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Time-Series Signals of Affect and Neural Dynamics with Technology to Identify Depression Risk

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ABSTRACT

Despite extensive research documenting the impact of depression on basic human developmental parameters (employment, health, education, social roles, and overall quality of life), multiple individual and systemic barriers limit accessibility to clinical assistance among vulnerable populations. Research-backed digital interventions, such as smartphone applications, may serve as convenient and reliable tools for detecting and monitoring depressive symptoms and attenuate the increasing pressure on conventional mental health resources. This review evaluates the significance of key time-series signals of affect dynamics (average levels, granularity, variability, instability, inertia) and electroencephalographic (EEG) patterns (power spectrum of frequency bands, alpha asymmetry) in predicting critical transitions in depressive symptom severity. An evidence-based prototype for a smartphone application that can reliably integrate multivariate time-series signals of affect dynamics and neural oscillations is proposed, to prospectively anticipate and detect affective abnormalities with greater accuracy in individuals susceptible to depression.

Background

With modernization increasingly leading to a higher prevalence of psychiatric disorders (Shephard & Rode, 1996; Colla et al., 2006; Hidaka, 2012), and with depression being globally acknowledged as a leading cause of disability (World Health Organization, 2021), researchers worldwide have consistently been documenting the impact of depression on basic human developmental parameters such as employment and productivity (Lerner et al., 2004; Beck et al., 2011), health and well-being (Fawcett, 1993; Sobocki et al., 2006), education (Kessler, 2012; Quiroga et al., 2013), social roles (Wells et al., 1989; Ormel et al., 1993), and overall quality of life (Pyne et al., 1997; Hansson et al., 2002).

In one of the most widely-cited early records on the deleterious nature of depression, Wells et al. (1989), in their analysis of the functioning and well-being of over 11,000 outpatients, revealed that the low levels of quality of life metrics associated with depression were as debilitating as those of some of the major chronic medical conditions, including hypertension, diabetes, and arthritis. Using the Quality of Well-Being (QWB) scale, Pyne et al. (1997) corroborated these results by further investigating the link between the quality of life and symptom severity among depressed patients. The authors reiterated that an increase in depressive symptom severity correlates with reduced quality of life that can be compared to that of pathologically unwell patients.

Studying the life events and psychological profiles for over a hundred victims of suicide, a global epidemic accounting for more than 700,000 deaths annually (World Health Organization, 2021), Séguin et al. (2007) established the significant prevalence of mood disorders, especially depression, in 66% of the cases examined. Even though suicide is an outcome of diverse intricate interactions involving biological and environmental factors (Turecki et al., 2019), an in-depth meta-analysis on the relationship between mental health disorders and suicide indicated that 87.3% of the subjects exhibited at least one psychiatric diagnosis preceding suicide, with depression comprising the majority of those cases (Chachamovich et al., 2009).

Following the investigation of a large sample of depressed individuals over the course of ten years, an extensive study by Solomon et al. (2000) highlighted the progressive increase in the risk of recurrence of depression with each subsequent episode. Major depressive disorder (MDD) is often characterized by chronic cognitive, affective, and neurological impairment (Marvel & Paradiso, 2004; Davidson et al., 2009), with genetics further influencing the susceptibility of individuals to environmental stressors and risk factors of depression (Kendler et al., 2003; Otte et al., 2016).

Despite the increasing efficacy of the treatment options available for MDD, several individual and systemic barriers, such as treatment cost, a shortage of services and providers, time constraints, and social stigmatization, limit accessibility to clinical assistance, especially among socially and economically vulnerable populations (Shen et al., 2015; Marshall et al., 2019). However, digital mental health interventions such as smartphone applications may serve as a convenient, accessible, and cost-effective tool for detecting and monitoring depressive symptoms to extend clinical reach and attenuate the increasing pressure on conventional mental health resources (Newman et al., 2011; Marshall et al., 2019).

In this review, we investigate multivariate time-series signals of affect dynamics (affect levels, granularity, variability, instability, inertia) and electroencephalographic (EEG) patterns (power spectrum of frequency bands, alpha asymmetry) that may predict impending critical transitions along the continuum of depressive symptoms. Finally, we propose a prototype for a smartphone application that can integrate the temporal dynamics of these multivariate early warning signals to reliably anticipate and detect affective abnormalities in individuals susceptible to depression and encourage them to seek clinical assistance when necessary.

Affect Dynamics as Time-Series Signals of Depression

Multivariate time-series signals in individual-level affect dynamics have been frequently considered by researchers as defining characteristics of psychological disorders (Koval et al., 2013; Trull et al., 2015; Wichers et al., 2020). The dynamics of affect are typically referred to as the phenomena characterizing the variation in people's emotional states over time (see e.g., Kuppens, 2015). An individual's emotions typically vary to allow them to manage and maintain psychological equilibrium (Houben et al., 2015; Ellsworth & Scherer, 2003; Frijda et al., 1989). Multivariate time-series signals of emotions provide researchers the ability to measure how people may respond to events on an affective level across time and regulate psychological processes (Chow et al., 2005; Larsen, 2000).

Multiple studies have examined the dynamic components of affect through periodic sampling over time, typically referred to as either experience sampling methods (ESM) or ecological momentary assessment (EMA), to establish their relation to major depressive symptoms (e.g. Csikszentmihalyi & Larson, 1987; Ebner-Priemer & Trull, 2009, Crowe et al., 2019). Different features relating to the fluctuation and variation in individual-level temporal affect may provide invaluable data regarding etiology, symptom severity, or treatment response (Wright & Zimmerman, 2019). Moreover, these time-series signals may potentially help precipitate technological innovations in clinical care by providing a deep understanding of temporal dynamics among affect variables (Trull & Ebner-Priemer, 2009). In this section, we explore the roles of affective valence, granularity, and the three most common measures of affective dynamics—variability, instability, and inertia—in influencing transitions to and from depressive symptoms, as well as their utility in predicting these transitions.

Affective Valence

Disorders involving maladaptive emotional experiences, such as MDD (American Psychiatric Association, 2013), often signal incongruencies in the magnitude of negative affect (NA) or positive affect (PA) (Thompson et al., 2017). Various studies establish a link between affective valence and major depressive episodes, with dynamic patterns of negatively valenced emotions being more predictive of psychological dysfunction (Koval et al., 2012; Holmes et al., 2012; Gruber et al., 2013; Houben et al., 2015). Even though higher levels of NA are strongly associated with depression (aan het Rot et al., 2012; Minaeva et al., 2020), positive emotion variability and high levels of PA also play an incrementally critical role in psychological health (Csikszentmihalyi & Seligman, 2000; Gruber et al., 2013).

Additionally, existing research indicates that both negative and positive affect are important parameters in predicting relapse of depression (van Rijsbergen et al., 2012; de Jonge et al., 2017; Wichers et al., 2010) and treatment response (Wichers et al., 2012, Geschwind et al., 2011). A study conducted by Rucci et al. (2011) demonstrated that an increase in NA levels after remission from MDD was associated with a higher likelihood of relapse in remitted patients. Another study involving affect dynamics was able to predict potential relapse over five years in 172 remitted recurrently depressed outpatients, suggesting that the lack of effective regulation of negative and positive affect during emotional or stressful events could play a role in the return of depressive symptoms (van Rijsbergen et al., 2013).

Even though positive psychology and dynamics of positive emotions play an important role in psychological health, research by Houben et al. (2015) has suggested that the dynamics of NA have greater significance in influencing emotional well-being, implying that the correlation between affect dynamics and depressive symptoms is stronger for negative emotions compared with positive affect. Furthermore, Wichers et al. (2012) reported that increases in NA in response to everyday stressors can predict depressive episodes (Wichers et al., 2009; Wichers et al., 2007), but the ability to experience higher levels of PA in response to everyday rewards may build resilience against future depressive symptoms (Geschwind et al., 2011).

In all, anomalies in the levels of positive and negative affect may prospectively predict psychological dysfunction, with an increase in negatively valenced emotions during stressful events being more indicative of relapse in depressed patients, suggesting a link between affective valence and major depressive episodes.

Granularity

Emotional granularity, sometimes referred to as emotion differentiation, signifies an individual's ability to distinctly identify specific temporal affective states within the same valence (e.g., annoyance vs. anger, trust vs. admiration, or disgust vs. loathing) (see Tugade et al., 2004; Smidt and Suvak, 2015). Granularity may potentially play a critical role in the prevention and prediction of the detrimental effects of NA such as mental health disorders precipitated by psychosocial maladjustment and emotional dysregulation, including major depression, which is associated with diminished levels of granularity (Erbas et al., 2014; Smidt & Suvak, 2015; Starr et al., 2017).

Granularity is typically measured using an emotion differentiation index, known as the intra-class correlation (ICC), to estimate the temporal correlation between an individual's self-reported positively or negatively valenced affect levels for various emotions across measurements (Smidt & Suvak, 2015; Hoemann et al., 2021). A high ICC value indicates highly correlated temporal fluctuations between different emotions, which denotes a reduced ability to differentiate between similar emotions and, hence, signals low emotional granularity and poor mental health outcomes (e.g. Tugade et al., 2004; Kashdan et al., 2015). For instance, Erbas et al. (2014) used varied approaches across three correlational studies to demonstrate that lower granularity of NA corresponds to elevated levels of depressive symptoms, lower self-esteem, and increased neuroticism.

Research shows that high emotional granularity may also be a key intervention method in psychotherapy (e.g. van der Gucht et al., 2019; Widdershoven et al., 2019), as individuals with the ability to perceive nuanced distinctions between emotions are less vulnerable to the onset of depressive symptoms (Kashdan et al., 2015). In fact, Widdershoven et al. (2019) proposed that the granularity of NA may improve when individuals with MDD report on their emotional experiences several times a day through ESM/EMA methodologies, thus increasing overall emotional well-being.

In sum, depressive symptoms have been tied to lower levels of emotional granularity, or a diminished ability to differentiate between emotions of the same valence. Improved emotional well-being and a reduction in depressive symptoms have been associated with an increase in negative granularity, which can be further improved with heightened emotional awareness.

Variability

Affect variability may be referred to as a measure of the standard deviation (SD) or general dispersion of an individual's positive or negative affect levels, with higher levels of variability corresponding to greater deviations from mean affect levels (Houben et al., 2015; Koval et al., 2013). It is also often regarded as a temporally independent component of affect dynamics (Bosley et al., 2019) that indicates the range or amplitude of participants' emotional states over time (Houben et al., 2015).

Studies have shown that affect variability, or the intra-individual standard deviation of emotions over time can be reliably measured (Trull et al., 2008; Houben et al., 2015; Eaton & Funder, 2001) and is independent of overall affect levels (Eid & Diener, 1999; Chow et al., 2005; Gruber et al., 2013). Elevated variability was found to be linked to psychological maladaptation, as increased variability in NA was exhibited by participants with worsened depressive symptoms (Peeters et al., 2006; Gruber et al., 2013; Crowe et al., 2019). A study by Thompson et al. (2017) involving 35 subjects diagnosed with MDD also established the predictive value of elevated emotional variability (as measured by the Affective Lability Scale) in potentially detecting the severity of depressive symptoms. Additionally, an extensive study by Gruber et al. (2013) suggested that high levels of variability in positive emotions may also be maladaptive and lead to deteriorating psychological well-being, including increased depressive symptoms.

Taken together, some of the major studies investigating affective variability (e.g. Peeters et al., 2006; Gruber et al., 2013) have suggested that, regardless of overall affect levels, greater emotional variability may be associated with greater depressive symptom severity, indicating that extreme highs and lows of both positive and negative emotions may be detrimental to an individual's psychological health.

Instability

Affective instability is another aspect of temporal dynamics that refers to the magnitude of moment-to-moment fluctuations in affect over time (Jahng et al., 2008; Koval et al., 2013; Trull et al., 2015). It may be characterized by several defining elements, such as recurring affective shifts, perturbations in affect intensity, accelerated emotion rise times, and delayed return to baseline, as well as sudden and extreme reactivity to psychosocial stimuli with overdramatic affective expression (Koenigsberg, 2010; Marwaha et al., 2014).

The mean square successive difference (MSSD) is considered a reliable measure of affective instability that takes into account both the variability and temporal dependency components of point-to-point shifts in emotions (Jahng et al., 2008; Koval et al., 2013), in contrast to the emotional variability, or standard deviation over time, which captures the magnitude but not the temporal dependency (Jahng et al., 2008). A high MSSD represents greater moment-to-moment fluctuations in affect, or emotional instability.

Several studies quantifying instability by measuring MSSD have associated greater affective instability with depression (e.g., Thompson et al., 2012; Schwerdtfeger & Friedrich-Mai, 2009; Koval et al., 2013). A study by Hallensleben et al. (2018) suggested the high clinical relevance of the association between instability and depression by finding a potential link between instability (measured as MSSD) and suicidal ideation. The experiment involving twenty depressed inpatients with current/lifetime suicidal ideation found MSSD values to range from 0.2 to 21.7, affirming the dynamic nature of depressive symptoms in psychiatric patients.

In another study, Thompson and colleagues (2012) examined individuals with MDD and found that depressed participants reported greater MSSD scores in NA compared to their healthy peers, highlighting the importance of emotional instability as one of the core features of depression. Thompson et al. (2012) also proposed that the correlates of emotional instability, such as interpersonal impairment and emotion dysregulation, may be further responsible for the link between MDD and emotional instability.

In summary, with MSSD being able to quantify the frequent and acute fluctuations in affect over time, emotional instability may serve as a reliable indicator of depression that integrates both the extremity and the temporal dynamics of affective response.

Inertia

Finally, we review affective inertia, another crucial time-series signal measured by first-order autocorrelation or the autoregression coefficient (AR). It is one of the key metrics of affect dynamics that reflects the temporal dependency of emotions, specifically their resistance to change, and refers to the degree to which affect self-perpetuates over time (Koval et al., 2013; Trull et al., 2015; Bosley et al., 2019). Inertia is often expressed as the lag-1 autocorrelation of affect, which measures the extent to which a person's current emotional state as observed at time *t* is predicted by their emotional state at the previous observation (*t*-1) (Kuppens et al., 2012; Bosley et al., 2019). Higher autocorrelation is indicative of emotions that show less homeostatic recovery and are self-predictive over time with current affective states being impacted considerably by previous emotions (Kuppens et al., 2012; Houben et al., 2015).

Low levels of affect inertia correspond to a more flexible and resilient emotional state that is responsive to an individual's psychological needs and promotes greater emotional well-being, whereas high inertia signals a slowing down of emotional experiences, which is characterized by psychological maladjustment, and is often accompanied by the phenomenon of "critical slowing down" that may prospectively predict the onset of major depressive disorder (van de Leemput et al., 2014).

In the experiments conducted by van de Leemput et al. (2014), the time-series of four emotions (cheerful, content, sad, and anxious) across 535 individuals from the general population and 93 depressed patients were analyzed. The subjects were prompted to fill out the ESM self-assessment forms including emotion scores on seven-point Likert scales. To analyze autocorrelation, each emotion was examined independently for emotion scores at time *t*-1 to predict scores at time *t*. The autoregression coefficient was found to be significantly higher for NA in individuals with an impending worsening of depressive symptoms, and greater for PA in depressed patients transitioning toward recovery, indicating a decline in resilience in the vicinity of a tipping point, where even a slight disruption in emotions may precipitate a dramatic transition.

Additionally, in a study done by Kuppens et al. (2010), the emotional inertia of an adolescent sample (n=141) was examined at the level of seconds during lab-based interactions with their parents. These family interactions provided an appropriate experimental environment for observing affective dynamics through multiple tasks to obtain data relating to differential levels of positive and negative affect. The results demonstrated that participants with depressive symptomatology displayed significantly higher levels of emotional inertia, providing evidence for the association between clinical depression and increased autocorrelation in recorded affective behavior during the experiments.

In general, elevated levels of affect inertia have been linked with greater severity of depressive symptoms, with the correlation significantly stronger for the inertia of NA. However, studies investigating the significance of inertia in predicting remittance from depressive symptoms have proposed that higher inertia of PA may also potentially predict patients' transition toward recovery.

Connections Between Time-Series Signals

As inertia refers to slower recovery from perturbations and greater resistance to affective change, some may infer that high inertia indicates low instability and variability. However, this is not necessarily the fitting interpretation for past findings, where the onset of MDD is characterized by the presence of early warning signals such as increased affect variability, elevated instability, and significantly higher levels of inertia (e.g. Houben et al., 2015; Scheffer et al., 2009; Koval et al., 2013; Jahng et al., 2008).

Even though each of these time-series variables of affect dynamics is often analyzed in isolation, the following mathematical equation derived by Jahng et al. (2008) considers the interrelationships of these measures by showing how they may be tied to each other (Jahng et al., 2008; Koval et al., 2013; Bos et al., 2019):

$$MSSD = 2 * SD^2(1 - AR)$$

The above interdependency among these core indicators of depressive affect may also be used to explain anomalies where for constant measures of recorded variability (SD), an increase in instability (MSSD) may be observed with decreasing levels of inertia (AR) (Houben et al., 2015).

In conclusion, even though mixed findings in the literature on MDD may at times suggest the lack of specificity in patterns of affective fluctuations, it has been well-established that depression is closely related to the mechanism of affect dynamics and its associated dysfunction. Reduced granularity, higher levels of NA, and elevated variability, instability, and inertia all contribute to the risk of greater symptom severity and relapse of major depressive episodes. Therefore, while designing a prototype for a robust, research-based mental health app for the early detection of depression, developers may reliably integrate measures of these time-series affect variables to provide individuals, including clinical professionals, with valuable insight to anticipate impending transitions to and from depressive states.

Neural Oscillations as Biomarkers of Depression

Although the diagnosis of core MDD symptoms primarily relies on subjective assessments and self-reported appraisals, such as the ESM/EMA methods (e.g., Crowe et al., 2019), electroencephalographic (EEG) analysis of neural affective states may be a more quantitative and objective psychological indicator of major depressive episodes (Hosseinifard et al., 2013; Newson & Thiagarajan, 2019). EEG is a non-invasive and relatively cost-effective electrical neuroimaging method of recording and processing minute voltage oscillations of neural synaptic activity (Acharya et al., 2018). Portable and user-friendly consumer EEG headsets, with a high temporal resolution to track neuropsychological affect dynamics on a millisecond time scale, can be used as an efficient tool for both the early diagnosis and prognosis of MDD (Mahato & Paul, 2019; McLoughlin et al., 2014; Mumtaz et al., 2015). In this section, we review two key prospective neurodiagnostic time series signals of MDD: EEG power spectrum of frequency bands and EEG frontal alpha asymmetry.

EEG Power Spectrum of Frequency Bands

The EEG power spectrum of frequency bands represents the power distribution of EEG signals over neural oscillating frequency domains, which may be used in analyzing and quantifying EEG signals to assess abnormalities in the cortical activity of individuals with MDD (Mumtaz et al., 2017; Newson & Thiagarajan, 2019). Neural oscillations are classified into categories based on their frequency and are typically associated with different cognitive states, such as active (gamma, γ, 30-100 Hz), alert (beta, β, 12–30 Hz), relaxed (alpha, α, 8-12 Hz), meditative (theta, θ, 4-8 Hz), and sleep (delta, δ, 0.5-4 Hz) (Kaiser et al., 2005; Hammond, 2011).

Extensive neuropsychological research reports a multitude of diverse findings concerning EEG frequency bands as a potential biomarker of MDD (e.g. McLoughlin et al., 2014; Mumtaz et al., 2017; Newson & Thiagarajan, 2019; Mahato & Paul, 2019), largely due to the heterogeneous nature of the methodologies involved. This included recording regional cortical activity during a) resting state with eyes open or closed (Grin-Yatsenko et al., 2009; Jaworska et al., 2012), b) memory tasks with encoding, maintenance, and retrieval phases (Segrave et al., 2010; Murphy et al., 2019; Kane et al., 2019), c) emotional stimuli exercises including affective valence identification (Siegle et al., 2010; Martin et al., 2019), and d) phonological and semantic linguistic studies (Spironelli et al., 2020), to name a few. However, one of the most consistent findings in the neuropsychiatric literature points to the association of an increase in the severity of depressive symptoms with elevated levels of alpha power during resting state (Henriques & Davidson, 1991; Segrave et al., 2010; Jaworska et al., 2012; Hosseinifard et al., 2013), as well as considerable evidence also suggesting the significance of beta band power as a favorable indicator of depressive disorders (Knott et al., 2001; Flor-Henry et al., 2004; Grin-Yatsenko et al., 2010).

Multiple studies have established EEG frequencies as significant indices of abnormal neural activity in MDD patients (e.g. Knott et al., 2001; Spironelli et al., 2020). One such study, evaluating neural oscillatory frequencies in MDD participants, discovered the presence of higher occipital upper alpha power along with hypoactivity of frontal midline theta power during the encoding phase of a working memory task, and although the performance between the depressed individuals and controls was deemed comparable, a substantial decrease in the levels of upper alpha and occipital gamma power during the maintenance phase was also found indicative of major depression (Murphy et al., 2019; Greco et al., 2021).

Neuropsychiatric EEG studies, investigating affective valence by inducing positive or negative stimuli, have strengthened the premise that the spectral power of frequency bands can be considered a promising biomarker of MDD. For example, the results of an elaborative affect study by Martin et al. (2019) that employed an emotional word valence identification task corroborated the empirical findings of Siegle et al. (2010), and reiterated a sustained augmentation in evoked gamma band activity in response to affectively valenced words, especially to negative stimuli, in the MDD group.

In all, the hypothesis that depression may be characterized by altered oscillatory activity of frequency bands has been substantiated by empirical observations of neural dynamics, including greater alpha power at resting state, augmented gamma activity in response to emotional stimuli, and reduced frontal theta levels during cognitive memory tasks, establishing spectral power of frequency bands as a prospective biomarker of MDD.

EEG Frontal Alpha Asymmetry

One of the most widely accepted EEG findings in neuropsychological MDD research is the utility of EEG frontal alpha asymmetry as a promising diagnostic tool for depression (e.g. Henriques & Davidson, 1991; Fingelkurts et al., 2006; Smit et al., 2007; Greco et al., 2021). This measure refers to the difference between left and right hemispheric alpha activity over the frontal cortical region (van der Vinne, 2017) and is typically represented by a frontal asymmetry index/score, which is calculated as $\ln(\alpha_{right}) - \ln(\alpha_{left})$ for each homologous pair of electrodes, where $\ln(\alpha_{right})$ and $\ln(\alpha_{left})$ represent the transformed natural logarithms of frontal right and left alpha power, respectively (Coan & Allen, 2004).

Numerous studies have recognized the role of hemispheric EEG activities in neural affect processing, with increased left hemispheric activity influencing levels of positive affect and greater right hemispheric activity responsible for impacting negative affect (e.g. Tomarken et al., 1990; Ahern and Schwartz, 1985; Thibodeau et al., 2006). In addition, due to the fact that an increase in EEG alpha power during resting state and a corresponding decrease during an alert state has been consistently observed (see Barry et al., 2007), the existing literature has corroborated the finding that EEG alpha power is inversely related to regional cortical activation (e.g. Davidson, 1988; Thibodeau et al., 2006).

Converging evidence from EEG frontal alpha asymmetry research has established that distinct interhemispheric activity in anterior neural regions, with greater NA associated with right frontal hyperactivation (or lower alpha power) (Tomarken et al., 1990; Thibodeau et al., 2006; Mumtaz et al., 2017) and reduced PA due to left frontal hypoactivation (or higher alpha power) (Ahern & Schwartz, 1985; Henriques & Davidson, 1991; Gotlib, 1998), has been found to be predictive of the onset and subsequent development of major depressive episodes.

A comprehensive meta-analysis by Thibodeau et al. (2006) supports the outcomes of a multitude of EEG studies that link depressive symptomatology to right lateralization of frontal hemispheric asymmetry, including one of the earliest studies by Schaffer et al. (1983) where participants who scored high on the Beck Depression Inventory (Beck et al., 1961) showed substantially lower alpha asymmetry scores, corresponding to relative right frontal hyperactivation as compared to participants with low self-reported depressed mood. Additionally, numerous interhemispheric asymmetry studies have revealed that left frontal hypoactivation may also predict the susceptibility to developing MDD due to increased vulnerability to negative affect, thereby corroborating the findings of Christianson et al. (1993), which demonstrated that reduced left hemispheric activity induced a negative affect state in subjects (e.g. Gotlib, 1998; Greco et al., 2021).

Collectively, with EEG alpha power inversely related to regional cortical activation, frontal interhemispheric abnormalities in the alpha band, such as high left alpha power resulting in left hypoactivation and reduced PA, or low right alpha power leading to right hyperactivation and increased NA, serve as potentially reliable biomarkers in depression, establishing the empirical significance of EEG frontal alpha asymmetry in neurodiagnostic MDD research.

To conclude, effective communication between indirect measurement of human brain activity and a smartphone application may be established using EEG-based Brain-Computer Interface (BCI), where neural oscillations can be converted into digital signals and analyzed to detect the power spectrum density of each hemispheric region to quantify levels of affect and their prospective impact on depressive symptoms (Gu et al., 2021). With mounting evidence for the utility of EEG power spectrum of frequency bands and EEG frontal alpha asymmetry in tracking neuropsychological affect dynamics, cost-effective EEG headsets may be used as an efficient tool in the design of a prototype for a smartphone-based digital intervention for both the early diagnosis and prognosis of MDD.

Digital Health Interventions for Depression

Despite the efficacy of various evidence-based psychological treatments such as cognitive behavioral therapy (CBT) (Fava et al., 1998; Oud et al., 2019) and mindfulness-based cognitive therapy (MBCT) (Kuyken et al., 2016; Segal et al., 2018) in addressing depression and preventing recurrent episodes, inadequate access to these treatment options in vulnerable and socioeconomically disadvantaged populations has been often attributed to geographic barriers, excessive treatment cost, deficiency of services and providers, poor mental health literacy, and time constraints, as well as cultural and societal stigmatization (Shen et al., 2015; Marshall et al., 2019). With approximately 6.6 billion smartphone users globally (Statista, 2020) and over 10,000 mental health apps available in various app stores (Torous et al., 2018), an evidence-based approach for the digital intervention and monitoring of depressogenic symptoms shows promise in confronting these major prohibitive obstacles (Shen et al., 2015; Garrido et al., 2019). Devising key strategies, such as involving input from the general population as well as mental health experts, in the design and development of smartphone apps may further help overcome these barriers and prioritize inclusion, leading to greater acceptance and endorsement by diverse cohorts of participants across the literacy, socio-economic, and adult age spectrums, especially disadvantaged and geriatric populations (Mummah et al., 2016; Ross et al., 2016; Carswell et al., 2018).

A Synopsis of Current Digital Mental Health Interventions

Studies and meta-analyses reviewing evidence-based digital psychiatric interventions have demonstrated the efficiency of self-help applications and online programs in extending clinical reach and reducing under-detection of MDD due to insufficient routine screening (e.g., Fleming et al., 2018). Additionally, owing to their increased user engagement and retention rates, several digital cognitive behavioral therapy (CBT) based apps, such as Happify and MoodMission, have also been reported to predict greater mental well-being and resilience in depressed individuals (Parks et al., 2018; Bakker & Rickard, 2019).

However, there have been serious concerns regarding the subclinical research methodologies and lack of adequate empirical evaluation used in the development of the majority of psychiatric digital interventions (Marshall et al., 2019; Torous et al., 2018). Various web-based digital intervention programs with complex and rigid interfaces featuring linear and didactic courses requiring extended engagement times (Mohr et al., 2017) may be ineffective in promoting mental health due to reduced adherence and higher attrition rates, such as the well-known CBT program MoodGYM, whose adherence rate has been reported to fall under 10% despite its free accessibility (Twomey & O'Reilly, 2017). Furthermore, one independent science-based review system has observed a few other notable mental health programs, such as Beating the Blues and Good Days Ahead, to offer linear, time-intensive, and minimally interactive courses that restrict users from focusing on activities that are important to them and skipping ones that are not, often resulting in diminished engagement rates (One Mind PsyberGuide, 2016).

When assessing digital mental health interventions, the American Psychiatric Association (APA) has outlined an app rating framework that includes guidelines such as reviewing (1) background information, including ownership, credibility, funding source, conflict of interest, or hidden costs; (2) risk, privacy, and data security; (3) clinical efficacy and evidence; (4) ease of use and customization; and (5) data integration and sharing (Neary & Schueller, 2018; Torous et al., 2018; American Psychiatric Association, 2022).

Byambasuren et al. (2020) highlighted some of the perceived obstacles to the widespread applicability of mental health apps as potential self-management tools, which include a generational disparity in digital aptitude, as well as concerns about privacy, safety, and trustworthiness of health apps. These guidelines and challenges may aid in influencing design, features, and strategies to prioritize ease of use, efficacy, privacy, scientific evidence, and security while developing an advanced research-backed digital intervention app.

Proposal for a Smartphone Application for the Screening and Monitoring of Depression

Signals of Importance

In this review, we have investigated the significance of multivariate time-series signals of affect dynamics and neural oscillations that may play a decisive role in the proposal of a prototype for a smartphone application to anticipate impending critical depressive transitions in vulnerable users.

Affect Dynamics

While outlining a prototype for a research-backed app for the early detection of depression, key time-series signals of affect dynamics, may provide valuable insight into the diagnostic and prognostic symptomatology of depressive episodes (see Affect Dynamics as Time-Series Signals of Depression). Increased levels of NA and low emotional granularity (high ICC) along with elevated measures of affective inertia (AR), instability (MSSD), and variability (SD) of NA may all serve as key parameters in the calculation of affect dynamics metrics of the prospective app configuration. With mounting scientific evidence substantiating the association between self-reported affect dynamics and psychological health, developing an automated computational approach using time-series signals for a smartphone application may effectively predict the onset and relapse in MDD symptomatology.

Neural Oscillations

Furthermore, developing technology pertinent to a more accurate screening algorithm for depression may be achieved by implementing techniques to derive EEG-based real-time affective digital data and eliminate retrospective, clinician, and personal biases associated with clinical or self-reported affect responses (McLoughlin et al., 2014; Yan et al., 2019; see Neural Oscillations as Biomarkers of Depression). Using cost-effective EEG headsets with a high temporal resolution, such as the reliably accurate Emotiv headsets (Debener et al., 2012; Badcock et al., 2013; Melek et al., 2020), EEG frequency bands and frontal alpha asymmetry metrics can aid in a more objective evaluation of neuropsychological affect dynamics, leading to even greater predictive value for the onset of MDD and the potential for personalizing digital interventions for individuals.

Suggested App-Based Intervention Protocol

Through frequent periodic ambulatory assessment methods of determining affective states of individuals in their naturalistic settings, the proposed app may ensure a more reliable and objective data collection process (e.g. Trull & Ebner-Priemer, 2013). Implementing a rolling window approach, both the self-report assessments and EEG headset may be used as tools to generate clinically relevant data and analyze temporally significant variables of affect to predict changes in depressive symptom severity (Curtiss et al., 2021).

With security procedures in place to address potential privacy and data safety risks, the user may be prompted to create an account during the initial interaction with the app. Once the identity or log-in credentials are validated, the user may be led to a brief evidence-based preliminary screening questionnaire to gauge individuals' initial risk and symptom severity of depression. From there onwards, each time participants log in, they may be asked to rate the experienced intensity of their perceived emotions from a pre-vetted list of specific emotions using a numerical slider widget (Figure 1). Additionally, they may also be provided with the option to wear an EEG headset for a specific duration at a relaxed or resting state for the app to detect and verify affective valence levels using EEG-based affective computing. The record of these intra-individual affect data over time may be presented to the user in an intelligible visual format through graphs and charts with a brief psychoeducational text explaining the scientific relevance of the statistic to help the user evaluate their progress.

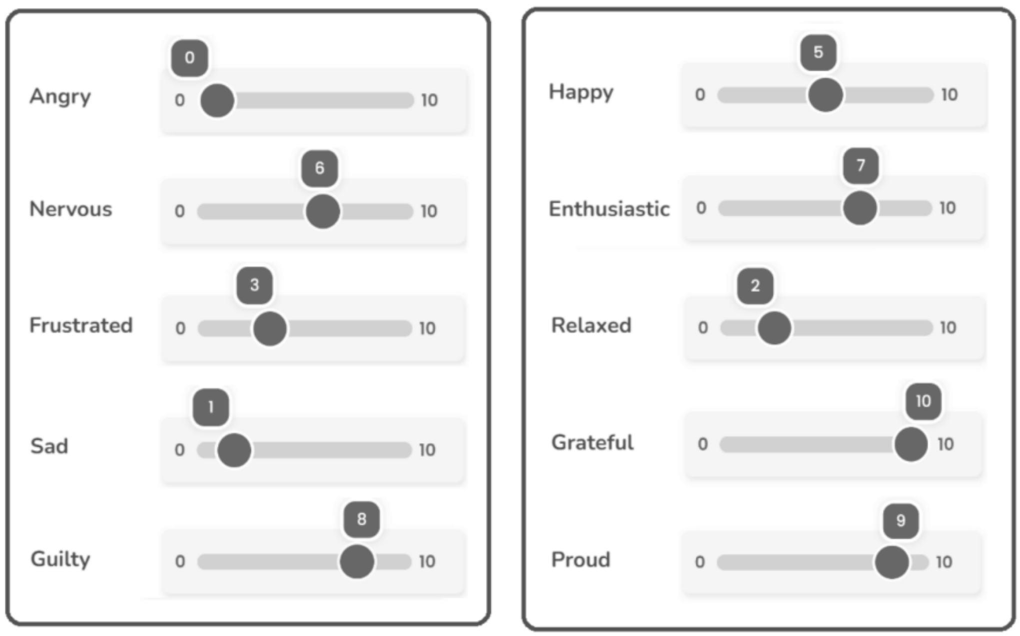

Figure 1. Levels of specific positive and negative affect states may be analyzed to assess participants' susceptibility to depressogenic risk factors and calculate multivariate time-series signals of affect dynamics (Kullar et al., 2023).

Based on factors such as the initial assessment and observed affective states, users may be encouraged to complete certain guided tasks and exercises designed to enhance their cognitive abilities, positive affect, emotional granularity, and overall engagement in order to improve their psychological well-being. These short and interactive exercises may be designed as intriguing activities and games to incorporate a combination of evidence-based therapeutic approaches, including humanistic and psychodynamic therapies, as well as other mediating strategies such as CBT and MBCT, to target negative affect, low self-esteem, obsessive rumination, stress, and depression in general (Leichsenring et al., 2018).

Once the objectives of these brief activities are met, the user may earn rewards and advance to higher levels. In addition, they may also track their progress, receive tips to further boost their cognitive and problem-solving abilities, and find help to overcome obstacles. To reflect on the impact of these therapy-based activities and exercises on their affective states, the users are asked again to rate the experienced intensity of their perceived emotions from the list. Participants wearing EEG devices at the completion of their task may be able to provide more accurate data regarding their affective states. High levels of PA resulting from rewards earned during the task may predict the user's emotional well-being and resilience against future depressive symptoms, whereas an ensuing pattern of increased NA, as well as other time-series signals of affect dynamics, may yield critical data signaling psychological dysfunction, suggesting the need for clinical intervention. Furthermore, guided by the data sharing objectives set by the APA framework, the app may also allow its data to be integrated with patients' electronic medical records, as well as other digital applications, such as Apple Health and Google Fit. Finally, this comprehensive data may then be shared with clinical providers for additional insight into the user's depression prognosis and overall psychological well-being.

Discussion

In this final section, we discuss essential ethical issues involved in the design and development of the proposed app prototype, as well as concerns relating to the efficacy of existing mental health applications and limitations regarding the scope of the prospective app. Finally, we conclude this review by evaluating the potential benefits of the suggested digital intervention over currently available solutions.

Ethical Concerns

Privacy is often considered a subjective construct that varies with participants' individual psychodynamic and socio-demographic perspectives. However, breach of privacy due to collecting and sharing of confidential analytical data related to sensitive personal health information may potentially involve physical, psychological, legal, social, and economic risks, including users' social profiling, tracking, or even loss of insurability (American Psychiatric Association, 2022). The Health Insurance Portability and Accountability Act of 1996 (HIPAA) equips patients with federal protection against the violation of safety, security, and privacy of their personal health information (ASPE, 1996). Therefore, it is critical to integrate key security features in the architecture and design of the proposed mental health app with audit and accountability, information integrity, and scalable encryption capabilities as primary data security objectives.

In addition, the app may need to strike an optimal balance between sensitive data acquisition and invasion of privacy by providing an unambiguous and transparent privacy policy and disclosing the extent of data use and its purpose when shared with clinical professionals and trusted third-party vendors. Furthermore, the provision to opt out of data collection, discontinue participation, and erase data from the application must be offered to ensure minimal risk to users' privacy and security. Moreover, all funding sources and conflicts of interest must be declared by app developers in order to maintain transparency and accountability.

Finally, complex matters such as responding to concerns of users' safety and well being (e.g. suicidal ideation), may be potentially addressed through customizable app configurations to alert the psychiatrist or mental health clinician in case of an emergency.

Limitations

With digital technology unfolding at a dramatic pace, it is important to identify some major challenges in the design of an effective digital mental health intervention. A key concern with all apps implementing self-report assessments is to recognize factors that influence the validity and usability of acquired data. Memory bias may be introduced in preliminary screening questionnaires, commonly developed on the basis of the Patient Health Questionnaire (PHQ-9), where app users are required to report their experiences retrospectively (e.g. over the last two weeks). Such recall effects along with other personal biases arising due to current state of mood, physiological stress on regulatory mechanisms (e.g. hunger, fatigue, aches), or other circumstantial elements may likely cause significant discrepancies in the outcomes reported by the app (see Burchert et al., 2021).

To overcome these limitations, the proposed app prototype aims to achieve a more accurate depression screening algorithm by implementing features and prospective technology to acquire EEG-based real-time affective digital data in conjunction with statistical inputs from time-series signals of affect dynamics.

Additionally, with the proposed app's suggested protocol recommending the use of EEG wearable devices to attain more conclusive results, a substantial section of the vulnerable population may find it difficult to access or afford reliable EEG headsets. However, as emerging neuropsychological EEG technology evolves even further and adequate published scientific research endorses its credibility, relevant government agencies and healthcare systems, including insurance networks, may deem it necessary to reimburse the cost of eligible EEG equipment essential for predicting and monitoring MDD.

Closing Remarks

High depressive symptom severity has been considered as debilitating as some of the major chronic medical conditions (e.g., Wells et al., 1989), and with each successive episode leading to a progressive increase in the risk of recurrence (e.g., Solomon et al., 2000), evidence-based digital psychiatric interventions may be viewed as an excellent tool in attenuating the under-detection and under-management of MDD. However, an apparent uncontrolled proliferation of mental health apps in the market points to the evidence of suboptimal research methods being employed in the development of the majority of these interventions.

This review proposed a science-backed digital intervention prototype that potentially applies EEG-based technology to assess real-time affective neural oscillation data, while concurrently evaluating temporal changes in the multivariate signals of affect dynamics to synthesize a comprehensive psychometric screening process for identifying and monitoring depression risk. The proposed app's framework to implement robust data security architecture, while still allowing the user's data to be shared with clinical providers and other trusted digital applications, may ensure valuable insight into the participant's depressive symptoms and their overall psychological health. Ultimately, prioritizing user-friendliness to address concerns of gaps in digital proficiency, knowledge, and time commitment required to learn and use the app, as well as inviting input from end users, academic institutions, and mental health experts, may lead to a more productive and efficient design of the prospective application in order to effectively confront mental health disparities in our society.

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