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Examining the Effects of Static Personality Traits with Dynamic Affective and Emotional States on Depression Severity

Abdullah Ahmed[1], Jayroop Ramesh[2], Sandipan Ganguly[3], Raafat Aburukba[2], Assim Sagahyroon[2], and Fadi Aloul[2]

[1] Department of Electrical and Computer Engineering, University of Massachusetts Amherst, MA 01003 USA,
amahmed@umass.edu
[2] Department of Computer Science and Engineering, American University of Sharjah, SHJ 26666 UAE,
b00057412@aus.edu; raburukba@aus.edu; asagahyroon@aus.edu; faloul@aus.edu
[3] Independent Researcher based in Bengaluru, Karnataka, India, 560077,
sandipanganguly96@gmail.com

Abstract. Depression is a condition that impacts individuals by causing low mood and a diminished interest in usual activities, ultimately affecting their quality of life. The Experience Sampling Method (ESM) offers a valuable tool for examining the relationships among depression, personality traits, and emotional experiences in the context of daily behaviors and responses to stimuli. In this study, multivariable logistic regression was employed to investigate the link between i) emotions during ESM with depression and ii) pre-ESM characteristics. The characteristics considered encompassed the Big Five personality traits (BFI), Meaning in Life Questionnaire (MLQ), Self-Concept Scale (SCS), Self-Esteem Scale (SES), Positive and Negative Affect Scale (PANAS), as well as valence and arousal.
The participants (N=142) considered in this study had the following categories of depression: moderate and severe. We observe that prior to ESM, the low self-esteem (odds ratio [OR], 0.787; 95% confidence interval [CI] 0.693-0.895; $P = 0.001$) and during ESM the negative affect adjusted for prior covariates (OR, 1.077; 95% CI 1.052 to 1.103; $P = 0.003$) were more apparent in individuals with severe depression.

Keywords: depression, affective states, Big five, Personality, statistical analysis, stress

1 Introduction

Depression is a debilitating mental health condition, affecting approximately 280 million individuals globally. It is a multifaceted condition manifesting as persistent feelings of sadness, mood fluctuations, emotional dysregulation, and sleep disturbances to varying degrees across individuals [1]. Experience sampling method (ESM) is a method that involves collecting real-time, repeated assessments of individuals' thoughts, feelings, and behaviors in their daily lives [2]. ESM in conjunction with different scales has been administered by psychologists for longitudinal assessment of mental health [3]. Self-monitoring with ESM shows promise for negative emotion differentiation cognitive impairment recognition [4]. Self-reports undertaken on a momentary basis can be used to assess subjective experiences in free-living conditions to characterize people's dynamic and transient emotional patterns. Specifically, valence, arousal, and affect can vary daily and can be influenced by various stimuli such as events or interactions, internal reactions, and external actions [1]. Valence refers to the positive or negative quality of an emotional experience, arousal refers to the level of activation or energy associated with an emotion, and affect encompasses the range of emotions and moods that individuals experience [5]. By examining the joint association between depression, personality traits, and affective/emotional states, it becomes possible to understand the general etiology and comorbidity to identify at-risk individuals and tailor treatment. While the Big Five personality traits are not always reflective because personality is a complex phenomenon and susceptible to inter-individual variances, it is leveraged as prior information in an attempt to represent yet another factor that may contribute to depression.

With the rise of machine learning and automated approaches that recognize emotions and affective states in naturalistic environments [6][7], the integration of personality traits can allow for more precise individual predictions. The rationale motivating the development of such approaches is to assist in the monitoring and screening of mental well-being using wearable physiological measurements [8]. Typically, the algorithms predict valence, arousal and affect as dynamic output variables. Examining their correspondence with depression in the context of static personality traits can provide insights for enhancing the applicability of the algorithms in practical settings. This is desirable because predicting the onset or progression of depression directly is not always possible or fully reliable [9][10]. This is due to data scarcity in training [11], large inter-individual variances [12], and the multi-faceted nature of mental health [13].

In our study, we seek to examine the often elusive relationship between depression and individual personality traits recorded prior to ESM with the transient affective and emotional states recorded during ESM. The participants are predominantly depressed, i.e., moderate or severe, and offer a unique opportunity to study the distinctive stratification of disease severity and particularities of emotional regulation in daily naturalistic settings.

2 Materials and Methods

Data regarding 142 participants (64 males and 74 females between 18 to 31 years having a mean age of 21.5 years) was acquired and made accessible by [2] over five days. The participants provided written informed consent and the relevant ethical review board approved the study. Time and date of collection, as well as individual records of gender, age, current education status, race/ethnicity, were not preserved or followed a procedure at a participant level to achieve de-identification and ensure differential privacy.

Baseline metrics reported by participants prior to ESM events include the i) Big-Five Inventory (BFI) to examine personality traits (OCEAN: openness, conscientiousness, extraversion, agreeableness and neuroticism), with 44 items; ii) the Self-Esteem Scale (SES) to measure self-esteem levels, with 10 items; iii) the Self-Concept Scale (SCS) to examine independent and interdependent self-construal, with 30 items; iv) the Meaning in Life Questionnaire (MLQ), with 10 items; and v) the Positive and Negative Affect Scale (PANAS) to evaluate the participants' predicted emotional experiences in the upcoming week, with 10 items. The constituent items of PANAS, Positive Affect (PA) included *inspired*, *determined*, *attentive*, *active* and *alert* and Negative Affect (NA) included *upset*, *hostile*, *ashamed*, *nervous* and *afraid*. During ESM, participants were instructed at six random times throughout the day (with minimum 90-minute intervals) to complete a questionnaire to report their momentary psychological states about their experiences over the last 30 minutes (relative time to start answering the questionnaires). A total of 3,789 ESM events were recorded across 142 participants, where the number of events varied for each participant from 12 to 30. The outcome variable is depression status defined by the Beck Depression Inventory-II (BDI-II), administered prior to ESM, and classified as moderate or severe based on scores in the ranges $[20, 28]$ and $[29, 63]$ respectively. The psychological assessment metrics of interest to this study are emotional valence and arousal in addition to the PANAS. Each questionnaire item was associated with a 5-point Likert-scale. Further stratification is available [2] for attribution of each event to a) location (dormitory, classroom, department building etc.), b) people (self, classmates, teacher etc.) and c) activity (personal, interests etc.), but we do not consider them in this study. To distinguish between PANAS measures recorded prior to and during ESM, we refer to them as $\mathrm{PA_{prior}}/\mathrm{NA_{prior}}$, and $\mathrm{PA_{esm}}/\mathrm{NA_{esm}}$ respectively. The parametric Independent t-test and non-parametric Wilcoxon Rank Sum Test were conducted on the variable and outcome distributions, yielding significant differences between populations ($P < 0.05$) on both tests for BDI-II scores, conscientiousness, openness, extraversion, SES, $\mathrm{NA_{prior}}$, and $\mathrm{NA_{esm}}$. The variance inflation factor (VIF) method was applied to estimate the existence of multicollinearity among the input variables. This revealed low levels of correlation, as $1< VIF <2$ for all the variables. Multivariable logistic regression (MLR) is an extension to Logistic regression that finds the best-fit model to depict the correlation between the dependent variable (BDI-II Scores) and the independent variables. MLR was used to 1) examine the effect of each baseline psychological scale on the incidence of depression severity prior to ESM events, and 2) measure the association between depression and momentary affective and emotional states in daily life, adjusted for baseline metrics to avoid confounding influences on results.

3 Results and Discussion

The results are reported with odds ratios (ORs) and 95% confidence intervals (CIs). ORs represent the odds that the outcome variable (i.e., depression severity) will occur given the presence of a particular input, compared to the odds of the outcome variable occurring in the absence of this same input. In terms of interpretation, $OR = 1$, $OR \geq 1$, and $OR \leq 1$ indicate negligible impact on odds of outcome, higher odds of outcome, and lower odds of outcome respectively. CIs indicate the precision of the OR, with large CI intervals suggesting low precision and smaller CI intervals suggesting higher precision. In practice, CI is often used as a proxy for the presence of statistical significance, if the null value ($OR = 1$) is not overlapped by the interval. However, spanning the null value can still possibly indicate evidence for association if additional tests accept/reject the hypothesis. A P value of < 0.05 is considered statistically significant.

The MLR analysis on the variables prior to ESM in Table 1 shows that SES (OR, 0.787; 95% CI 0.693-0.895; $P = 0.001$) and $\mathrm{NA}_{\mathrm{prior}}$ (OR, 1.178; 95% CI 1.034-1.343; $P = 0.014$) were significantly associated with severe depression. No significant associations between the Big Five personality traits and depression were noted. MLR analysis on the variables during ESM adjusted for prior covariates in Table 1 shows that only $\mathrm{NA}_{\mathrm{esm}}$ (OR, 1.077; 95% CI 1.052 to 1.103; $P = 0.003$) was significantly associated with severe depression. No significant associations between valence-arousal, $\mathrm{PA}_{\mathrm{esm}}$, and depression were noted.

Table 1. ORs and 95% CIs for self-reported personality traits associated with depression.

Self-Reported Characteristics	**OR (95% CI)**	P
Openness	1.064 (0.882 to 1.284)	0.515
Conscientiousness	1.156 (0.966 to 1.383)	0.115
Extraversion	0.909 (0.745 to 1.111)	0.351
Agreeableness	1.084 (0.940 to 1.250)	0.267
Neuroticism	1.059 (0.903 to 1.244)	0.481
SES	0.787 (0.693 to 0.895)	0.001
MLQ	0.974 (0.913 to 1.039)	0.426
SCS-Independent	1.099 (0.520 to 2.323)	0.805
SCS-Interdependent	0.849 (0.444 to 1.621)	0.620

Our findings in Table 2 indicate both prior and ESM reported negative affect and SES is strongly associated with severe depression. In contrast, the other variables do not provide increased discernability between the two states of depression. This brings to light that individuals can be inclined toward the propensity of depression severity based on both static and dynamic traits.

Our work is in concordance with previous work where depression occurs with negative affect and decreased positive affect [14], negative affect increases with severity [15] and negative affect is likely connected to depressive symptoms due

Table 2. ORs and 95% CIs for self-reported affective states associated with depression.

Self-Reported Characteristics	**OR (95% CI)**	*P*
PA_{prior}	1.003 (0.846 to 1.188)	0.977
NA_{prior}	1.178 (1.034 to 1.343)	0.014
PA_{esm}	1.012 (0.984 to 1.041)	0.391
NA_{esm}	1.077 (1.052 to 1.103)	0.003
Valence	0.946 (0.845 to 1.059)	0.331
Arousal	1.024 (0.943 to 1.113)	0.573

to rumination [16]. Lower self-esteem has been observed as a marker for severity of depression in [17] and linked maladaptive perfectionism to major depression [18], however, the exact nature of their relationship remains inconclusive. Neuroticism has consistently proven to predispose certain individuals to negative thinking patterns and is often associated with depression [19]. Yet, this relationship is not evident from our results, which implies a causal one. Perhaps, neuroticism is similar across depressed populations and only emerges as an objective measure when compared against a healthy population. This should be assessed in future studies. Limitations in this study stem from not knowing if individuals were on anti-depressants, undergoing psychological counseling, or if their responses to the questionnaire were intentionally disingenuous due to the stigma around mental health. This is because psycho-therapeutic treatment elicit low to moderate effects in increasing positive affect and decreasing negative affect [20], which in turn might affect the strength of the observed associations.

Our work can inform the development and promote the incorporation of additional context in machine learning models that estimate affective and emotional states [6]. Additionally, our findings can help guide feature selection of future depression-oriented studies. Utilizing the found association between transient features (i.e. negative affect and self-esteem) and chronic psychopathologies (i.e. depression), lends to developing depression screening frameworks with quicker inference time frames. This has value in enabling continual unobtrusive monitoring and facilitating personalized treatment for stress management.

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