





A Predictive ML Model of Self-Compassion, Shame-Proneness, and Emotion Regulation Strategies in Counseling Outcomes

Padma. Dolderer¹, Lilit. Hayrapetyan¹, Nathan C. Mathewson^{2*}, Andrea. Campostrini³


¹ Campbell Family Mental Health Institute, Centre for Addiction and Mental Health, Toronto, Canada

² Department of Educational and Counselling Psychology, McGill University, Montreal, QC H3A 1Y2, Canada

³ Department of Psychology, Iowa State University, Ames, Iowa, US

* Corresponding author email address: nathan.c.mathewson@mcgill.ca

Editor

Mehdi Rostami¹
Assistant Professor, Department of Psychology and Counseling, KMAN Research Institute, Richmond Hill, Ontario, Canada
mehdirostami@kmanresce.ca

Reviewers

Reviewer 1: Selva Turan¹
Necmettin Erbakan University, Ahmet Keleşoğlu Faculty of Education, Konya, Türkiye. Email: selvaturan@erbakan.edu.tr
Reviewer 2: Ana Amelia Coder¹
Department of Psychology, University of New Brunswick, Saint John, New Brunswick, Canada. Email: anaameliacoder@gmail.com

1. Round 1

1.1. Reviewer 1

Reviewer:

The theoretical background on shame-proneness, emotion regulation, and self-compassion is rich and well-referenced, yet it remains largely narrative; it would strengthen the paper to translate this synthesis into a more explicit conceptual or graphical model (e.g., hypothesized paths or interactions among the three constructs and outcome), which can then be directly linked to the choice of predictors and to the machine-learning approach.

The clinical translation of the model's output remains underspecified: while the authors claim the model will facilitate personalized psychotherapy, the paper does not clearly articulate how a clinician would use the predicted outcome (e.g., thresholds for "poor prognosis," illustrative case vignettes, or decision rules for tailoring interventions based on high shame-proneness vs. low self-compassion); adding concrete examples, calibration plots, and a discussion of acceptable error levels in clinical decision-making would greatly improve practical relevance.

The limitations section, as implied by the current text, appears relatively underdeveloped given the ambitious claims about AI/ML; the authors should expand this section to include issues such as overfitting risk given sample size, absence of external validation on an independent cohort, cultural specificity of shame/self-compassion in a Canadian sample, and the risk of

algorithmic misclassification in high-stakes clinical contexts, along with clear recommendations for replication and external validation.

Authors revised and uploaded the document.

1.2. Reviewer 2

Reviewer:

The description of participants and sampling procedures is currently incomplete (e.g., missing exact N, age cutoffs, and minimum session counts), which impedes evaluation of statistical power, risk of overfitting, and generalizability; these details must be fully reported according to standard reporting guidelines (e.g., CONSORT-extension for psychotherapy trials or STROBE for observational studies) and clearly summarized in a dedicated subsection or table.

The exclusive reliance on self-report instruments for both predictors and outcomes (SCS, TOSCA, ERQ, CORE-OM) introduces substantial shared-method variance and potential response biases, yet this is not adequately problematized; I suggest a more thorough discussion of this limitation and, if possible, a sensitivity analysis or robustness check (e.g., examining whether certain subscales drive relationships disproportionately) to reassure readers that findings are not trivially due to common method bias.

The machine-learning pipeline (k-NN imputation, standardization, RFE, Random Forest, cross-validation) is generally appropriate, but key analytic decisions are insufficiently justified and documented: the authors should specify hyperparameters, exact train-test split proportions, k in k-fold CV and k-NN, criteria for RFE stopping, and provide at least one performance baseline (e.g., linear regression, LASSO, or a simple mean-prediction model) to contextualize the reported RMSE and R².

The paper emphasizes “feature importance hierarchies” derived from Random Forest Gini importances as a central contribution, but this metric is known to be biased toward variables with greater variance or more categories; I recommend either (a) supplementing Gini importances with more robust approaches (e.g., permutation importance, SHAP values, or partial dependence plots) or, at minimum, explicitly acknowledging these limitations and tempering claims about precise “hierarchical” ordering of psychological constructs.

The design is observational and conducted in heterogeneous routine outpatient settings (community and university clinics across Canada), which is a strength for ecological validity but also introduces substantial treatment heterogeneity; the manuscript should describe and, if possible, statistically adjust for key treatment variables (e.g., number of sessions, therapist orientation, site, or baseline severity), or explicitly discuss how uncontrolled treatment variability may affect model performance and limit causal interpretation.

Authors revised and uploaded the document.

2. Revised

Editor’s decision after revisions: Accepted.

Editor in Chief’s decision: Accepted.