MULTIMODAL SCREENING & MANAGEMENT SYSTEM OF MENTAL WELLBEING IN LOW-RESOURCE SETTINGS

Abstract

In low-resource settings (LRS), psychological distress is rarely discussed in terms of clinical categories such as depression or anxiety. Instead, it is described in everyday terms such as tension, financial strain, sleep disturbance, family responsibilities, bodily discomfort, sadness and uncertainty. Therefore, standard screening with one questionnaire or data source might only identify a proportion of the underlying vulnerability. This thesis explores the integration of community evidence, statistical analysis, machine learning, natural-language processing, physiological signals and facial expressions, and culturally aware implementation strategies into a multimodal system for early screening and management of mental wellbeing in LRS.

The first phase was a community-based survey of 718 adults from ten purposefully selected low-resource rural and semi-rural sites in Uttarakhand and Uttar Pradesh, with respondents randomly selected within the study sites. The questionnaire consisted of 56 bilingual items and included socio-demographic, behavioural, lifestyle, health-related and contextual variables and the PHQ-9, GAD-7 and an open-ended response item. Descriptive analysis, psychometric evaluation, exploratory factor analysis, group comparisons and regression modelling were used to assess mental-health awareness, perception and related vulnerability. Seven items were used to construct a Mental Health Perception Index with acceptable internal consistency (Cronbach's $\alpha = 0.798$), sampling adequacy (KMO = 0.830) and a significant Bartlett's test. Awareness was mixed: 91.5% of respondents identified anxiety and 56.3% depression, but awareness of several other conditions was strikingly low. Although 61.1% considered doctor consultation important, only 4.9% reported an observed community healing practice, indicating a significant gap between favourable belief and actual help-seeking pathways.

Screening indicated that 38.44% of the sample (276 respondents) were at increased risk for either depression, anxiety or both. The greatest elevated-risk category was comorbid depression-anxiety risk (136 respondents, 18.94%) compared with depression risk alone (69 respondents, 9.61%) and anxiety risk alone (71 respondents, 9.89%). The correlation between PHQ-9 and GAD-7 scores was strong ($r = 0.776$), indicating a high symptom overlap. Depression and anxiety scores were significantly higher in female respondents. Robust regression models explained 43.7% of adjusted variance in PHQ-9 and 34.29% in GAD-7 scores. Income and sleep duration were consistently associated with lower symptom scores, while disturbed eating, junk-food intake, age, social discrimination, and perception-related variables were associated with greater symptom burden. The findings show that vulnerability in low resource communities is not restricted to symptoms but is spread across economic, behavioural, social and health-related domains.

We then built a machine-learning pipeline to classify respondents into normal and elevated mental-health-risk groups. Tabular-only , text-only , early fusion and probability level soft fusion architectures were evaluated for structured survey attributes and informal Hindi open-ended responses . The best performing model was a combined prediction model with 60% tabular and 40% textual predictions with accuracy of 0.875, balanced accuracy of 0.871, recall of 0.855, F1-score of 0.839, Matthews correlation coefficient of 0.737, ROC-AUC of 0.954 and average precision of 0.924. The structured variables contained the dominant

predictive signal, and the text analytics provided additional complementary information about lived experiences not fully captured by fixed-response items. The explainability with logistic coefficients, permutation importance and SHAP analysis showed that the tabular features accounted for approximately 81% of the predictive influence and the textual features for approximately 19%. Eating pattern, age, social connectedness, perception, income, gender, stressors, alcohol use, discrimination and open-ended responses were predictive features of influence.

The multimodal investigation was extended to alexithymia, where the limitations of self-report may be particularly limiting. Of 207 adults screened with the TAS-20, 24 were above the alexithymia cut-off. The experimental sample consisted of 16 matched controls and 16 volunteers with traits of alexithymia. Emotion was evoked by culturally relevant Navarasa video stimuli and data was collected using a portable 14-channel EEG device and facial-expression analysis. The fused EEG and facial-expression features were tested with eight machine-learning classifiers under the five-fold stratified cross-validation. The highest mean accuracy was achieved by the Random Forest (98.01 ± 1.19%) followed by Logistic Regression (97.65 ± 1.08%). These findings provide promising exploratory evidence that physiological and behavioural modalities can complement self-report, but the small sample size requires cautious interpretation and larger external validation.

Lastly, the empirical and computational results were integrated with field observations, open-response themes, technological interventions and feedback from sixteen experts from multiple disciplines. The resulting six-dimensional framework links mental-health literacy, stigma reduction, access and referral, early risk stratification, digital and multimodal decision support, and counselling, family support, rehabilitation and follow-up. The framework, with the help of a bilingual website, awareness resources and an analytical dashboard, makes room for technology to be understood as an explainable and ethically supervised bridge from unrecognised distress to human care, rather than an automated diagnostic authority. Thus, the thesis contributes to a context-sensitive computational pathway that moves beyond risk identification, but rather connects awareness, screening, interpretation and ongoing support in LRS.