Predicting Prolonged Grief Disorder Severity: A Machine Learning Approach to Prediction and Interpretation Using the MARBLES Archive

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Abstract. Prolonged Grief Disorder (PGD) is a distressing response to bereavement, impacting approximately 10-20% of individuals [1, 2]. PGD is often associated with physical, social and functional impairments [3, 4]. Traditional approaches to identifying predictors for PGD have made significant progress. For example, a meta-analysis has shown that pre-existing depression is among the strongest predictors [5]. Machine learning can improve prediction performance by uncovering complex, non-linear relationships among predictors. When combined with explainable AI methods, machine learning also clarifies how specific features influence the predictions [6, 7].

Our primary objective is to explore the predictive power of several features related to PGD severity using machine learning and explainable AI. Compared with previous studies [6, 7], we use a larger dataset and a wider range of predictors, i.e., socio-demographic variables (e.g., age), loss characteristics (e.g., time since loss), concurrent psychological symptoms (e.g., depression), and cognitive-behavioural variables (e.g., avoidance). Specifically, we investigate (RQ1) the relative contribution of individual features, (RQ2) the direction and linearity of overall relationships of features and PGD severity, (RQ3) the direction and linearity of individual-level relationships of features and PGD severity, (RQ4) interaction effects, and (RQ5) the contributions of specific features to predictions of PGD severity for individual cases.

To achieve our goals, we employ a machine-learning approach using data from the MARBLES data archive. We handle missing data through multiple imputations and split the imputed datasets into training (70%) and testing (30%) sets. Three machine learning algorithms, Random Forest, eXtreme Gradient Boosting (XGBoost), and Support Vector Regression, are applied to build the prediction models. Hyperparameter tunings are performed via cross-validation and grid search to optimise predictive performance. Model evaluations are conducted using evaluation metrics (e.g., Root Mean Squared Error) to assess the prediction models and to select the best performance models. To interpret the prediction models, we use explainable AI techniques. We apply feature importance analysis, Partial Dependence Plots, Individual Conditional Expectation curves, and SHapley Additive exPlanations to assess feature contributions, relationship patterns, and feature interactions in predicting PGD severity. Local explanations are also generated for cases with the highest and lowest PGD severity.

Our preliminary analysis shows that XGBoost performed best in predicting PGD severity, with depressive avoidance behaviours as the top predictor. However, these findings are preliminary, as hyperparameter tuning has not yet been conducted, and the models have only been built on one of the five imputed datasets. The poster will present findings on feature importance, relationship patterns, interactions, and individualised predictions.

This study contributes to the growing field of machine learning in mental health by improving our understanding of the prediction of PGD severity and offering interpretable models for clinical practices.

Keywords: Prolonged Grief Disorder Prediction, Machine Learning, Explainable AI.

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