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Journal Website

Article history:
Received 19 September 2025
Revised 14 December 2025
Accepted 17 December 2025
Published online 01 January 2026

Journal of Assessment and Research in Applied Counseling

Open-Peer Review

E-ISSN: 3041-8518

Identifying Predictors of Treatment Dropout Using ML Analysis of Motivational Interviewing Processes and Attachment-Related Avoidance

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E d i t o r	R e v i e w e r s
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1. Round 1

1.1. Reviewer 1

Reviewer:

The theoretical rationale is generally strong, particularly in its positioning of attachment-related avoidance as a likely barrier to alliance formation and treatment retention, but the introduction would benefit from a sharper narrowing of scope. While the manuscript appears well cited and ambitious in connecting adult attachment processes to dropout vulnerability, some of the cited literature seems broad relative to the specific empirical question. The authors may improve coherence by more explicitly distinguishing which prior findings directly support their predictive model of dropout and which are included only as broader contextual justification.

The discussion is conceptually rich and does a good job of interpreting dropout as the product of a complex interplay between interpersonal pathology and therapeutic micro-processes, but there is some risk of overstatement in the causal language. Given that the design appears predictive rather than experimentally manipulative, claims that certain therapist behaviors or patient verbal patterns “drive” dropout should be phrased more cautiously unless the authors can justify a stronger causal interpretation.

The discussion would benefit from clearer acknowledgment that even highly interpretable ML findings remain correlational and may reflect unmeasured confounding or site-specific treatment dynamics.

The manuscript would be considerably improved by fuller reporting of sample characteristics and contextual details, as these are essential for evaluating external validity and generalizability. Based on the retrieved sections, the exact sample size, dropout rate, participant demographics, and clinical setting are not yet clearly available, and these omissions make it difficult to determine whether the model was built on a sufficiently large and representative dataset. This issue is particularly important in machine learning studies, where limited sample size relative to feature complexity can produce unstable or overly optimistic findings even when cross-validation is used.

Authors revised and uploaded the document.

1.2. Reviewer 2

Reviewer:

A major methodological strength is the use of established and recognizable measures, especially the Experiences in Close Relationships–Revised (ECR-R) for attachment-related avoidance and the Motivational Interviewing Skill Code (MISC) for coding early-session interactional processes. The decision to operationalize attachment avoidance as a continuous standardized score is appropriate for predictive modeling, and the use of audio-recorded, transcribed sessions coded by trained independent raters who were blind to outcomes and attachment scores enhances internal validity. That said, the manuscript should report inter-rater reliability indices for all MISC-derived variables, as the credibility of the behavioral coding depends heavily on demonstrated coding consistency.

The machine learning pipeline is thoughtfully designed in several respects, particularly through the use of standardization, k-nearest neighbors imputation, SMOTE for class imbalance, stratified cross-validation, and comparison across multiple supervised classifiers. These choices indicate commendable methodological awareness and are well aligned with best practices in predictive modeling of clinically imbalanced outcomes. However, the manuscript should provide more granular technical detail, including the value of k used for imputation, the number of cross-validation folds, the hyperparameter tuning strategy, and whether preprocessing and resampling steps were fully nested within the cross-validation framework to prevent information leakage.

The identification of XGBoost as the best-performing model is plausible and methodologically interesting, but the current reporting appears insufficiently transparent for full evaluation of model quality. Although the manuscript states that XGBoost achieved superior predictive performance and an excellent AUC, the exact numerical performance values for AUC, precision, recall, and F1-score need to be clearly presented and discussed in the main text, not only in a table. Without these values, the reader cannot judge the model's practical utility, class-wise tradeoffs, or the degree to which prediction was clinically meaningful rather than merely statistically impressive.

The SHAP-based interpretability analysis is one of the manuscript's strongest features, as it moves the work beyond black-box prediction and toward clinically interpretable inference. The finding that attachment-related avoidance emerged as the most influential predictor, followed by patient Sustain Talk, is both theoretically coherent and clinically useful. Likewise, the observation that Change Talk and therapist empathy appear protective helps translate the results into actionable psychotherapy insights. Still, the manuscript would be strengthened by a clearer explanation of how stable these SHAP rankings were across validation folds and whether the reported variable importance patterns were robust to sampling variability.

The reported interaction between high attachment avoidance and low therapist complex reflections is especially compelling and represents a potentially important contribution to psychotherapy process research. This finding supports a relational and dyadic model of dropout rather than an overly patient-blaming framework, which is conceptually sophisticated and clinically valuable. However, the manuscript should present this interaction with greater statistical and visual clarity, ideally through SHAP dependence plots or other interpretable graphical representations, so that readers can better understand the magnitude, shape, and practical implications of the non-linear effect.

JARAC Assessment and Research in Applied Counseling
E-ISSN: 3041-8518

Authors revised and uploaded the document.

2. Revised

Editor's decision after revisions: Accepted.
Editor in Chief's decision: Accepted.

E-ISSN: 3041-8518