conceptual proximity to the broader relationship-quality criterion, even though sensitivity analyses indicated that the model retained substantial predictive ability after its removal.

Future research should replicate the model in larger and more diverse samples and should prioritize external validation across countries, cultural contexts, age groups, and relationship types. Longitudinal designs would be particularly valuable because they would allow researchers to predict changes in relationship quality over time rather than estimating only concurrent functioning. Dyadic designs incorporating data from both partners could be integrated with actor-partner interdependence modeling and machine-learning approaches to capture reciprocal influence. Future studies could also incorporate behavioral observations, ecological momentary assessment, digital communication indicators, physiological data, and passive sensing alongside questionnaire measures. Model development should further explore architectures designed for longitudinal or dyadic data, including recurrent neural networks, transformers, and multimodal models. Comparative studies should examine whether deep learning consistently outperforms simpler methods when tested across independent datasets. In addition, future work should continue to develop interpretable machine-learning methods so that high predictive performance can be accompanied by clinically and theoretically meaningful explanations of individual predictions.

From a practical perspective, the findings suggest that multidimensional assessment may be more informative than

relying on a single measure of relationship satisfaction. Couple therapists, counselors, and relationship educators may benefit from evaluating communication quality, destructive conflict, perceived responsiveness, intimacy, attachment insecurity, commitment, stress, and emotion-regulation capacities together when identifying areas of relational vulnerability. Predictive models should not be used as substitutes for professional judgment, but they may eventually support screening, case formulation, and early identification of couples who could benefit from preventive intervention. Interventions may be particularly useful when they target modifiable relational mechanisms such as responsiveness, constructive communication, conflict repair, appreciation, trust-building, and adaptive emotion regulation. Where high stress, depressive symptoms, or attachment insecurity are present, couple-based interventions may also need to incorporate individual psychological support. Any applied use of predictive algorithms should additionally include transparent communication, appropriate privacy safeguards, bias monitoring, and clear recognition that algorithmic predictions represent probabilistic estimates rather than deterministic judgments about the future of a relationship.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

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

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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Authors' Contributions

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

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References

- Adamczyk, K., Kleka, P., & Frydrychowicz, M. (2022). Psychometric Functioning, Measurement Invariance, and External Associations of the Relationship Assessment Scale in a Sample of Polish Adults. *Scientific reports*, 12(1). <https://doi.org/10.1038/s41598-022-26653-6>
- Aguilar-Raab, C., Winter, F., Jarczok, M. N., Ditzen, B., & Warth, M. (2022). Feeling Low and Unhappy Together? An Actor-Partner-Interdependence Model Uncovering the Linkage Between Different Operationalizations of Relationship Quality and Depression in Different-Sex Couples. *PLoS One*, 17(11), e0274756. <https://doi.org/10.1371/journal.pone.0274756>
- Arora, M., & Chauhan, T. (2024). The Relationship Between Sex-Roles and Romantic Relationship Satisfaction. *International Journal for Multidisciplinary Research*, 6(3). <https://doi.org/10.36948/ijfmr.2024.v06i03.21213>
- Baez, G., Castillo, L. P. D., & Guzmán, J. A. P. (2023). Romantic Partnership and Perceived Risk of Separation During COVID-19 Lockdown in the Dominican Republic. *Ciencia Y Sociedad*, 48(4), 57-89. <https://doi.org/10.22206/cys.2023.v48i4.2806>
- Bagheri, R., Ostovar, S., Griffiths, M. D., & Hashim, I. H. M. (2023). Server Connection Versus Marital Disconnection: An Investigation of the Effect of Internet Addiction on Couple Burnout in Iran. *Technology in Society*, 72, 102163. <https://doi.org/10.1016/j.techsoc.2022.102163>
- Brock, R. L., & Gervais, S. J. (2025). The Psychometric Properties of a New Scale of Dehumanizing Deindividuation in Couples. *Journal of Family Psychology*, 39(2), 171-183. <https://doi.org/10.1037/fam0001311>
- Brock, R. L., Ramsdell, E. L., Franz, M. R., Stasik-O'Brien, S. M., Gervais, S. J., & Calkins, F. C. (2023). Free to Be Me With You: Development of the Individuality in Couples Questionnaire. *Psychological assessment*, 35(7), 602-617. <https://doi.org/10.1037/pas0001238>
- Brown, A. M., Landor, A. M., & Zeiders, K. H. (2023). Weathering Racism and Colorism: Exploring Concurrent and Short-Term Longitudinal Associations Between Discrimination, Colorism, Psychosocial Health, and Black and Latinx Emerging Adults' Relationship Satisfaction. *Journal of Social and Personal Relationships*, 40(10), 3244-3268. <https://doi.org/10.1177/02654075231170900>
- Castillo-López, Á. G. d., Berenguer-Soler, M., Pineda, D., & José, A. G. d. C. (2024). Emotional Flooding in Couple Relationships: Psychosocial Aspects and Regulatory Strategies. <https://doi.org/10.5772/intechopen.1006183>
- Cruwys, T., South, E. I., Halford, W. K., Murray, J., & Fladerer, M. P. (2022). Measuring "We-ness" in Couple Relationships: A Social Identity Approach. *Family Process*, 62(2), 795-817. <https://doi.org/10.1111/famp.12811>
- Estlein, R., Gewirtz-Meydan, A., & Opuda, E. (2022). Love in the Time of COVID-19: A Systematic Mapping Review of

- Empirical Research on Romantic Relationships One Year Into the COVID-19 Pandemic. *Family Process*, 61(3), 1208-1228. <https://doi.org/10.1111/famp.12775>
- Fernandes, M. I. A., Sousa, C., Conde, A. R., Silva, F. F. d., & Ferreira, M. J. (2023). Exploring the Relationship Between Capacity to Love and Well-Being: A Comparative Study of Emerging Adults and Middle-Aged Adults. *Sexuality & Culture*, 28(4), 1424-1445. <https://doi.org/10.1007/s12119-023-10184-x>
- Genç, E., & Büyükkada, E. (2026). The Impact of Obsessive-Compulsive Relationship Symptoms on Marital Instability: Mediating Role of Infidelity Tendency. *Journal of marital and family therapy*, 52(2). <https://doi.org/10.1111/jmft.70122>
- Glavač, T., Poštuvan, V., Schmeckenbecher, J., & Kapusta, N. D. (2024). Slovenian Validation of the Capacity to Love Inventory: Associations With Clinical Measures and Mindfulness. *Frontiers in psychology*, 15. <https://doi.org/10.3389/fpsyg.2024.1440013>
- Kanth, D. B. (2022). Effects of Personal Relationships on Physical and Mental Health Among Young Adults- A Scoping Review. *The Open Psychology Journal*, 15(1). <https://doi.org/10.2174/18743501-v15-e2208180>
- Khani, P., Dezfouli, M. A., Nasri, F., Rahemi, M., Ahmadloo, S., Afkhami, H., Saeidi, F., Tereshchenko, S., Bigdeli, M. R., & Modarressi, M. H. (2023). Genetic and Epigenetic Effects on Couple Adjustment in Context of Romantic Relationship: A Scoping Systematic Review. *Frontiers in Genetics*, 14. <https://doi.org/10.3389/fgene.2023.1002048>
- Kreuzer, M., & Gollwitzer, M. (2021). Neuroticism and Satisfaction in Romantic Relationships: A Systematic Investigation of Intra- And Interpersonal Processes With a Longitudinal Approach. *European Journal of Personality*, 36(2), 149-179. <https://doi.org/10.1177/08902070211001258>
- Lassri, D., & Zamir, O. (2026). The Role of Self-Compassion in the Association Between Childhood Maltreatment and Marital Quality: An Actor-partner Interdependence Model. *Psychological Trauma Theory Research Practice and Policy*, 18(1), 138-147. <https://doi.org/10.1037/tra0001680>
- Madsen, J. W., Hernández, L., Sedov, I. A., & Tomfohr-Madsen, L. (2023). Romantic Relationship Satisfaction Is Associated With Sleep in Undergraduate Students. *Couple and Family Psychology Research and Practice*, 12(1), 39-54. <https://doi.org/10.1037/cfp0000163>
- Miscioscia, M., Carli, P. D., Sacchi, C., Tasker, F., & Simonelli, A. (2021). Attachment Matching and Coparental Interactions in Same-Sex and Different-Sex Couples Planning Parenthood. 153-179. https://doi.org/10.1007/978-3-030-51988-9_8
- Nguyen, P. (2023). Investigating Assortative Mating Patterns by Expanding Personality Assessments Beyond Static and Universal Personality Traits: Written Doctoral Preliminary Exam. <https://doi.org/10.31234/osf.io/c3q7x>
- Özdemir, P. G. (2025). Does Sacrifice Always Lead to Burnout in Romantic Relationships? The Role of Relational Equity and Appreciation. *Journal of Social and Personal Relationships*, 42(10), 3056-3081. <https://doi.org/10.1177/02654075251359607>
- Park, C., & Harris, V. W. (2025). Consensus, Need Fulfillment, Commitment, and Satisfaction in Couple Relationships: Structural Equation Modeling. *Journal of marital and family therapy*, 51(1). <https://doi.org/10.1111/jmft.70001>
- Quan, L., Zhang, K., & Chen, H. (2025). The Relationship Between Childhood Trauma and Romantic Relationship Satisfaction: The Role of Attachment and Social Support. *Frontiers in Psychiatry*, 15. <https://doi.org/10.3389/fpsyg.2024.1519699>
- Relvas, A. P., Lacomba-Trejo, L., Portugal, A., Chiarolanza, C., Major, S., Rosa, C., Sotero, L., & Randall, A. K. (2023). YES, WE COPE: Dyadic Coping as a Mediator Between Perceived Relationship Quality and Emotional Representation of COVID-19. *Cognitive therapy and research*, 47(4), 563-573. <https://doi.org/10.1007/s10608-023-10379-4>
- Ricafronte, G. R., Sumicad, R., Lirazan, M. E., & Gerzon, K. J. (2024). Correlations of Personality Traits and Romantic Relationship Satisfaction. *Journal of Psychology and Behavior Studies*, 4(1), 38-50. <https://doi.org/10.32996/jpbs.2024.1.5>
- Rice, T. M., Bryant, C. M., & Dush, C. M. K. (2025). Multidimensional Racism-Related Stress and the Undermining of Black Romantic Relationships. *Journal of marriage and family*, 88(2), 413-424. <https://doi.org/10.1111/jomf.70028>
- Rizzo, M., Matera, C., Caso, D., Donizzetti, A. R., Grano, C., Nerini, A., & Rollero, C. (2025). Satisfaction in Romantic Relationships: The Role of Body Appreciation, Sexual Esteem and Sexual Assertiveness. *Behavioral Sciences*, 15(12), 1730. <https://doi.org/10.3390/bs15121730>
- Rostami, M. (2024). Beyond the Bedroom: How Resilience and Thought Control Influence Sexual Satisfaction. *KMAN Counsel and Psych Nexus*, 2(1), 10-16. <https://doi.org/10.61838/kman.psychnexus.1.2.3>
- Shrestha, P. S., Shaver, S. R., Perlman, T. T., & Walsham, W. (2023). Emotional Dimensions of Infidelity: An Analysis of Psychological and Emotional Factors Affecting Relationship Infidelity. *Jurnal Sosial Sains Terapan Dan Riset (Sosateris)*, 11(2), 88-103. <https://doi.org/10.35335/85rbw180>
- Swets, J. A., Cox, C. R., & Ekas, N. V. (2024). Preliminary Evidence That Relationship Nostalgia Might Offset Romantic Conflict to Aid Relationship Commitment. *Couple and Family Psychology Research and Practice*, 13(4), 276-295. <https://doi.org/10.1037/cfp0000248>
- Uluyol, F. M., & Özen-Çıplak, A. (2024). Dyadic Relationship of Adult Attachment Patterns and Interpersonal Schemas in Marital Adjustment: Actor-partner Effect Model. *Family Relations*, 73(3), 2152-2169. <https://doi.org/10.1111/fare.13002>
- Ventura-León, J., Tocto-Muñoz, S., Lino-Cruz, C., Sánchez-Villena, A. R., Martínez-Munive, R., Talledo-Sánchez, K., & Casiano-Valdivieso, K. (2025). Validation and Reliability of the Negative Interaction Scale for Couple Relationships in Peru: A Bayesian Confirmatory Factor Analysis Approach. *Family Process*, 64(1). <https://doi.org/10.1111/famp.70029>
- Warth, M., Stoffel, M., Winter, F., Jarczok, M. N., Aguilar-Raab, C., & Ditzgen, B. (2020). Instructed Partnership Appreciation in Depression: Effects on Mood, Momentary Relationship Satisfaction, and Psychobiological Arousal. *Frontiers in Psychiatry*, 11. <https://doi.org/10.3389/fpsyg.2020.00701>
- Xu, M., Wu, S., Lin, C., Tang, R., & Gao, D. (2026). Tacit Cooperation Influenced Intimate Relationship Satisfaction: The Moderating Roles of Coordination Game Type and Developmental Stage of Relationship. *Design for Augmented Humanity*, 1(2), 159-172. <https://doi.org/10.1177/29776481261453225>
- Zhu, M., Tan, J., Zuli, Z., Liang, L., Li, Q., Wen, J., Wang, Z., Zhang, A., Wu, G., Liu, J., & Shu, Y. (2026). Adult Attachment and Intimate Relationship Satisfaction Among University Students: The Chain Mediating Roles of Appreciation and Sense of Giving. *Frontiers in Psychiatry*, 17. <https://doi.org/10.3389/fpsyg.2026.1758775>