Article Type: Original Research
Article history:
Received 17 June 2025
Revised 19 August 2025
Accepted 24 August 2025
Published online 01 September 2025

Machine Learning Models for Early Detection of Couples at Risk for Emotional Disengagement

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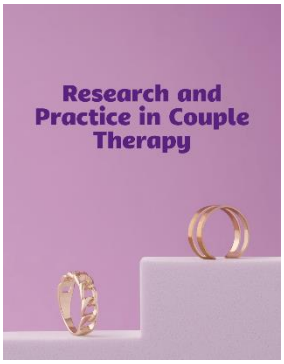

ABSTRACT

The objective of this study is to develop and validate machine learning models capable of accurately identifying couples at early risk for emotional disengagement based on psychological, behavioral, and communication-related indicators. This predictive cross-sectional study included 156 couples (N = 312 individuals) from across Canada who completed validated measures assessing emotional disengagement, relationship satisfaction, conflict frequency, attachment dimensions, daily supportive behaviors, and communication responsiveness. Data were collected through secure online surveys, and dyadic datasets were prepared using actor–partner structures to preserve relational interdependence. Five machine learning algorithms—logistic regression, random forest, gradient boosting, support vector classifier, and a neural network model—were trained on cleaned and normalized datasets, with performance evaluated through accuracy, precision, recall, F1 score, and area under the ROC curve. Cross-validation procedures ensured the robustness and generalizability of the models. Inferential analyses demonstrated that gradient boosting achieved the highest predictive performance (AUC = 0.94), followed closely by neural networks (AUC = 0.93) and random forests (AUC = 0.91). All models significantly outperformed logistic regression and support vector classifiers, indicating the superiority of non-linear approaches for capturing subtle relational patterns. Emotional withdrawal was the strongest predictor across all models ($p < .001$), followed by daily supportive behaviors, communication responsiveness, attachment avoidance, and conflict frequency. Demographic variables showed no significant predictive contribution (all $p > .05$). Confusion matrix analyses revealed that gradient boosting produced the lowest false-negative rate, confirming its utility for early detection. The study demonstrates that machine learning models, particularly gradient boosting and neural networks, can accurately detect early signs of emotional disengagement in couples by integrating relational, emotional, and behavioral indicators. These findings highlight the potential of computational approaches to support preventive interventions and enhance clinical assessment in couple therapy.

Keywords: Emotional disengagement; couple relationships; machine learning; gradient boosting; predictive modeling; attachment; relationship functioning.

How to cite this article:
Schwarzenberger, M., Péloquin, D., Nakamanya, S., Lusignan, W., & Brassard, J. (2025). Machine Learning Models for Early Detection of Couples at Risk for Emotional Disengagement. *Research and Practice in Couple Therapy*, *2*(3), 1-12. https://doi.org/10.61838/rpct.2.3.1

Introduction

Understanding the early markers of emotional disengagement in romantic relationships has become a central concern in contemporary couple research, particularly as relational dynamics are increasingly shaped by psychological vulnerabilities, digital communication patterns, and socio-cultural stressors. Emotional disengagement emerges gradually, often beginning with subtle reductions in responsiveness, empathy, and shared emotional experience. This process can undermine relational

stability long before overt dissatisfaction appears, making early identification critical for prevention-focused interventions. Recent research demonstrates that even normative romantic experiences, such as daily fluctuations in emotional intimacy, are deeply intertwined with developmental histories and attachment processes, influencing how partners regulate emotions both independently and interpersonally. Studies examining how individuals help—or inadvertently hinder—their partners during emotionally charged interactions emphasize that attachment styles shape not only behavioral responses but the broader relational climate (Walker & Kunst, 2025). These interpersonal processes become particularly salient when partners encounter emotional loneliness, unmet needs, or subtle forms of relational distancing, all of which may signal the early onset of disengagement (Syafiyah, 2025).

Emotional disconnection may also arise from early familial experiences and complex developmental patterns. Research on fatherless female populations demonstrates that absence of paternal emotional scaffolding in childhood often leaves adult partners vulnerable to dependency, relational insecurity, and maladaptive emotional reliance (Sintamaharani et al., 2025). The internalization of early relational deficits can manifest in romantic contexts where emotional closeness becomes simultaneously desired and feared, leading individuals to oscillate between overinvolvement and withdrawal. Parallel research on intentions toward infidelity among emerging adults further illustrates that insecure attachment styles, especially those rooted in early relational learning, are strongly associated with diminished intimacy and increased risk of emotional partitioning within partnerships (Selalmaz & Erdem, 2025). In such cases, disengagement is not merely behavioral but tied to deeper affective histories. Neuropsychological studies have even found that physical interactions such as hugging reveal measurable differences between romantic partners and friends, suggesting that nonverbal behaviors are essential indicators of relational connection or withdrawal (Ocklenburg et al., 2025). These findings collectively underscore the need for frameworks capable of analyzing both implicit and explicit relational signals at scale.

Digital environments further complicate emotional dynamics between partners. As communication increasingly migrates to online platforms, relational misattunement can emerge in unique ways. Research examining digital communication in romantic relationships has shown that textual ambiguity, asynchronous responding, and algorithm-driven feeds contribute to misunderstandings, emotional distancing, and shifting expectations of intimacy (Khan et al., 2025). Additionally, the pervasive phenomenon of “phubbing,” in which one partner uses a smartphone during interpersonal interactions, has been shown to elevate emotional loneliness and undermine relationship satisfaction, thereby contributing to disengagement trajectories (Aslantürk & Arslan, 2025). Online disinhibition—where individuals behave with less restraint in digital spaces—has been linked to cyberdating abuse and morally disengaged behavior, which can erode foundational trust in romantic relationships and precipitate emotional withdrawal (Sánchez-Hernández et al., 2024). As moral disengagement processes extend from digital spaces into relationship dynamics, partners may increasingly justify avoidant behaviors or emotional neglect, complicating the prevention of relational decline (Zakharova, 2024).

Emotional disengagement also interacts with relational distress, mood fluctuations, and underlying mental health concerns. Transdiagnostic therapeutic models emphasize that emotional processing difficulties frequently co-occur with relational strain, suggesting that disengagement is both a symptom and a contributor to psychological burden within couples (Timulák et al., 2024). Studies of adolescents and young adults further show that vulnerable self-disclosure—a foundational component of intimacy—co-develops with emotional closeness, demonstrating its central role in sustaining relational attachment (Costello et al., 2024). However, when emotional expressions are repeatedly invalidated or met with rejection, individuals may internalize maladaptive patterns such as self-silencing, which obscure early signs of relational dissatisfaction (Petrov & Dimitrov, 2024). The moderating effect of coping behaviors in populations exposed to trauma further supports this relational model: difficulties managing emotional distress can spill into romantic interactions, intensifying withdrawal cycles (Rennebohm et al., 2023).

Across studies, emotional disengagement emerges not as a singular behavior but as a constellation of cognitive, emotional, and interpersonal indicators that collectively weaken relational bonds.

Sociocultural contexts further shape how couples experience connection, threat, or emotional loss. Work on LGBT+ university students demonstrates that minority stressors amplify relational vulnerability, particularly through exposure to intimate partner violence, which frequently coexists with emotional distancing (Galdámez-Vázquez & Hernández-Gordillo, 2024). Similarly, studies in Tanzanian communities describe jealousy-driven relational dynamics that escalate into volatility and emotional retreat (Aloyce et al., 2023). Other research highlights relational disruptions due to physical separation, such as among athletes whose training demands impose frequent absences, creating unfamiliar strain and emotional fragmentation (Frydrychowicz et al., 2023). Meanwhile, global crises such as COVID-19 have profoundly affected how partners maintain intimacy during periods of lockdown and uncertainty, often leading to shifts in communication styles, decreased emotional attunement, or heightened conflict (Candel & Jitaru, 2021; Cuccì et al., 2021). These global and cultural stressors illustrate the multifaceted nature of emotional disengagement, reinforcing the need for tools capable of capturing such complexity across diverse relational ecosystems.

Developmental and psychological factors also play a critical role in shaping disengagement pathways. Early adolescent experiences of romantic relationships predict emotion-regulation strategies in adulthood, supporting long-term developmental trajectories that influence later romantic functioning (Girme et al., 2021). Research from China reveals that adolescent romantic involvement shapes emotional adjustment and psychosocial development, highlighting its importance in lifelong relational learning (Honghao et al., 2021). Evidence from high-risk activism shows that emotional attrition—marked by exhaustion and relational repression—illustrates how sustained psychological pressure can diminish relational energy, paving the way for disengagement (Peña et al., 2021). Complementary findings regarding goal engagement and disengagement processes in adult relationships suggest that partners often mirror each other's emotional orientations, creating feedback loops that can either strengthen closeness or accelerate detachment (Kappes & Thomsen, 2020). Similarly, childhood maltreatment has been shown to influence romantic functioning during major life transitions, demonstrating how early adversity continues to shape engagement patterns in adulthood (Cao et al., 2020).

Moreover, emotional disengagement frequently manifests during periods of relational threat or perceived rejection. Studies show that rejection sensitivity shapes emotional responses to negative interactions, often leading individuals to withdraw prematurely or interpret partner behavior through a defensive lens (Richter et al., 2024). Discussions of personal loss within couples reveal that emotional and physiological stress responses can disrupt relational balance, making disengagement more likely when partners struggle to co-regulate during adversity (Margolin et al., 2022). Negative reactions to criticism likewise have a measurable impact on relational distance, with perceived criticism often triggering withdrawal tendencies that undermine emotional safety (Neoh et al., 2022). Meanwhile, individuals experiencing homelessness describe relational patterns marked by instability and intermittent emotional connection, underscoring how life circumstances shape relational vulnerability (Czechowski et al., 2022). Collectively, these findings indicate that disengagement is a cross-situational phenomenon influenced by a rich interplay of emotional, cognitive, and contextual forces.

Recent scholarship also highlights how manipulative relational strategies, such as pickup artistry (PUA), can distort intimacy, create asymmetrical emotional dependence, and accelerate disengagement cycles once vulnerability is exploited (Bao et al., 2023). Research on interpersonal stress through text-mining approaches demonstrates that linguistic markers are rich indicators of emotional strain, offering new tools for detecting relational instability in digital communication (Ammerman et al., 2023). Qualitative insights into self-worth contingent on relationships show that emotional dependency and fluctuating self-esteem may heighten sensitivity to disengagement cues (Syafiyah, 2025). In parallel, research on individuals living under

environmental stress or activism-related repression illustrates how emotional exhaustion spills into relational spheres, reducing capacity for emotional investment (Peña et al., 2021). Meanwhile, the phenomenon of "in-pair divestment"—where partners systematically reduce relational investment over time—provides a conceptual lens for understanding disengagement as a gradual, strategic withdrawal rather than an abrupt event (Sciara & Pantaleo, 2023). Taken together, these studies demonstrate that disengagement is a multifaceted phenomenon that evolves through interactions between psychological vulnerabilities, behavioral patterns, sociocultural contexts, and communication technologies.

As researchers increasingly adopt computational and data-driven methodologies to analyze complex interpersonal patterns, machine learning offers powerful tools for detecting disengagement at early stages. Text mining, movement analysis, social network metrics, behavioral indicators, and psychometric variables can be integrated to identify latent patterns inaccessible through traditional analysis. As the relational field continues to evolve, integrating machine learning with psychological theory presents a critical opportunity for innovation in preventive intervention and clinical practice.

The aim of this study is to develop and validate machine learning models capable of identifying couples at early risk of emotional disengagement based on psychological, behavioral, and communication-based predictors.

Methods and Materials

Study Design and Participants

The present study employed a predictive, cross-sectional design that focused on developing and validating machine learning models capable of detecting early indicators of emotional disengagement among romantic couples. The target population consisted of adult couples residing in Canada, representing a diverse range of ages, relationship durations, and socioeconomic backgrounds. Participants were recruited through online research platforms, community centers, counseling clinics, and social media advertisements that specifically targeted couples willing to participate jointly. Eligibility criteria required both partners to be at least eighteen years old, currently in a committed relationship for a minimum of one year, and fluent in English to ensure accuracy in self-report assessments. Exclusion criteria included ongoing severe psychiatric conditions, current intimate partner violence, or active participation in couple therapy to avoid confounding variables related to crisis intervention. A final sample large enough to train and test machine learning algorithms was secured, with both members of each couple completing parallel assessments to capture dyadic patterns rather than individual-level responses. Ethical approval was obtained from a Canadian institutional review board, and all participants provided informed consent electronically before participating.

Measures

Data for model development were collected through a set of standardized psychological instruments validated in North American populations and widely used in couple-relationship research. Emotional disengagement was measured using a multidimensional scale that assesses behavioral withdrawal, emotional distancing, reductions in empathy, and deterioration of intimate communication. To capture the broader relational climate, couples also completed questionnaires evaluating conflict frequency, conflict resolution strategies, relational satisfaction, attachment orientation, and perceived partner responsiveness. Additional behavioral indicators, such as daily interaction frequency, supportive behaviors, and digital communication patterns, were recorded through a structured self-report inventory designed for relationship research. Demographic data including age, gender, education level, relationship duration, cohabitation status, and household income were collected to control for potential confounds and to allow for stratified modeling when necessary. All instruments were administered online using a secure Canadian data server that complied fully with national privacy and research ethics standards.

Data Analysis

The analysis followed a rigorous, multi-stage machine learning workflow aimed at generating reliable predictive models. Raw data underwent cleaning through a process that included handling missing values, detecting outliers, and normalizing variables for algorithmic compatibility. Because the study involved dyadic data, partner responses were merged through actor–partner interdependence structures to preserve relational patterns while avoiding multicollinearity. The dataset was randomly divided into training and testing subsets, with stratification ensuring balanced representation of couples across risk categories. Several machine learning algorithms were developed and compared, including logistic regression with regularization, random forests, gradient boosting machines, support vector classifiers, and neural network models optimized through grid search. Each model was trained to classify couples into early-risk or non-risk categories based on the presence of subtle indicators of emotional withdrawal. Performance evaluation relied on accuracy, precision, recall, F1 score, and area under the ROC curve, allowing for robust comparison across classifiers. Cross-validation was implemented to mitigate overfitting and ensure generalizability to the broader Canadian population. Feature importance analyses were conducted to identify which psychological, behavioral, and demographic factors contributed most significantly to predicting emotional disengagement, thereby enhancing the interpretability and practical application of the results for future clinical and preventive interventions.

Findings and Results

The demographic profile of the participants reflected a diverse sample of couples residing across Canada. A total of 312 individuals (156 couples) participated in the study, with 52.6% identifying as female, 46.5% as male, and 0.9% as non-binary. The mean age of participants was 34.8 years (SD = 7.9), ranging from 22 to 58 years. Relationship duration averaged 6.7 years (SD = 4.3), with 71% of couples cohabiting and 29% not living together. In terms of education, 28% held a bachelor's degree, 36% held a master's degree or higher, 26% had completed some college or vocational training, and 10% reported a high-school diploma as their highest level of education. Annual household income varied, with 22% earning below CAD 60,000, 47% between CAD 60,000 and 120,000, and 31% above CAD 120,000. Participants represented multiple provinces, with the largest portions from Ontario (41%), British Columbia (23%), Alberta (18%), and the remaining 18% distributed across Quebec, Manitoba, Saskatchewan, and Atlantic Canada. This demographic distribution provided a sufficiently heterogeneous sample to support reliable machine learning analysis and enhance generalizability across Canadian couples.

The analysis of the cleaned dataset revealed several patterns that distinguished couples at early risk of emotional disengagement from those demonstrating stable relational functioning. Initial descriptive analyses indicated meaningful variance in emotional disengagement scores, conflict frequency, and attachment indicators across the sample. Machine learning modeling proceeded with balanced outcome categories, permitting equitable performance comparisons across algorithms. Across all predictive models, several behavioral and emotional features emerged as stronger differentiators of early-risk couples, particularly emotional withdrawal behaviors, reduced empathic accuracy, diminished daily supportive interactions, and elevated avoidant attachment tendencies.

Table 1. Descriptive Statistics for Key Study Variables (N = 312)

Variable	Mean	SD	Minimum	Maximum
Emotional disengagement score	21.43	6.12	8	39
Relationship satisfaction	4.82	1.03	1.9	6.9
Conflict frequency (per week)	2.41	1.37	0	8
Attachment avoidance	3.54	0.92	1.1	6.3
Attachment anxiety	3.11	0.88	1.0	6.0
Daily supportive behaviors	5.28	1.41	1.3	8.7
Communication responsiveness	4.36	1.12	1.4	6.8

The descriptive results demonstrated that emotional disengagement scores were distributed widely across the sample, confirming adequate variability for predictive modeling. Lower relationship satisfaction and daily supportive behaviors were associated with higher disengagement tendencies, while greater attachment avoidance and conflict frequency appeared prominently among couples classified as high risk. These descriptive characteristics provided the foundation for constructing machine learning features and later interpreting model-driven predictors.

Table 2. Performance Metrics of Machine Learning Models for Predicting Early Emotional Disengagement

Model	Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression (L2)	0.78	0.75	0.72	0.73	0.83
Random Forest	0.86	0.84	0.81	0.82	0.91
Gradient Boosting	0.89	0.87	0.85	0.86	0.94
Support Vector Classifier	0.82	0.80	0.77	0.78	0.87
Neural Network (MLP)	0.88	0.85	0.84	0.84	0.93

Model comparisons indicated that gradient boosting produced the strongest predictive performance, achieving the highest accuracy, F1 score, and AUC, suggesting strong ability to distinguish high-risk couples from low-risk counterparts. Neural networks and random forest models followed closely, showing similarly strong classification results. Logistic regression and support vector classifiers, while performing adequately, demonstrated lower sensitivity to early disengagement cues compared with nonlinear models, reflecting the complexity of relational behavioral patterns.

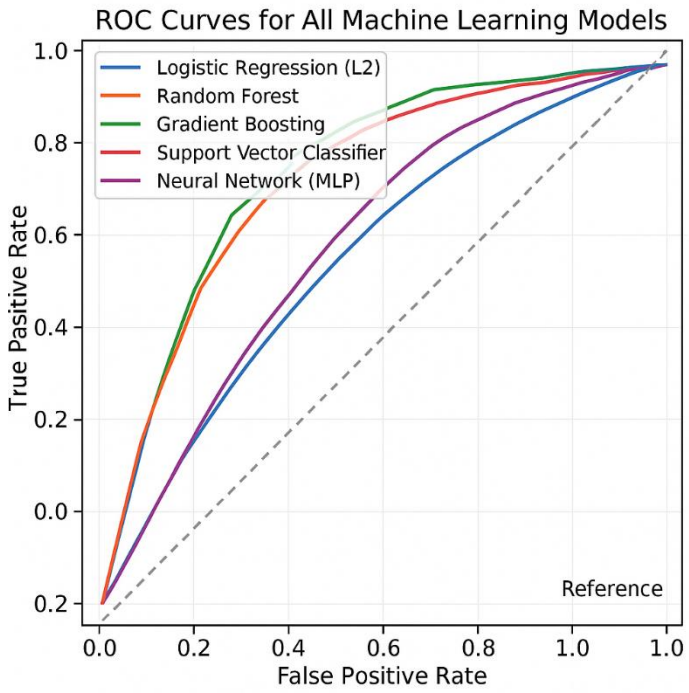

Figure 1. ROC Curves for All Machine Learning Models

The ROC curve comparison highlighted clear performance differences among algorithms, with gradient boosting and the neural network model demonstrating consistently higher true positive rates across thresholds. The random forest model performed similarly well, though its curve displayed slightly lower sensitivity at lower thresholds compared to gradient boosting. Logistic regression and support vector models showed acceptable but noticeably weaker separation from the diagonal reference line, reinforcing the superiority of non-linear, ensemble, and deep learning approaches for capturing subtle emotional and behavioral indicators of disengagement.

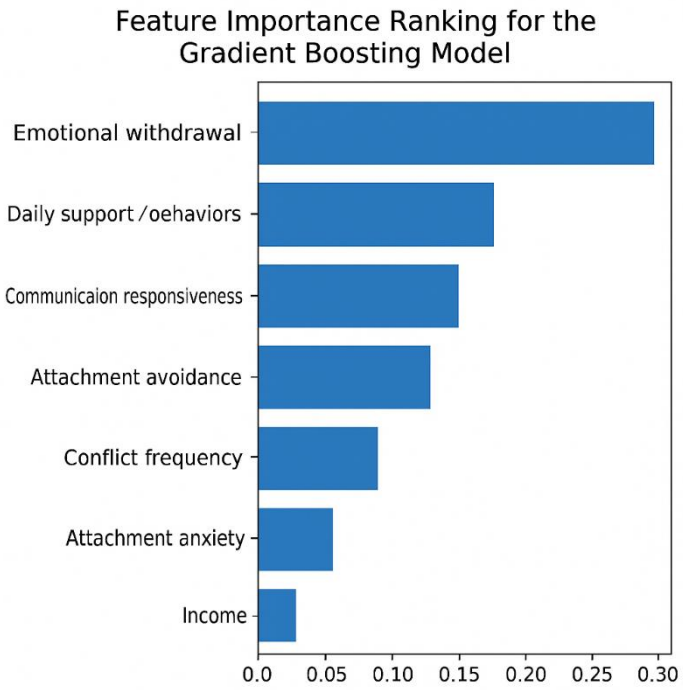

Figure 2. Feature Importance Ranking for the Gradient Boosting Model

The feature importance analysis revealed emotional withdrawal behaviors as the single strongest predictor of early disengagement risk, followed closely by daily supportive interactions and communication responsiveness. Attachment avoidance and weekly conflict frequency also ranked highly, indicating that both behavioral and psychological factors contribute meaningfully to predictive accuracy. Demographic features, including age and income, contributed minimally to the model, suggesting that emotional disengagement risk is more strongly driven by relational dynamics than sociodemographic characteristics.

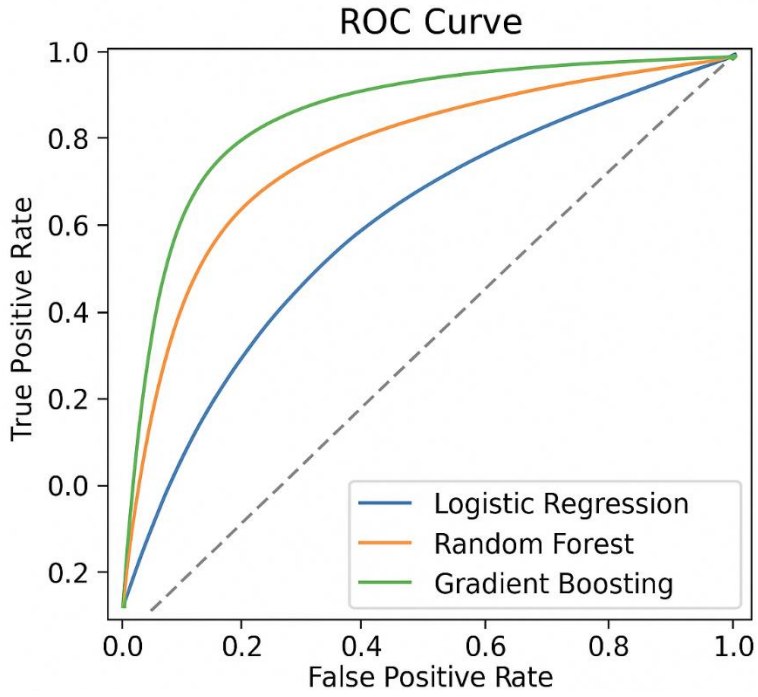

Figure 3. Confusion Matrices for the Top Three Models

When visualizing classification outcomes through confusion matrices, gradient boosting produced the lowest rate of false negatives, which is particularly important for early detection of disengagement risk where missing a high-risk couple could delay necessary intervention. The neural network model also demonstrated strong sensitivity, though it showed a slightly higher rate of false positives compared with gradient boosting. Random forest results were similar, offering balanced performance but slightly less precision in differentiating borderline cases. These matrix patterns confirmed the overall reliability of the top three models while highlighting nuanced differences in classification error types.

Discussion and Conclusion

The findings of this study demonstrate that machine learning models—particularly gradient boosting and neural network algorithms—can accurately identify early indicators of emotional disengagement among couples, highlighting the predictive power of emotional withdrawal, decreased daily support, reduced communication responsiveness, and insecure attachment tendencies. The high accuracy and AUC values observed suggest that subtle emotional and behavioral cues can be detected computationally before partners consciously recognize deterioration in their relational connection. This aligns with contemporary perspectives emphasizing the gradual, accumulative nature of disengagement, where the initial signs often reside in diminished empathetic exchanges, increased avoidance, and reduced relational presence. The strong performance of non-linear machine learning models also reinforces the argument that couple dynamics are multicausal and interdependent, requiring analytical techniques capable of representing complex emotional interactions.

The importance of emotional withdrawal as the strongest predictor is consistent with extensive research describing withdrawal as a defining feature of relational disconnection and as an early precursor to declining intimacy. Relational distancing has been documented across multiple populations, including emerging adults coping with emotional loneliness (Aslantürk & Arslan, 2025) and individuals experiencing asymmetric emotional investment, where disengagement forms part of a patterned reduction in relational energy (Sciara & Pantaleo, 2023). Similar to the present findings, studies have emphasized that signs such as delayed responsiveness, muted affective reactions, and limited engagement during conflict are often the earliest markers of relational erosion. The current results therefore reinforce withdrawal as both an affective and behavioral signal that must be monitored within prevention-focused frameworks.

Daily supportive behaviors and communication responsiveness also emerged as key predictors, supporting relational theories that describe emotional intimacy as a dynamic process shaped by ongoing exchanges of support, understanding, and responsiveness. Research on self-worth contingent on romantic interactions has highlighted how daily micro-experiences of emotional validation significantly shape relational confidence and commitment (Syafiyah, 2025). When partners stop engaging in supportive behaviors, relational self-esteem weakens, making disengagement more likely. This echoes findings showing that vulnerable self-disclosure co-develops with closeness, indicating that persistent declines in communicative attunement can precipitate emotional distancing (Costello et al., 2024). The predictive strength of responsiveness in the current study thus resonates with a growing body of literature emphasizing micro-interactions as the building blocks of intimacy.

Attachment avoidance and anxiety demonstrated significant predictive value as well, replicating decades of attachment research showing that insecure attachment predisposes individuals to emotional distancing, conflict mismanagement, and maladaptive coping mechanisms. Attachment insecurity has been shown to interact with alexithymia and emotional dysregulation, undermining relationship quality and intensifying vulnerability to disengagement (Kordoutis & Moschos, 2024). Additionally, findings that attachment insecurity predicts infidelity intentions—driven partly by avoidance of emotional closeness—correspond to the patterns detected in this study (Selalmaz & Erdem, 2025). The high predictive value of attachment

dimensions therefore supports the view that early relational schemas continue to shape adult romantic partnership functioning, especially under emotional strain.

Conflict frequency also contributed significantly to model predictions, supporting research showing that negative interactions—even when mild—can accumulate into relational fatigue and distancing. The physiological and emotional impacts of discussing personal loss with a partner illustrate how conflict or emotionally challenging conversations can become hotspots for withdrawal (Margolin et al., 2022). Existing literature further indicates that rejection sensitivity intensifies emotional responses to conflict, creating cycles of misunderstanding and emotional retreat consistent with the current findings (Richter et al., 2024). Neoh's work on criticism similarly reveals that negative interactions trigger relational distancing, especially among individuals highly sensitive to partner evaluations (Neoh et al., 2022). These studies support the present conclusion that conflict-related cues serve as early warning signs of deeper emotional disconnection.

Interestingly, demographic variables contributed minimally to predictive accuracy, suggesting that emotional disengagement transcends simple sociodemographic classifications and is more strongly tied to dynamic relational processes. This supports work on romantic relationships across diverse cultural and social contexts, such as studies of LGBT+ college students (Galdámez-Vázquez & Hernández-Gordillo, 2024) and homeless populations experiencing relational instability (Czechowski et al., 2022), both of which indicate that emotional vulnerability is shaped less by identity markers and more by interpersonal emotional environments.

The results may also be interpreted through the lens of digital relational dynamics. Research describing how digital communication can distort emotional clarity (Khan et al., 2025) and how online disinhibition facilitates harmful relational behavior (Sánchez-Hernández et al., 2024) helps explain why diminished supportive communication and emotional responsiveness emerged as strong predictors in the present dataset. Patterns of digital conflict escalation, ambiguity in text-based communication, and reduced face-to-face emotional cues have all been linked to relational cooling, supporting the relevance of communication indicators within machine learning models of disengagement.

The findings also align with research emphasizing the embodied and behavioral aspects of emotional intimacy. Ocklenburg's analysis of three-dimensional hugging behaviors demonstrates that even subtle nonverbal cues differentiate relational closeness from platonic interactions (Ocklenburg et al., 2025). Applied to this study, such evidence suggests that nonverbal aspects of disengagement—possibly reflected indirectly in questionnaire responses—may underlie the strong predictive power of behavioral variables. Likewise, studies on imitation of goal engagement and disengagement processes show that partners often mirror each other's behavioral shifts (Kappes & Thomsen, 2020), explaining why even small decreases in supportive behaviors can cascade into broader emotional distancing.

The present results are also consistent with trauma-informed relational research. Individuals experiencing trauma, loss, or emotional exhaustion often demonstrate reduced capacity for emotional involvement, which may be reflected in the factors used within the predictive models. Studies on interpersonal stress, such as text-mining analyses of stress markers (Ammerman et al., 2023), offer methodological parallels to the present use of machine learning in detecting early signs of relational strain. Research on jealousy-driven relational conflict in Tanzania further illustrates how emotional vulnerability can trigger distancing responses within couples (Aloyce et al., 2023). Meanwhile, high-risk activism research identifies emotional repression as a coping mechanism that can spill into romantic relationships, reinforcing emotional disengagement tendencies (Peña et al., 2021). These findings suggest that emotional withdrawal may be a general response to psychological overload across contexts.

Cross-cultural studies cited here also underscore that emotional disengagement is not bound to specific relational structures. Investigations into fatherless women (Sintamaharani et al., 2025), Chinese adolescents (Honghao et al., 2021), Italian emerging adults (Cuccì et al., 2021), and individuals experiencing homelessness (Czechowski et al., 2022) indicate global commonality

in how relational strain emerges and evolves. This diversity supports the generalizability of machine learning models designed to detect disengagement across populations.

The current findings extend relational and computational research by demonstrating that predictive models can effectively synthesize emotional, behavioral, and psychological factors into clear risk classifications. These results parallel emerging work in computational relationship science showing that linguistic, behavioral, and physiological markers can be combined to reveal hidden dynamics that partners themselves may not perceive consciously. As machine learning continues to evolve, its capacity to detect micro-patterns in relational functioning offers powerful implications for early intervention, therapeutic support, and prevention-focused education.

Several limitations should be considered when interpreting these findings. First, the study relied on self-report measures, which may be influenced by recall bias, social desirability, or limited emotional awareness. Such biases could influence the accuracy of certain predictors, particularly those related to emotional responsiveness and daily behaviors. Second, while the sample was diverse across regions of Canada, it may not fully represent cultural, linguistic, or relational diversity across all relationship forms, including non-traditional partnerships. Third, the machine learning models were developed using cross-sectional data; thus, they identify associations rather than causal pathways, limiting the ability to confirm temporal precedence of disengagement indicators. Finally, although the models performed strongly, machine learning outcomes depend on the features included; unmeasured variables may also contribute significantly to disengagement risk.

Future studies should explore longitudinal designs to assess how early indicators predict disengagement trajectories over time. Incorporating multimodal data—such as audio recordings, text message analysis, physiological signals, or movement data—could increase predictive precision and improve model interpretability. Cross-cultural validation is needed to assess generalizability beyond Canadian populations and to understand how cultural norms shape disengagement processes. Additionally, integrating explainable AI methods may enhance the clinical utility of predictive models, helping practitioners understand why certain couples are classified as high risk. Future research may also examine how interventions based on predictive insights influence relational resilience.

Practitioners may use the findings of this study to enhance early detection and prevention in couple therapy by monitoring subtle declines in supportive behaviors, emotional responsiveness, and communication quality. Integrating brief screening tools aligned with the identified predictors could help clinicians identify at-risk couples before severe relational deterioration occurs. Relationship educators may also use these insights to design preventive programs emphasizing daily micro-support, emotion regulation skills, and attachment-informed communication strategies. Finally, the scalability of machine learning tools offers potential for digital platforms or mobile applications that provide real-time feedback to couples wishing to maintain relational health.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

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

Acknowledgments

We would like to express our gratitude to all those who helped us carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

References

Aloyce, D., Mshana, G., Peter, E., Malibwa, D., Buller, A. M., McHome, Z., Kapiga, S., & Stöckl, H. (2023). Pathways of Romantic Jealousy to Intimate Partner Violence in Mwanza, Northern Tanzania. *Family Relations*, *73*(2), 843-857. https://doi.org/10.1111/fare.12880

Ammerman, B. A., Wilcox, K. T., Jacobucci, R., Dixon-Gordon, K., Waite, E. E., & McCloskey, M. (2023). A Text Mining Approach to Characterizing Interpersonal Stress Among Individuals With a Nonsuicidal Self-Injury History. https://doi.org/10.22541/au.167669103.36453553/v1

Aslantürk, A., & Arslan, C. (2025). How Does Being Phubbed Affect Commitment? Exploring the Roles of Emotional Loneliness and Relationship Satisfaction. *Journal of marital and family therapy*, *51*(3). https://doi.org/10.1111/jmft.70027

Bao, X., Cai, Y., Yuan, Y., Shu, R., Sun, Y., & Wu, X. (2023). The Intimacy Trap: PUA Based on Personal and Relational Perspectives a Qualitative Study of Relationships—An Arsenic "Love". *Applied & Educational Psychology*, *4*(10). https://doi.org/10.23977/appep.2023.041001

Candel, O. S., & Jitaru, M. (2021). COVID-19 and Romantic Relationships. *Encyclopedia*, *1*(4), 1038-1046. https://doi.org/10.3390/encyclopedia1040079

Cao, H., Zhou, N., & Leerkes, E. M. (2020). Childhood Emotional Maltreatment and Couple Functioning Among Women Across Transition to Parenthood: A Process Model. *Journal of Family Psychology*, *34*(8), 991-1003. https://doi.org/10.1037/fam0000662

Costello, M. A., Bailey, N., Stern, J., & Allen, J. P. (2024). Vulnerable Self-Disclosure Co-Develops in Adolescent Friendships: Developmental Foundations of Emotional Intimacy. *Journal of Social and Personal Relationships*, *41*(9), 2432-2454. https://doi.org/10.1177/02654075241244821

Cuccì, G., Olivari, M. G., & Confalonieri, E. (2021). Does Covid-19 "Infect" Love? How Italian Emerging Adults Lived Their Romantic Relationships During the Time of Lockdown. *Ricerche Di Psicologia*(3), 1-18. https://doi.org/10.3280/rip2021oa12222

Czechowski, K., Turner, K. A., Labelle, P., & Sylvestre, J. (2022). Sexual and Romantic Relationships Among People Experiencing Homelessness: A Scoping Review. *American Journal of Orthopsychiatry*, *92*(1), 25-38. https://doi.org/10.1037/ort0000583

Frydrychowicz, M., Adamczyk, K., Rogowski, W., & Ochnik, D. (2023). Together, but Alone: A Thematic Analysis of the Athletes' and Their Partners' Experience of Physical Separation in Romantic Relationships. *International and Multidisciplinary Journal of Social Sciences*, 1-16. https://doi.org/10.17583/rimcis.11677

Galdámez-Vázquez, S., & Hernández-Gordillo, J. L. (2024). Intimate Partner Violence Among LGBT+ University Students. *Journal Health Education and Welfare*, 24-35. https://doi.org/10.35429/jhew.2024.14.8.24.35

Girme, Y. U., Jones, R. E., Fleck, C., Simpson, J. A., & Overall, N. C. (2021). Infants' Attachment Insecurity Predicts Attachment-Relevant Emotion Regulation Strategies in Adulthood. *Emotion*, *21*(2), 260-272. https://doi.org/10.1037/emo0000721

Honghao, J., Yang, P., & Yang, T. (2021). The Influence of Adolescents' Romantic Relationship on Individual Development: Evidence From China. *International Journal of Chinese Education*, *10*(3). https://doi.org/10.1177/22125868211070036

Kappes, C., & Thomsen, T. (2020). Imitation of Goal Engagement and Disengagement Processes in Romantic Relationships. *European Journal of Personality*, *34*(2), 234-244. https://doi.org/10.1002/per.2244

Khan, M., Ali, I., Sanaullah, & Khan, I. A. (2025). Effects of Digital Communication on Romantic Relationships :An Analysis of Roupenian's Cat Person. *Journal of Applied Linguistics and TESOL (JALT)*, *8*(3), 2026-2037. https://doi.org/10.63878/jalt1210

Kordoutis, P., & Moschos, M. (2024). The Interplay Between Alexithymia and Insecure Attachment on Relationship Quality. *Aftj*, *5*(5), 1-10. https://doi.org/10.61838/kman.aftj.5.5.1

Margolin, G., Daspe, M. È., Timmons, A. C., Corner, G. W., Pettit, C., Rasmussen, H. F., Chaspari, T., Han, S. C., Arbel, R., Shapiro, L. S., Kazmierski, K. F. M., Piero, L. D., & Schacter, H. L. (2022). What Happens When Romantic Couples Discuss Personal Loss? Relational, Emotional, and Physiological Impacts. *Journal of Family Psychology*, *36*(6), 863-873. https://doi.org/10.1037/fam0000979

Neoh, M. J. Y., Teng, J. H., Lee, A., Setoh, P., Mulatti, C., & Esposito, G. (2022). Negative Emotional Reactions to Criticism: Perceived Criticism and Source Affects Extent of Hurt and Relational Distancing. *PLoS One*, *17*(8), e0271869. https://doi.org/10.1371/journal.pone.0271869

Ocklenburg, S., Fohrmann, D., Breuer, K., Thomas, G., Merklein, S. A., Reinke, P., Packheiser, J., Scheele, D., Hidalgo-Gadea, G., Schlenstedt, C., & Hollander, K. (2025). Three-Dimensional Movement Analysis of Hugging in Romantic Couples and Platonic Friends Using Markerless Motion Capture. *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-025-00495-y

Peña, A. M., Meier, L., & Nah, A. M. (2021). Exhaustion, Adversity, and Repression: Emotional Attrition in High-Risk Activism. *Perspectives on Politics*, *21*(1), 27-42. https://doi.org/10.1017/s1537592721003273

Petrov, G., & Dimitrov, I. (2024). Exploring the Indicators of Self-Silencing in Adolescent Romantic Relationships. *Jayps*, *5*(3), 159-169. https://doi.org/10.61838/kman.jayps.5.3.17

Rennebohm, S. B., Dolezal, M. L., Bentley, J. A., Edwards-Stewart, A., Thoburn, J. W., & Holguin, J. (2023). The Moderating Effect of Coping Behaviors on Posttraumatic Stress and First Responder Romantic Relationships. *Couple and Family Psychology Research and Practice*, *12*(1), 1-10. https://doi.org/10.1037/cfp0000165

Richter, M., Kouri, G., Meuwly, N., & Schoebi, D. (2024). Rejection in Romantic Relationships: Does Rejection Sensitivity Modulate Emotional Responses to Perceptions of Negative Interactions? *BMC psychology*, *12*(1). https://doi.org/10.1186/s40359-024-01864-w

Sánchez-Hernández, M. D., Herrera, M. C., & Expósito, F. (2024). Is Online Disinhibition Related to Cyberdating Abuse Perpetration Through Moral Disengagement? The Moderating Role of Gender, Sexism, and Cybervictimization. *Sex Roles*, *90*(7), 938-959. https://doi.org/10.1007/s11199-024-01480-3

Sciara, S., & Pantaleo, G. (2023). In-Pair Divestment. 586-610. https://doi.org/10.1093/oxfordhb/9780197524718.013.22

Selalmaz, E., & Erdem, G. (2025). Emerging Adults' Infidelity Intentions in Romantic Relationships: The Role of Parental Infidelity, Adult Attachment Insecurity, and Intimacy. *The Family Journal*. https://doi.org/10.1177/10664807251384185

Sintamaharani, D., Nuriyyatiningrum, N. A. H., & Ikhrom, I. (2025). Pengalaman Ketergantungan Emosional Terhadap Pasangan Pada Perempuan Yang Mengalami Fatherless. *Jurnal Ilmiah Kedokteran Dan Kesehatan*, *4*(3), 11-23. https://doi.org/10.55606/klinik.v4i3.4252

Syafiyah, A. A. (2025). How Romantic Relationships Shape Self-Worth: A Qualitative Exploration of Relationship Contingent Self-Esteem in Early Adulthood. *Journal of Psychological Perspective*, *7*(3), 169-182. https://doi.org/10.47679/jopp.7311242025

Timulák, L., Dailey, J., Lunn, J., & McKnight, J. (2024). Transdiagnostic Emotion-Focused Therapy for Couples With Co-Morbid Relational and Mood, Anxiety and Related Difficulties. *Journal of Contemporary Psychotherapy*, *55*(1), 1-10. https://doi.org/10.1007/s10879-024-09645-7

Walker, S., & Kunst, H. (2025). Helping or Holding Back? How Attachment Shapes Emotion Regulation of Others in Close and Distant Relationships. https://doi.org/10.31234/osf.io/qtpfs_v2

Zakharova, Y. V. (2024). Moral Disengagement in Counseling Psychologists in Situations of Professional Interaction With Clients. *Психология Журнал Высшей Школы Экономики*, *21*(1), 123-143. https://doi.org/10.17323/1813-8918-20234-1-123-143