




# Machine-Learning Prediction of Therapeutic Alliance Quality from Client Readiness to Change and Affective Dysregulation

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## ABSTRACT

**Objective:** The aim of this study is to utilize and compare advanced machine-learning algorithms to predict the early quality of the therapeutic alliance based on a multidimensional assessment of client readiness to change and specific facets of affective dysregulation.

**Methods and Materials:** A prospective observational design was utilized, involving  $n = 452$  treatment-seeking adults initiating outpatient psychotherapy in Canada. Baseline predictor variables were collected prior to the first therapy session using the University of Rhode Island Change Assessment (URICA) and the Difficulties in Emotion Regulation Scale (DERS). The criterion variable, therapeutic alliance quality, was measured after the fourth session using the Working Alliance Inventory (WAI). Missing data (<2.5%) were handled via multiple imputation. The dataset was standardized and split into an 80%training set ( $n = 361$ ) and a 20%testing set ( $n = 91$ ). Support Vector Regression (SVR), Multilayer Perceptron (MLP), and Random Forest (RF) models were trained and compared using randomized grid search with 10-fold cross-validation.

**Findings:** The sample had a mean age of  $M = 34.6(SD = 11.2)$  years. Preliminary analyses indicated that the WAI Total Score correlated positively with URICA ( $r = .46, p < .01$ ) and negatively with DERS ( $r = -.52, p < .01$ ). On the testing set, the Random Forest model demonstrated the highest predictive accuracy ( $R^2 = .67, RMSE = 7.15$ ), outperforming the MLP ( $R^2 = .56, RMSE = 8.22$ ) and SVR ( $R^2 = .48, RMSE = 8.95$ ) algorithms. SHAP feature importance analysis of the RF model revealed that the strongest negative predictors of the alliance were the DERS Strategies ( $M.Abs.SHAP = 2.84$ ) and Goals ( $M.Abs.SHAP = 2.45$ ) subscales. The URICA Action stage ( $M.Abs.SHAP = 2.10$ ) and Precontemplation stage ( $M.Abs.SHAP = 1.95$ ) emerged as the most significant positive and negative motivational predictors, respectively.

**Conclusion:** Advanced machine-learning models can accurately forecast the early quality of the therapeutic alliance, computationally demonstrating that specific

baseline deficits in emotion regulation and distinct motivational stages are fundamental determinants of the therapeutic bond.

**Keywords:** *Therapeutic Alliance, Affective Dysregulation, Readiness to Change, Machine Learning*

## 1. Introduction

The therapeutic alliance—broadly defined as the collaborative and affective bond formed between a clinician and a client—remains one of the most robust and consistent predictors of positive treatment outcomes across the vast landscape of psychotherapy. Rooted in early psychodynamic theory but now recognized as a transdiagnostic and trans-theoretical mechanism of change, the alliance comprises three core dimensions: agreement on the goals of treatment, agreement on the therapeutic tasks required to achieve those goals, and the development of a secure, trusting personal bond. Extensive empirical literature has repeatedly demonstrated that the quality of this alliance significantly drives clinical improvement, extending across diverse therapeutic modalities and clinical presentations. For instance, in exposure-based cognitive-behavioral therapies aimed at treating pediatric irritability, the strength of the therapeutic alliance is fundamentally tied to treatment adherence and subsequent clinical outcomes (Naim et al., 2025). The necessity of a strong therapeutic relationship is not limited to traditional verbal psychotherapies; it is equally critical in emerging pharmacological and somatic interventions. In trials investigating psilocybin-assisted therapy for major depressive disorder, the alliance between study participants and intervention facilitators has been shown to be intrinsically associated with both acute subjective drug effects and long-term clinical outcomes (Levin, 2024). Furthermore, qualitative phenomenological analyses reveal that even in disciplines traditionally viewed as purely physical, such as pediatric physical therapy, the unspoken “between the lines” elements of the therapeutic alliance are central to patient engagement and rehabilitation success (Crom et al., 2020). Understanding the developmental trajectory of this alliance is critical, as foundational client factors—including baseline expectancy for change and inherent youth characteristics—often interact with the alliance to increase subjective well-being more profoundly than isolated positive psychology interventions (Savage, 2011).

As the modalities and delivery systems of psychological interventions expand, the conceptualization of the therapeutic alliance has inherently grown more complex. In the realm of systemic and relational treatments, the alliance is no longer a simple dyadic construct but a multifaceted web

of loyalties and collaborations. Within couples therapy, multiple perspectives must be actively managed; the therapeutic alliance and its contribution to treatment progress rely heavily on how both partners uniquely perceive their bond with the therapist (Glebova et al., 2011). Patterns of alliance formation in randomized controlled trials of emotionally focused couple therapy demonstrate significant variations based on both the treatment modality and the sex of the client (Fang et al., 2023). Furthermore, the clinician’s own psychological maturity, often operationalized as therapist differentiation, profoundly impacts how couple clients perceive the therapeutic alliance (Bartle-Haring et al., 2016). In family therapy contexts, establishing a robust systemic alliance is particularly vital when treating highly vulnerable populations, such as adolescents at elevated risk for mood disorders (Wong et al., 2022). Beyond relational dynamics, the establishment of the alliance is also heavily mediated by overarching sociocultural factors. Enhancing the therapeutic alliance requires a high degree of cultural humility and competence, particularly when utilizing critical race theoretical approaches to navigate sensitive and potentially rupturing conversations about systemic racism with marginalized clients (Fripp & Adams, 2022).

The modern evolution of psychiatric and psychological care has also introduced digital and non-human elements into the therapeutic space, further complicating our understanding of the working alliance. As digital mental health interventions for serious mental illnesses become increasingly prevalent, accurately predicting and measuring the therapeutic alliance through remote interfaces has emerged as a critical clinical imperative (Tremain et al., 2019). The rapid integration of artificial intelligence into mental health care has sparked profound questions regarding human versus AI capabilities in psychotherapy; intriguingly, client expectancy plays a massive role in whether an alliance can be forged with a non-human agent (Kabrel, 2025).

To understand how a strong alliance forms—whether in person, digitally, individually, or systemically—one must examine the microscopic emotional and cognitive processes occurring within the client. The alliance is heavily predicated on the depth of emotional processing achieved during sessions. For example, in emotion-focused therapy for complex trauma, the client’s depth of experiencing directly interacts with the therapeutic alliance to predict distinct therapeutic outcomes, highlighting that the alliance

provides the safe container necessary for profound emotional processing (Harrington et al., 2021). The biological underpinnings of this safe container are becoming clearer, as research demonstrates that physiological synchrony between client and therapist serves as a somatic indicator of a strong therapeutic alliance, particularly in imagery-based treatments (Bar-Kalifa et al., 2019). Similarly, higher-order cognitive capacities, such as reflective functioning—the ability to understand one’s own and others’ mental states—are deeply intertwined with the psychotherapeutic alliance and ultimately dictate symptom trajectory in treatments for severe conditions like bulimia nervosa (Katznelson et al., 2020).

However, a critical barrier to establishing this essential therapeutic alliance lies in client baseline psychopathology, specifically affective dysregulation. Emotion dysregulation represents a core transdiagnostic vulnerability factor characterized by an inability to flexibly respond to and manage intense emotional experiences. This profound psychological deficit is linked to an array of severe clinical manifestations. Longitudinal analyses have firmly established that affective instability and chronic impulsivity are primary predictors of nonsuicidal self-injury within the general population (Peters et al., 2016). The physiological toll of chronic emotional dysregulation is equally severe, frequently manifesting as dysregulation in inflammatory markers, altered neurobiology, and impaired cognitive functioning in individuals suffering from post-traumatic stress disorder (Quiñones et al., 2020). Under conditions of acute global stress, such as the COVID-19 pandemic, pre-existing psychological distress and emotional dysregulation have been shown to precipitate profound somatic conversion symptoms, including functional movement disorders (Janiri et al., 2023).

Because affective dysregulation severely impairs interpersonal functioning, it poses an immediate and direct threat to the formation of the therapeutic alliance. Clients who lack emotional clarity, who cannot accept their distressed states, or who lack access to adaptive emotion regulation strategies often struggle to form trusting bonds or agree on clinical tasks. Direct evidence of this phenomenon indicates that higher levels of emotion dysregulation severely impede the establishment of the therapeutic alliance, as observed in highly volatile settings like post-divorce group interventions (Alvarez et al., 2024). Consequently, explicitly treating these affective deficits is paramount. Modalities such as mindfulness meditation are frequently deployed specifically for their documented

impact on enhancing attentional control and reducing emotion dysregulation (Prakash, 2021). In highly traumatized populations, such as refugees and asylum-seekers, specialized protocols integrating narrative exposure therapy with skills training in affective and interpersonal regulation are required specifically to stabilize emotional dysregulation before deeper trauma processing can occur (Tissue et al., 2022).

While the detrimental impact of affective dysregulation on the alliance is evident, it does not operate in a vacuum. A client’s intrinsic readiness to change—conceptualized through the transtheoretical model encompassing precontemplation, contemplation, action, and maintenance stages—acts as a crucial interactive variable. A client may be highly emotionally dysregulated yet simultaneously possess a profound, action-oriented motivation to engage in the therapeutic process. Conversely, a client with mild emotional difficulties who remains in a state of precontemplation (denial of the problem) may present an impenetrable barrier to alliance formation. Historically, psychological research has attempted to model the interplay of such variables using traditional, linear statistical methods, such as multiple hierarchical regression. However, human psychology is rarely linear. The complex interactions between varying facets of emotion dysregulation (e.g., lack of impulse control versus lack of emotional awareness) and shifting stages of readiness to change create multidimensional, nonlinear data topologies that traditional statistics struggle to accurately map.

To overcome these methodological limitations, the integration of advanced machine-learning algorithms into clinical psychology research is urgently required. Machine learning models, such as Random Forests, Support Vector Machines, and Multilayer Perceptron neural networks, possess the mathematical flexibility to capture highly complex, non-monotonic relationships between a multitude of predictor variables and a continuous clinical outcome. By deploying these computational techniques, researchers can identify the specific hierarchical importance of distinct readiness stages and discrete emotion regulation deficits in forecasting therapeutic alliance quality. Such predictive modeling is not merely an academic exercise; it holds profound clinical utility. If a mathematical model can accurately predict the trajectory of the therapeutic alliance based on data collected at intake, clinicians can preemptively adapt their interpersonal style, pacing, and early therapeutic interventions to mitigate the risk of premature termination and alliance ruptures. Despite the clear theoretical links

between motivation, emotional stability, and therapeutic relationships, there remains a distinct scarcity of literature utilizing advanced predictive analytics to synthesize these domains early in the treatment timeline.

The present study addresses this critical gap in the existing clinical literature by applying computational modeling to baseline psychometric profiles. Therefore, the singular aim of this study is to utilize and compare advanced machine-learning algorithms to predict the early quality of the therapeutic alliance based on a multidimensional assessment of client readiness to change and specific facets of affective dysregulation.

## 2. Methods and Materials

### 2.1. Study Design and Participants

This study utilized a prospective observational design to investigate the predictive relationship between initial client readiness to change, early affective dysregulation, and the subsequent quality of the therapeutic alliance. The sample comprised exactly 452 treatment-seeking adults recruited from multiple community mental health clinics and private psychological practices across diverse urban and suburban centers in Canada. To be eligible for inclusion in the study, participants were required to be at least 18 years of age, fluent in English or French, and initiating a new course of individual outpatient psychotherapy for primary presentations of mood, anxiety, or adjustment disorders. Individuals actively experiencing psychosis, acute suicidal ideation requiring immediate intensive care hospitalization, or those mandated to treatment by the justice system were strictly excluded from the study to ensure that the observed readiness to change was entirely internally motivated and not a product of external coercion. The final cohort of 452 participants provided written informed consent prior to engaging in any study procedures. The demographic profile of the sample was carefully monitored to reflect a broad cross-section of the Canadian population seeking psychological services, ensuring a representative and generalizable clinical cohort. Data regarding the independent predictor variables were collected immediately prior to the commencement of the first therapy session, while the criterion variable, therapeutic alliance quality, was evaluated after the completion of the fourth clinical session, a time point widely established in psychotherapy research as critical for alliance formation and stabilization.

### 2.2. Measures

To comprehensively capture the psychological constructs central to this investigation, three extensively validated psychometric instruments were deployed. Client readiness to change was operationalized and measured using the University of Rhode Island Change Assessment scale, a multidimensional self-report inventory that evaluates the stages of change across precontemplation, contemplation, action, and maintenance domains. This tool allows for the calculation of a composite readiness score by subtracting the precontemplation subscale score from the sum of the contemplation, action, and maintenance subscale scores. Affective dysregulation was rigorously assessed utilizing the Difficulties in Emotion Regulation Scale, an exhaustive instrument designed to measure multiple facets of emotion dysregulation. This includes nonacceptance of emotional responses, difficulties engaging in goal-directed behavior when distressed, impulse control difficulties, lack of emotional awareness, limited access to emotion regulation strategies, and lack of emotional clarity. Higher aggregate scores on this scale denote more severe and pervasive impairments in emotional regulation capabilities. Finally, the quality of the therapeutic alliance, which served as the primary target variable for the machine-learning prediction models, was quantified using the client version of the Working Alliance Inventory. This widely utilized questionnaire captures three foundational dimensions of the therapeutic relationship: agreement on therapeutic goals, agreement on the clinical tasks required to achieve those goals, and the development of a secure affective bond between the client and the therapist. All psychometric assessments were administered through a secure, encrypted digital platform to ensure maximum data integrity and protect participant privacy.

### 2.3. Data analysis

The analytical pipeline was constructed using advanced machine-learning methodologies to identify complex, potentially nonlinear patterns linking the predictor variables to therapeutic alliance outcomes. Initial data preprocessing involved handling missing values through multiple imputation by chained equations, ensuring that the full dataset of 452 participants was preserved without introducing substantial bias. Continuous variables were subsequently standardized to have a mean of 0 and a standard deviation of 1, which is a critical step for optimizing the convergence and performance of distance-based and

gradient-descent algorithms. The dataset was partitioned into a training set, comprising 80% of the data, and an independent testing set, containing the remaining 20%. To rigorously evaluate predictive capacity, three distinct machine-learning algorithms were trained and compared: Support Vector Regression, Random Forest, and a Multilayer Perceptron artificial neural network. Hyperparameter tuning for each model was executed utilizing a randomized grid search integrated with 10-fold cross-validation on the training data, thereby systematically mitigating the risk of model overfitting. The predictive performance of the optimized models was then assessed exclusively on the unseen testing set. Evaluation metrics included the Root Mean Square Error, calculated as  $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$ , and the coefficient of determination, denoted as  $R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$ , where  $y_i$  represents the actual alliance score,  $\hat{y}_i$  represents the predicted alliance score, and  $\bar{y}$  represents the mean of the actual scores within the testing sample. Furthermore, sophisticated feature importance algorithms, specifically permutation importance and SHapley Additive exPlanations values, were applied to the best-performing model. These explanatory techniques were utilized to elucidate the relative contribution and directional impact of specific emotional

dysregulation facets and distinct stages of change on the computationally predicted quality of the therapeutic alliance.

### 3. Findings and Results

The initial phase of the data analysis focused on evaluating the demographic characteristics of the sample and the descriptive statistics of the primary study variables to ensure the integrity of the data prior to the deployment of the machine-learning algorithms. The sample consisted of 452 treatment-seeking adults. The mean age of the participants was  $M = 34.6$  years with a standard deviation of  $SD = 11.2$  years, ranging from 18 to 68 years. Regarding gender identity, the cohort was composed of 278 females (61.5%), 156 males (34.5%), and 18 individuals identifying as non-binary or gender diverse (4.0%). The primary clinical presentations, as assessed during the intake process, included major depressive disorder (42.3%), generalized anxiety disorder (31.6%), social anxiety disorder (15.0%), and adjustment disorders (11.1%). Missing data accounted for less than 2.5% of the total data points and were successfully managed using multiple imputation by chained equations, ensuring no cases were listwise deleted. The descriptive statistics for the University of Rhode Island Change Assessment scale, the Difficulties in Emotion Regulation Scale, and the Working Alliance Inventory are presented in Table 1.

**Table 1**

*Descriptive Statistics for Readiness to Change, Affective Dysregulation, and Therapeutic Alliance Measures*

Variable	<i>M</i>	<i>SD</i>	Minimum	Maximum
URICA (Readiness to Change)				
Precontemplation	10.45	3.21	5.00	22.00
Contemplation	24.56	4.10	12.00	35.00
Action	22.10	5.34	9.00	34.00
Maintenance	18.44	4.88	6.00	31.00
Total Readiness Score	54.65	11.05	24.00	85.00
DERS (Affective Dysregulation)				
Nonacceptance	14.22	5.11	6.00	30.00
Goals	15.30	4.65	5.00	25.00
Impulse	12.85	4.90	6.00	30.00
Awareness	16.40	5.05	6.00	30.00
Strategies	18.75	6.20	8.00	40.00
Clarity	11.90	3.85	5.00	25.00
Total DERS Score	89.42	21.50	36.00	160.00
WAI (Therapeutic Alliance)				
Goal	25.60	5.12	10.00	35.00
Task	26.15	4.85	11.00	35.00
Bond	27.30	4.95	12.00	35.00
Total Alliance Score	79.05	12.45	38.00	105.00

To examine the linear relationships between the primary constructs before applying the complex machine-learning algorithms, bivariate Pearson correlation coefficients were calculated among the aggregate scores of the independent and dependent variables. The results of these preliminary correlational analyses are detailed in Table 2. As anticipated by the theoretical framework of the study, the URICA Total Readiness Score demonstrated a significant and robust positive correlation with the WAI Total Alliance Score, suggesting that clients who entered treatment with a higher internal motivation to modify their behavioral patterns were

more likely to establish a strong collaborative relationship with their therapist by the fourth session. Conversely, the DERS Total Score exhibited a significant negative correlation with the WAI Total Alliance Score, indicating that clients presenting with severe baseline impairments in processing and regulating their emotions experienced greater difficulty in forging a secure bond and agreeing on therapeutic tasks. Furthermore, a moderate inverse relationship was observed between readiness to change and affective dysregulation, highlighting the interconnected nature of these baseline client characteristics.

**Table 2**

*Bivariate Pearson Correlations Among Total Scores of Primary Study Variables*

Variable	1	2	3
1. URICA Total Readiness Score	–		
2. DERS Total Score	–.38**	–	
3. WAI Total Alliance Score	.46**	–.52**	–

Following the preliminary statistical evaluations, the analytical focus shifted to the machine-learning phase to determine the predictive capacity of the baseline client variables. The dataset was split into an 80% training set ( $n = 361$ ) and a 20% holdout testing set ( $n = 91$ ). The models utilized all subscales of both the URICA and the DERS to predict the continuous WAI Total Alliance Score. Three distinct algorithms—Support Vector Regression, Random Forest, and a Multilayer Perceptron—were trained utilizing 10-fold cross-validation coupled with randomized grid search optimization to tune their respective hyperparameters. For the Random Forest model, the optimal configuration yielded 500 estimators with a maximum depth

of 15. The Multilayer Perceptron achieved optimal convergence using two hidden layers containing 64 and 32 neurons, respectively, utilizing the ReLU activation function and the Adam optimizer. The predictive performance of each optimized model was subsequently evaluated exclusively on the unseen testing set, with the comparative metrics displayed in Table 3. The Random Forest algorithm emerged as the superior predictive model, accounting for a substantial proportion of the variance in the therapeutic alliance scores, outperforming both the Support Vector Regression and the Multilayer Perceptron networks in terms of both the coefficient of determination and the minimization of prediction error.

**Table 3**

*Performance Metrics of Machine-Learning Models on the Testing Set*

Model	RMSE	$R^2$
Support Vector Regression (SVR)	8.95	.48
Multilayer Perceptron (MLP)	8.22	.56
Random Forest (RF)	7.15	.67

Given that the Random Forest model demonstrated the highest predictive accuracy, achieving an  $R^2 = .67$ , sophisticated feature importance techniques were applied to this specific model to deconstruct the “black box” of the algorithm and interpret the driving factors behind the predictions. Utilizing SHapley Additive exPlanations (SHAP) values, the relative importance and directional impact of each specific URICA and DERS subscale on the

predicted WAI Total Alliance Score were calculated. The results of this feature importance analysis are presented in Table 4. The SHAP analysis revealed that specific facets of affective dysregulation were the most potent predictors of the alliance. Notably, the DERS Strategies subscale (limited access to emotion regulation strategies) and the DERS Goals subscale (difficulties engaging in goal-directed behavior) emerged as the two most critical features, both exerting a

strong negative impact on the predicted alliance quality. Among the readiness to change dimensions, the URICA Action and Precontemplation subscales contributed most significantly to the model, with Action scores driving alliance predictions upward and Precontemplation scores

driving them downward. The lack of emotional clarity and impulse control difficulties, while contributing to the overall model, demonstrated a comparatively lower magnitude of impact on the final alliance prediction.

**Table 4**

*Feature Importance for the Random Forest Model Predicting Therapeutic Alliance*

Predictor Feature (Subscale)	Mean Absolute SHAP Value	Direction of Impact on Alliance
DERS Strategies	2.84	Negative
DERS Goals	2.45	Negative
URICA Action	2.10	Positive
URICA Precontemplation	1.95	Negative
DERS Nonacceptance	1.52	Negative
URICA Contemplation	1.25	Positive
DERS Awareness	0.98	Negative
URICA Maintenance	0.85	Positive
DERS Clarity	0.64	Negative
DERS Impulse	0.55	Negative

**4. Discussion**

The primary objective of this investigation was to utilize advanced machine-learning algorithms to predict the quality of the early therapeutic alliance based on comprehensive baseline assessments of client readiness to change and multidimensional facets of affective dysregulation. Our computational models successfully demonstrated that these baseline characteristics can robustly forecast alliance quality. Among the tested algorithms, the Random Forest model exhibited superior predictive accuracy, accounting for a substantial portion of the variance in the Working Alliance Inventory scores ( $R^2 = .67$ ). Through the application of SHapley Additive exPlanations (SHAP) feature importance analysis, we unraveled the specific hierarchies of these predictor variables. The most critical determinants of the therapeutic alliance were distinct dimensions of emotional dysregulation—specifically, a lack of access to emotion regulation strategies and difficulties engaging in goal-directed behavior when distressed. Both of these factors exerted a profound negative impact on the predicted alliance. Following these emotional deficits, the motivational dimensions of the client, namely the Action and Precontemplation stages of change, emerged as the next most significant predictors, driving the alliance in positive and negative directions, respectively.

The finding that specific facets of emotion dysregulation, rather than just the overarching presence of distress, are the primary saboteurs of the early therapeutic alliance aligns

strongly with and expands upon existing clinical literature. Previous research has established that high levels of emotion dysregulation severely impair the establishment of a working alliance, as clients who cannot manage acute affective distress often lack the cognitive and emotional bandwidth to form a collaborative bond (Alvarez et al., 2024). When clients lack access to adaptive emotion regulation strategies, they frequently resort to maladaptive coping mechanisms under stress. Over time, chronic affective instability and impulsivity severely undermine interpersonal functioning (Peters et al., 2016). In a therapeutic context, a client who cannot self-soothe or regulate intense emotions is likely to perceive the standard tasks of therapy as overwhelming or threatening, thus rupturing the agreement on clinical goals and tasks. This is further contextualized by findings indicating that acute psychological distress and emotional dysregulation can manifest in profound physiological and somatic symptoms (Janiri et al., 2023), alongside the well-documented dysregulation of neurobiology and cognitive functioning observed in highly traumatized populations (Quiñones et al., 2020). Therefore, clients scoring high on these specific DERS subscales are not merely resistant; they are functionally impaired in their capacity to engage in the relational and cognitive demands of therapy. Interventions specifically targeting these deficits, such as mindfulness meditation (Prakash, 2021) or integrated skills training in affective and interpersonal regulation (Tissue et al., 2022), are likely necessary precursors to establish a foundation

upon which a secure alliance can be built, particularly before engaging in deeper emotional processing where depth of experiencing is required (Harrington et al., 2021).

Our computational analysis also highlighted the powerful role of client motivation, revealing that high scores on the Action subscale of the readiness to change measure strongly facilitated alliance formation, whereas high scores on Precontemplation hindered it. This suggests that a client's conscious, internal expectancy and willingness to modify their behavior are highly relevant to the collaborative nature of the alliance. Clients in the Action stage inherently agree with the necessity of therapeutic tasks, thereby fulfilling a core dimension of the working alliance. This finding supports previous theoretical frameworks demonstrating that client expectancy for change is a critical variable that interacts with the alliance to produce positive outcomes (Savage, 2011). In modern contexts, whether in traditional settings or when navigating the integration of AI in psychotherapy, client expectancy remains a massive driving force behind alliance formation (Kabrel, 2025). When clients are internally motivated, they demonstrate higher treatment adherence, which creates a reciprocal positive feedback loop strengthening the therapeutic alliance and improving clinical outcomes across diverse modalities, from exposure-based therapies (Naim et al., 2025) to psilocybin-assisted treatments (Levin, 2024). Even in fields focused on physical rehabilitation, the internal motivation of the patient profoundly influences the unspoken, relational aspects of the therapeutic dynamic (Crom et al., 2020).

The complexity captured by our machine-learning approach reflects the broader, multifaceted nature of the therapeutic alliance observed across various therapeutic modalities. Just as our model synthesized multiple internal client states, systemic therapies must synthesize multiple interpersonal perspectives. For instance, in couples therapy, the alliance is highly dependent on varying perceptual patterns based on sex, treatment type, and the individual perspectives of each partner (Fang et al., 2023; Glebova et al., 2011). The relational dynamics are further influenced by the therapist's own emotional maturity and differentiation (Bartle-Haring et al., 2016), and the necessity of a strong systemic alliance is critical for at-risk populations, such as adolescents (Wong et al., 2022). Furthermore, broader sociocultural and systemic factors heavily influence the alliance; clinicians must utilize culturally competent frameworks to navigate conversations about race and marginalization, which inherently requires navigating the emotional regulation and motivational states of both client

and therapist (Fripp & Adams, 2022). The shift toward digital mental health interventions also relies heavily on understanding these baseline client factors, as the absence of physical proximity requires new methods of fostering the alliance (Tremain et al., 2019). Ultimately, whether examining physiological synchrony (Bar-Kalifa et al., 2019) or higher-order cognitive capacities like reflective functioning (Katznelson et al., 2020), the capacity to form an alliance is intricately tied to the client's baseline emotional and motivational architecture.

## 5. Conclusion

This study provides compelling evidence that the early therapeutic alliance can be accurately predicted using sophisticated machine-learning techniques applied to baseline assessments of client emotional dysregulation and readiness to change. By utilizing a Random Forest model and SHAP feature importance analysis, we discovered that a lack of access to emotion regulation strategies and an inability to engage in goal-directed behaviors during distress are the most significant barriers to forming a strong collaborative bond with a therapist. Furthermore, clients presenting with an active motivation to change significantly bolster the alliance, while those in the precontemplation stage present substantial relational challenges. These findings computationally validate and extend existing clinical theories, demonstrating that the therapeutic relationship is profoundly dictated by the specific, nonlinear interplay of the client's internal emotional scaffolding and motivational state at the very outset of treatment.

## 6. Limitations & Suggestions

Despite the robust predictive accuracy of the utilized models, several methodological limitations must be acknowledged. First, the sample, while adequately sized for the deployed algorithms, was sourced exclusively from Canadian clinical settings, which may limit the generalizability of these specific computational weights to diverse international or cross-cultural populations. Second, the study relied solely on self-report measures to quantify both the predictor variables and the criterion variable. This mono-method bias introduces the potential for shared method variance, wherein the correlations and predictive patterns might be partially inflated by the participants' subjective reporting styles or varying levels of insight. Third, the therapeutic alliance was measured at a single time point (the fourth session). While this is a critical juncture for

alliance formation, the alliance is dynamic and subject to ruptures and repairs over the course of treatment. Consequently, our models predict the initial establishment of the alliance but do not account for its longitudinal fluctuations throughout an entire clinical intervention.

Future empirical investigations should seek to build upon these computational findings by addressing the highlighted limitations and expanding the scope of the predictive models. Researchers should incorporate multi-informant data, integrating therapist-rated alliance scores and independent observational coding of session recordings to provide a more objective triangulation of the therapeutic relationship. Additionally, future machine-learning protocols should utilize longitudinal study designs equipped with continuous or session-by-session measurements of the alliance, allowing algorithms like Recurrent Neural Networks to model the temporal trajectory, ruptures, and repairs of the therapeutic bond over time. It would also be highly beneficial for future studies to incorporate objective physiological metrics—such as heart rate variability or galvanic skin response—as surrogate markers of emotion dysregulation to complement self-report inventories. Finally, replicating this methodology across diverse cultural demographics and specific, severe psychiatric populations will be crucial to determining the universality of these specific predictor features.

The findings from this predictive modeling study hold immediate and highly actionable implications for daily clinical practice. Clinicians are strongly encouraged to routinely administer brief, standardized assessments of emotion regulation and readiness to change during the initial intake process. Armed with the knowledge that a lack of emotional coping strategies and a lack of goal-directed behavior during distress are the primary saboteurs of the therapeutic bond, therapists can proactively pivot their early clinical approach. If a client presents with a high degree of affective dysregulation upon intake, the clinician should temporarily suspend pressure to engage in deep, insight-oriented work or rigorous exposure tasks. Instead, the initial sessions should be explicitly dedicated to psychoeducation regarding emotional states and the teaching of concrete, foundational distress tolerance and grounding skills. By first prioritizing the stabilization of the client's emotional architecture, the clinician creates a safe psychological environment that naturally fosters a stronger, more resilient therapeutic alliance. Furthermore, recognizing a client's low readiness to change should prompt the use of motivational interviewing techniques early on, rather than prematurely

attempting to establish consensus on rigorous behavioral goals. Utilizing baseline data to inform the pacing and immediate focus of early sessions can significantly reduce the likelihood of premature therapeutic dropouts.

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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 equally contributed in this article.

### Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

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