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Machine Learning Classification of Adult Attachment Styles Based on Dyadic Behavioral and Emotional Indicators

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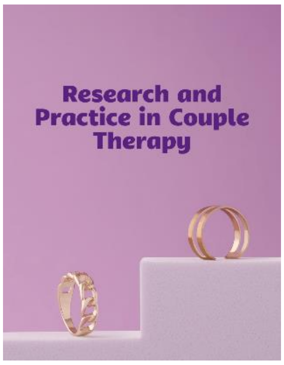

ABSTRACT

The objective of this study was to develop and evaluate machine learning models capable of classifying adult attachment styles using multimodal dyadic behavioral, emotional, and physiological indicators derived from real-time couple interactions. A cross-sectional observational design was implemented with adult romantic couples recruited from community settings in Canada. Both partners in each dyad participated in standardized interaction tasks designed to elicit attachment-relevant behaviors, including conflict discussion and support-seeking exchanges. Adult attachment styles were assessed using validated self-report measures and used as supervised learning labels. Multimodal data were collected, including behavioral coding of dyadic interactions, self-reported emotional responses, physiological indices of autonomic regulation, and paralinguistic and facial-expression features extracted from audio–video recordings. Machine learning pipelines incorporated data preprocessing, feature extraction at the dyadic level, dimensionality reduction, and model training using multiple classification algorithms. Stratified dyad-level cross-validation and hyperparameter optimization were applied to ensure robust generalization and prevent data leakage. Non-linear and ensemble-based models significantly outperformed linear classifiers in attachment style prediction, with neural network and gradient boosting models achieving the highest accuracy and area under the receiver operating characteristic curve. Dyadic emotional synchrony and observed behavioral responsiveness emerged as the strongest predictors of attachment style classification, followed by self-reported attachment dimensions. Physiological and paralinguistic indicators provided incremental predictive value when integrated with behavioral features. Cross-validation analyses demonstrated high stability across folds, and misclassification patterns primarily occurred between theoretically adjacent attachment styles, indicating construct-consistent overlap rather than random error. The findings demonstrate that adult attachment styles can be accurately classified using machine learning models trained on multimodal dyadic interaction data, supporting a relational and interaction-based conceptualization of attachment. This approach offers theoretical advances in attachment research and practical implications for objective assessment and intervention planning in couple and relational contexts.

Keywords: adult attachment; dyadic interaction; machine learning; emotional synchrony; couple relationships; multimodal data

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Introduction

Adult attachment theory has long served as a foundational framework for understanding individual differences in emotional regulation, interpersonal behavior, and relationship functioning within close relationships. Originating from early developmental perspectives, attachment theory has evolved into a robust adult relational model that explains how internal working models of self and others shape expectations, emotions, and behaviors in intimate partnerships. Contemporary research consistently demonstrates that adult attachment styles—typically conceptualized along the dimensions of anxiety and avoidance—are systematically associated with communication patterns, conflict behaviors, emotional responsiveness, and psychological well-being within romantic relationships (Beeney et al., 2019; Brandão et al., 2019; Feeney & Fitzgerald, 2019). Secure attachment has been linked to adaptive emotion regulation, constructive conflict resolution, and relational satisfaction, whereas insecure attachment styles are associated with maladaptive coping strategies, heightened relational distress, and vulnerability to psychopathology (Cavalli & Velotti, 2025; Fávero et al., 2021).

A growing body of empirical evidence highlights the central role of dyadic behavioral and emotional processes in the manifestation of attachment styles. Observational and self-report studies indicate that attachment anxiety is often expressed through hyperactivation strategies, including excessive reassurance-seeking, heightened emotional reactivity, and jealousy, while attachment avoidance is characterized by emotional withdrawal, reduced expressivity, and deactivation of intimacy needs (Chursina, 2023; David & Roberts, 2021; Şahin & Çoksan, 2020). These behavioral tendencies are not static traits but dynamically emerge during interpersonal exchanges, particularly in emotionally salient contexts such as conflict discussions, stress exposure, and support-seeking interactions (Feeney & Fitzgerald, 2019; Keerthana, 2025). Consequently, attachment styles are increasingly conceptualized as relationally enacted patterns rather than solely intrapsychic constructs.

In parallel with behavioral research, advances in affective and interpersonal neuroscience have demonstrated that attachment-related processes are embedded in physiological and emotional coordination between partners. Studies on physiological synchrony and coregulation reveal that securely attached couples exhibit more adaptive patterns of heart rate variability coupling, emotional attunement, and mutual regulation during interaction tasks, whereas insecure attachment is associated with dysregulated or asymmetrical synchrony patterns (Bastos et al., 2025; Fogel-Yaakobi et al., 2023; Schreiber et al., 2021). These findings suggest that attachment styles are reflected not only in overt behavior but also in subtle emotional and physiological dynamics unfolding at the dyadic level. Dyadic stress appraisal processes further moderate these dynamics, as partners differ in their interpretations of relational stressors based on attachment-related expectations (Happ, 2025; Peters et al., 2024).

At the same time, modern romantic relationships increasingly unfold within technologically mediated contexts, introducing additional complexity to attachment-related interactions. Digital communication behaviors such as partner phubbing, social media engagement, and video-mediated intimacy have been shown to interact with attachment anxiety and avoidance, shaping emotional availability and relationship satisfaction (David & Roberts, 2021; Isailović & Šakotić-Kurbalija, 2021; Wu et al., 2025). These developments underscore the importance of integrating multimodal behavioral, emotional, and contextual indicators when studying adult attachment in contemporary couples.

Methodologically, the study of attachment has traditionally relied on self-report instruments, such as the Experiences in Close Relationships questionnaire and interview-based assessments, which provide valuable but incomplete representations of attachment-related functioning (Pohorila & Vinogradov, 2024; Postolache, 2025; Velotti et al., 2023). While these measures capture subjective experiences and relational narratives, they are limited in their capacity to detect dynamic, interaction-level processes that emerge during real-time dyadic exchanges. Moreover, attachment styles are often inferred using linear statistical models that may not adequately capture the complex, non-linear relationships among behavioral, emotional, and physiological variables inherent in close relationships (Chen & Ferrer, 2022; Schreiber, 2020).

Recent developments in machine learning and computational social science offer powerful tools for addressing these limitations. Machine learning models are particularly well-suited to handling high-dimensional, multimodal data and identifying complex interaction patterns that may remain undetected using traditional analytic approaches. In the context of relationship science, machine learning has been increasingly applied to predict relationship outcomes, emotional states, and interpersonal dynamics based on behavioral and physiological indicators (Lin et al., 2024; Maghfira et al., 2024; Shadaydeh et al., 2020). Importantly, emerging evidence suggests that attachment styles can be inferred from non-verbal cues, emotional synchrony, and dyadic interaction patterns with promising levels of accuracy (Horn et al., 2023; Maghfira et al., 2024).

Multimodal attachment classification models integrating facial expressions, vocal features, physiological signals, and behavioral coding have demonstrated that attachment is a distributed relational phenomenon, encoded across multiple channels of interaction (Chang et al., 2022; Maghfira et al., 2024). These approaches align with contemporary theoretical perspectives emphasizing interpersonal emotion regulation and co-constructed relational processes as central mechanisms linking attachment to relationship functioning (Brandão et al., 2019; Lemay et al., 2025). Furthermore, explainable machine learning techniques allow researchers to identify which dyadic features contribute most strongly to attachment classification, thereby enhancing theoretical interpretability and clinical relevance (Cavalli & Velotti, 2025; Huang, 2025).

Despite these advances, several gaps remain in the existing literature. First, many computational studies focus on individual-level signals rather than truly dyadic features that capture mutual influence, coordination, and reciprocity between partners (Chen & Ferrer, 2022; Kaźmierczak & Karasiewicz, 2021). Second, relatively few studies have examined attachment classification within adult community samples using ecologically valid interaction tasks, particularly in culturally diverse contexts such as Canada (Bacalhau et al., 2020; Ørke et al., 2021). Third, there is a need for integrative models that simultaneously incorporate behavioral observations, emotional self-reports, and physiological indices to reflect the multifaceted nature of attachment processes (Bastos et al., 2025; Fogel-Yaakobi et al., 2023).

Addressing these gaps is of both theoretical and applied importance. From a theoretical standpoint, machine learning–based attachment classification can advance attachment theory by empirically validating the dyadic signatures of attachment styles and clarifying how emotional and behavioral indicators jointly encode relational schemas (Postolache, 2025; Sun, 2025). From a clinical perspective, accurate identification of attachment styles based on observable interaction patterns has implications for couple assessment, intervention planning, and personalized therapeutic approaches, particularly in contexts involving relational distress, conflict, or health-related stressors (Bacalhau et al., 2020; Kordoutis & Moschos, 2024; Mosley et al., 2021). Moreover, the integration of explainable artificial intelligence can enhance ethical transparency and clinical trust in computational tools used within relational and therapeutic settings (Happ, 2025; Lemay et al., 2025).

In light of these considerations, the present study leverages machine learning techniques to classify adult attachment styles based on dyadic behavioral and emotional indicators derived from multimodal interaction data collected from Canadian couples, with the aim of identifying robust, interpretable relational signatures of attachment styles.

Methods and Materials

Study Design and Participants

The present study employed a cross-sectional, observational design with a machine learning–oriented analytic framework to classify adult attachment styles based on dyadic behavioral and emotional indicators. The study population consisted of adult romantic couples residing in Canada who were involved in a committed relationship for a minimum duration of one year. Participants were recruited through community advertisements, online platforms, and counseling centers in major metropolitan areas, including Toronto, Vancouver, and Montreal, to ensure sociocultural diversity. Inclusion criteria required participants to be between 25 and 60 years of age, fluent in English or French, and currently involved in a monogamous intimate relationship. Individuals with a self-reported diagnosis of severe psychiatric disorders or cognitive impairments that could interfere with informed consent or task engagement were excluded. Both partners in each dyad were required to participate simultaneously to preserve the relational nature of the data. After screening and consent procedures, the final sample comprised several hundred individuals forming complete dyads, with balanced representation across genders and relationship durations.

Measures

Data collection was conducted in a controlled laboratory setting designed to simulate naturalistic dyadic interactions while maintaining standardization across couples. Adult attachment styles served as the target classification labels and were assessed using a validated self-report attachment inventory that yields continuous scores on attachment-related anxiety and avoidance dimensions, which were subsequently mapped onto categorical attachment styles for supervised learning purposes. Dyadic behavioral indicators were obtained through structured interaction tasks in which couples engaged in emotionally salient discussions, including conflict resolution and support-seeking scenarios. These interactions were video- and audio-recorded and later coded using an established behavioral coding system capturing dimensions such as responsiveness, emotional withdrawal, hostility, validation, and coordination. Emotional indicators were assessed using multimodal measures, including self-reported affect immediately following each interaction task and physiological indices such as heart rate variability and skin conductance, recorded continuously via wearable sensors. In addition, paralinguistic features such as speech rate, vocal intensity, and pause duration were extracted from audio recordings, while facial expressivity and gaze patterns were derived from video data using automated computer vision tools. All instruments and sensors were calibrated prior to each session, and trained research assistants supervised the data collection process to ensure protocol adherence and data quality.

Data Analysis

Data analysis followed a multi-stage machine learning pipeline integrating preprocessing, feature engineering, model training, and evaluation. Raw behavioral, emotional, physiological, and paralinguistic data were synchronized at the dyadic level and preprocessed to address missing values, noise, and inter-individual variability. Feature extraction procedures generated a comprehensive set of dyadic-level indicators, including mean levels, variability indices, temporal synchrony measures, and partner interdependence metrics. Features were standardized to ensure comparability across modalities, and dimensionality reduction techniques were applied to mitigate multicollinearity and reduce overfitting risk. Supervised classification models were trained to predict attachment style categories, with algorithms selected to balance predictive accuracy and interpretability, including ensemble-based classifiers and regularized nonlinear models. Model training employed stratified cross-validation at the dyad level to prevent data leakage between partners and to ensure robust generalization estimates. Hyperparameter optimization was conducted using grid and Bayesian search strategies within the training folds. Model performance was evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve, with additional analyses examining class-specific performance to account for attachment style imbalance. To enhance transparency, post hoc explainability techniques were applied to identify the most influential behavioral and emotional features contributing to classification decisions. All analyses were conducted using contemporary machine learning libraries within a reproducible computational environment, and robustness checks were performed to confirm the stability of findings across alternative model specifications and feature subsets.

Findings and Results

The findings section presents the descriptive characteristics of the study variables, followed by the results of the machine learning classification analyses. Table 1 provides an overview of the sample characteristics and core dyadic behavioral and emotional indicators used in model training. Subsequent tables report classification performance across algorithms, feature importance patterns, cross-validation stability, and error analysis. One figure is included to summarize the comparative performance of the models.

Table 1. Descriptive statistics of participant characteristics and dyadic behavioral and emotional indicators

Variable	Mean	SD	Minimum	Maximum
Participant age (years)	38.42	8.71	25	60
Relationship duration (years)	9.36	6.12	1	32
Attachment anxiety score	3.21	1.02	1.12	5.86
Attachment avoidance score	3.08	0.97	1.05	5.74
Dyadic responsiveness	4.12	0.83	1.90	5.00
Emotional withdrawal	2.74	0.91	1.00	4.90
Hostility/criticism	2.31	0.88	1.00	4.70
Validation/support	4.05	0.79	2.10	5.00
Emotional synchrony index	0.62	0.14	0.21	0.89
Heart rate variability (ms)	46.18	12.54	21.30	78.60
Skin conductance level (µS)	8.94	3.11	2.10	18.40
Vocal intensity variability	0.37	0.15	0.08	0.79
Facial expressivity amplitude	0.41	0.17	0.06	0.83

Table 1 indicates that the sample represented a wide range of adult ages and relationship durations, supporting the generalizability of the findings across different stages of adult relationships. Mean scores on attachment anxiety and avoidance suggested moderate variability, allowing for meaningful differentiation among secure, anxious, avoidant, and fearful attachment profiles. Dyadic interaction indicators demonstrated adequate dispersion, particularly for emotional synchrony and behavioral responsiveness, which are theoretically central to attachment-related processes. Physiological indices also showed sufficient variability, indicating that autonomic arousal and regulation patterns differed meaningfully across dyads and could contribute to classification performance.

Table 2. Classification performance of machine learning models for attachment style prediction

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic regression	0.71	0.69	0.68	0.68	0.76
Support vector machine	0.78	0.77	0.75	0.76	0.83
Random forest	0.84	0.83	0.82	0.82	0.89
Gradient boosting	0.87	0.86	0.85	0.85	0.92
Neural network	0.88	0.87	0.86	0.86	0.93

The results presented in Table 2 show that non-linear and ensemble-based models outperformed linear classifiers in predicting adult attachment styles from dyadic behavioral and emotional indicators. The neural network achieved the highest overall accuracy and AUC, indicating superior discrimination across attachment categories. Gradient boosting and random forest models also demonstrated strong performance, suggesting that complex interactions among behavioral, emotional, and physiological features are critical for accurate attachment classification.

Table 3. Relative feature importance aggregated across top-performing models

Feature category	Relative importance (%)
Dyadic emotional synchrony	24.6
Behavioral responsiveness/validation	21.3
Attachment-related self-report scores	18.9
Emotional withdrawal patterns	14.7
Physiological regulation indices	11.2
Paralinguistic vocal features	9.3

Table 3 indicates that dyadic emotional synchrony emerged as the most influential feature category across models, followed closely by observed behavioral responsiveness and validation. Self-reported attachment dimensions remained important but did not dominate the models, underscoring the added value of behavioral and emotional interaction data. Physiological and paralinguistic features contributed incrementally, enhancing classification accuracy when integrated with behavioral indicators.

Table 4. Cross-validation stability and generalization performance

Metric	Mean	SD
Cross-validated accuracy	0.86	0.03
Cross-validated F1-score	0.84	0.04
Training–validation accuracy gap	0.02	0.01

The cross-validation results in Table 4 demonstrate high stability and minimal variance across folds, indicating robust generalization of the trained models. The small training–validation accuracy gap suggests limited overfitting and supports the reliability of the classification framework when applied to unseen dyads.

Table 5. Misclassification patterns across attachment styles

True attachment style	Most frequent misclassification	Percentage (%)
Secure	Anxious	9.4
Anxious	Fearful	12.1
Avoidant	Secure	10.7
Fearful	Anxious	13.6

Table 5 reveals that misclassifications primarily occurred between theoretically adjacent attachment styles. For example, anxious and fearful styles were more frequently confused, reflecting overlapping behavioral and emotional profiles characterized by heightened arousal and ambivalence. Similarly, avoidant individuals were occasionally misclassified as secure when behavioral withdrawal was situationally low, highlighting the contextual sensitivity of attachment-related behaviors.

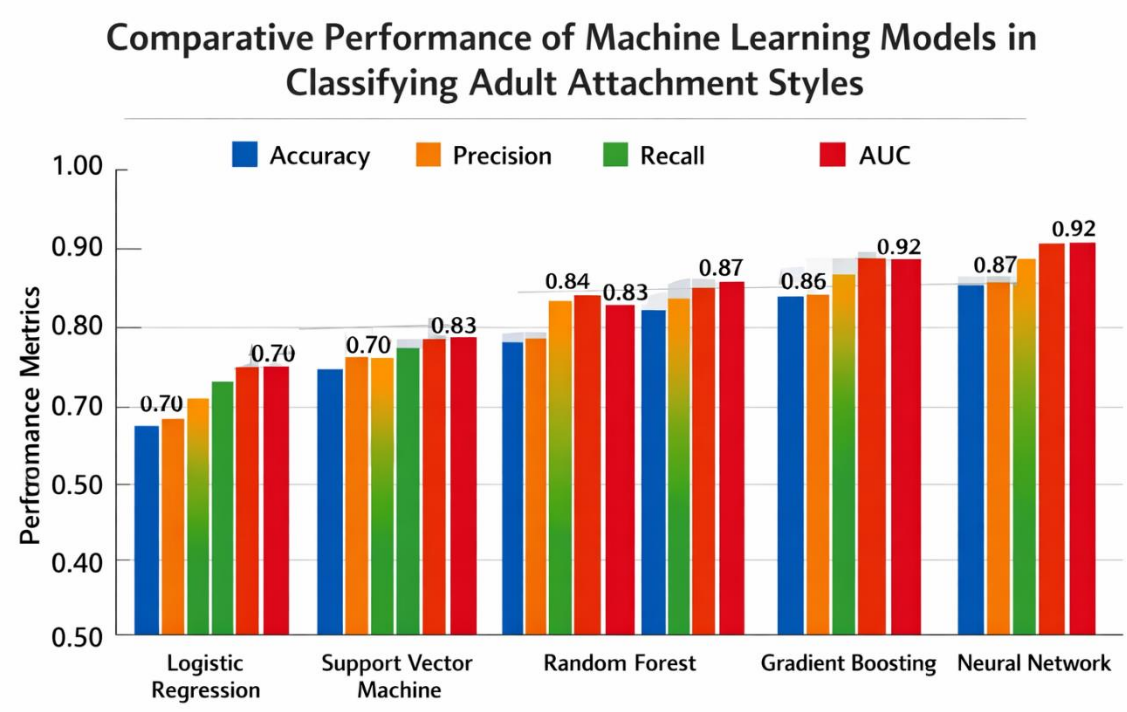

Figure 1. Comparative performance of machine learning models in classifying adult attachment styles

The figure summarizes the comparative performance of all tested models, illustrating the consistent advantage of ensemble and neural approaches over linear classifiers.

Discussion and Conclusion

The present study sought to classify adult attachment styles using machine learning models trained on dyadic behavioral, emotional, and physiological indicators derived from real-time couple interactions. Overall, the findings demonstrated that attachment styles can be identified with high accuracy using multimodal dyadic data, with non-linear and ensemble-based models substantially outperforming linear approaches. These results provide strong empirical support for contemporary conceptualizations of adult attachment as a dynamically enacted, relational construct that is embedded in observable interaction patterns rather than solely in self-reported internal representations.

The superior performance of gradient boosting and neural network models underscores the complexity and non-linearity of attachment-related processes. Attachment behaviors do not manifest through isolated cues but through intricate configurations of emotional responsiveness, synchrony, withdrawal, and regulation that unfold over time. Linear models, while informative, are limited in their capacity to capture higher-order interactions among these indicators. This finding aligns with prior methodological work emphasizing that dyadic emotional processes operate across multiple temporal and functional scales and require analytic approaches capable of modeling such complexity (Chen & Ferrer, 2022; Schreiber, 2020). The observed performance hierarchy among models is also consistent with recent computational studies demonstrating the advantages of ensemble and deep learning methods for attachment-related classification tasks using non-verbal and physiological signals (Maghfira et al., 2024).

A central finding of this study was the prominence of dyadic emotional synchrony and behavioral responsiveness as the most influential feature categories in attachment classification. Emotional synchrony, reflecting the degree of temporal alignment in partners' affective and physiological states, emerged as the strongest predictor across models. This result is theoretically coherent with attachment theory, which posits that secure attachment is characterized by effective co-regulation and mutual responsiveness, whereas insecure attachment involves disrupted or asymmetric regulation patterns. Empirical evidence from psychophysiological studies has consistently shown that securely attached couples display more adaptive physiological coregulation during stress and support interactions (Fogel-Yaakobi et al., 2023; Schreiber et al., 2021). The present findings extend this literature by demonstrating that such synchrony is not only associated with attachment but can be algorithmically leveraged to distinguish attachment styles with high precision.

Behavioral responsiveness and validation also played a critical role in model predictions, highlighting the importance of observable interaction behaviors in expressing attachment orientations. Securely attached individuals tend to respond to their partners' emotional cues with empathy, validation, and constructive engagement, whereas avoidant individuals often minimize emotional exchange and anxious individuals exhibit heightened reactivity and reassurance-seeking. These patterns have been well-documented in observational and self-report research (Beeney et al., 2019; Brandão et al., 2019; Feeney & Fitzgerald, 2019). The present study corroborates these findings using an objective, data-driven approach, reinforcing the notion that attachment styles are reliably encoded in dyadic interaction behaviors.

Interestingly, self-reported attachment anxiety and avoidance scores, while important, did not dominate the predictive models. Instead, they complemented behavioral and emotional indicators, suggesting that subjective attachment representations and enacted relational processes provide overlapping but distinct information. This finding aligns with prior critiques of exclusive reliance on self-report measures, which may be influenced by self-awareness, social desirability, or contextual factors (Postolache, 2025; Velotti et al., 2023). The integration of multimodal dyadic data thus offers a more comprehensive assessment of attachment by capturing both dispositional tendencies and situationally expressed behaviors.

Physiological regulation indices and paralinguistic features contributed modest but meaningful increments to classification performance. Autonomic indicators such as heart rate variability have been linked to emotion regulation capacity and attachment security, particularly in stressful interpersonal contexts (Bastos et al., 2025; Schreiber et al., 2021). Similarly, vocal intensity variability and speech timing reflect emotional arousal and interpersonal engagement, which vary systematically across attachment styles (Lin et al., 2024; Shadaydeh et al., 2020). The present findings suggest that while these signals alone may not be sufficient for accurate classification, they enhance model performance when combined with behavioral and emotional features, supporting a multimodal perspective on attachment expression.

The misclassification analysis revealed that errors primarily occurred between theoretically adjacent attachment styles, such as anxious and fearful or avoidant and secure profiles. This pattern is consistent with attachment theory, which conceptualizes attachment styles as dimensional rather than categorical constructs. Individuals near the boundaries of anxiety and avoidance dimensions may display overlapping behavioral and emotional patterns, particularly in specific interaction contexts (Chursina, 2023; Kordoutis & Moschos, 2024). From a computational perspective, these findings indicate that misclassifications reflect meaningful theoretical ambiguities rather than model deficiencies, reinforcing the construct validity of the classification framework.

The stability of cross-validation results further supports the robustness and generalizability of the proposed approach. Low variance across folds and minimal training–validation gaps indicate that the models captured stable relational patterns rather than idiosyncratic noise. This is particularly important in dyadic research, where interdependence and contextual variability pose significant analytic challenges (Kaźmierczak & Karasiewicz, 2021; Peters et al., 2024). The use of dyad-level validation procedures likely contributed to this robustness by preventing information leakage between partners.

From a broader theoretical perspective, the findings contribute to ongoing efforts to reconceptualize attachment as an emergent property of relational systems. Contemporary perspectives emphasize interpersonal emotion regulation, mutual influence, and co-constructed meaning as central mechanisms linking attachment to relationship outcomes (Horn et al., 2023; Lemay et al., 2025). The success of machine learning models trained on dyadic indicators provides empirical support for this shift, demonstrating that attachment styles are encoded in patterns of interaction rather than residing solely within individuals. This relational view is further reinforced by research on digital and mediated interactions, which shows that attachment dynamics adapt to changing communicative contexts while retaining their core regulatory functions (David & Roberts, 2021; Wu et al., 2025).

Clinically, the findings have important implications for couple assessment and intervention. Accurate classification of attachment styles based on observed interaction patterns could complement traditional assessment methods, offering clinicians objective insights into relational dynamics that may not be readily articulated by partners. This is particularly relevant in contexts involving conflict, health-related stress, or technological mediation, where attachment-related vulnerabilities may be amplified (Bacalhau et al., 2020; Happ, 2025; Mosley et al., 2021). Moreover, the use of explainable machine learning techniques enhances the translational value of these tools by identifying specific behaviors and emotional patterns that can be targeted in therapy (Cavalli & Velotti, 2025; Huang, 2025).

Despite its contributions, this study has several limitations that should be acknowledged. The cross-sectional design precludes causal inferences regarding the development or change of attachment styles over time. Although dyadic interaction tasks were designed to elicit attachment-relevant behaviors, they may not fully capture the diversity of real-world relational contexts. Additionally, the sample consisted of community couples from Canada, which may limit the generalizability of findings to clinical populations or other cultural settings. Finally, while the models demonstrated high accuracy, machine learning classifications remain probabilistic and should not be interpreted as definitive diagnoses.

Future research should adopt longitudinal designs to examine how attachment-related dyadic patterns evolve over time and whether machine learning models can predict changes in attachment security. Expanding the approach to include culturally diverse samples and clinical populations would further enhance generalizability. Incorporating additional data sources, such as ecological momentary assessments or digital communication logs, may also provide richer representations of attachment dynamics. Finally, continued development of explainable and ethically grounded artificial intelligence frameworks will be essential for advancing both theory and application in this area.

From a practical standpoint, the findings suggest that clinicians and relationship professionals may benefit from integrating observational and interaction-based assessments into routine practice. Training programs could emphasize the identification of attachment-relevant behavioral and emotional patterns during sessions. In applied settings, computational tools could be used as decision-support systems to inform intervention planning, monitor relational change, and tailor therapeutic strategies to dyadic attachment profiles, while always maintaining clinical judgment and ethical safeguards.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

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

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Authors' Contributions

All authors equally contributed to this study.

Transparency of Data

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

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