Predicting and understanding psychological well-being in Young Adult: new insight for digital health

Understanding the determinants of psychological well-being is crucial for promoting mental health, particularly within the evolving fields of digital health and precision mental health. However, research on well-being is often challenged by the need for clear definitions and valid measurement tools.

This study addresses these challenges by employing advanced Machine Learning (ML) techniques, including Random Forest Regression (RFR), Support Vector Regression (SVR), XGBoost (XGB), and Linear Regression (LR), to explore predictive features associated with psychological well-being in the HCP Young Adult cohort. By integrating feature importance analysis and explainable approaches such as SHapley Additive exPlanations (SHAP), we identified key predictors of psychological well-being, focusing on data from the Emotional Battery of the National Institute of Health (NIH) Toolbox.

RFR and LR demonstrated comparable performance, with RFR yielding a marginally lower mean absolute error (MAE) of 3.85 compared to LR's MAE of 3.86, while LR had a slightly higher R^2 value (0.48 vs. 0.47). SVR and XGB showed lower predictive power, with higher MAE values (5.3 and 5.5). Across most models, sadness, emotional support, and perceived stress consistently emerged as the top predictors of psychological well-being, with sadness being the most significant.

These findings have important implications for both research and clinical practice. By identifying the most influential predictors of psychological well-being, our work highlights the potential of ML models in informing targeted mental health interventions. In the context of cognitive science, this study contributes to understanding the interplay between emotional and cognitive processes, demonstrating how emotional states like sadness and perceived stress can influence overall well-being.

The integration of AI-driven approaches into clinical settings could enable the development of personalized treatment plans that are better aligned with individuals' unique psychological profiles. Furthermore, our results underscore the importance of addressing emotional factors in mental health strategies, suggesting that interventions focused on these areas may be particularly effective. Overall, this study enhances the application of cognitive science in precision mental health, supporting the broader use of ML techniques to improve mental health outcomes.