A commentary on the potential of smartphones and other wearable devices to be used in the identification and monitoring of mental illness

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Introduction

Background

Wearable devices (such as smartphones, smartwatches, activity trackers, and goniometers) have gained widespread traction on a planetary scale, with an estimated 5 billion users of smartphones alone worldwide in 2019 (1). These devices can unobtrusively and continuously collect objective and quantifiable data from their user about physical activity (using metrics such as step count, calorie expenditure, and distance travelled), physiological signs (such as heart rate and heart rate variability), and behavioural patterns (using trends in smartphone use). In health care, current uses of wearable devices have been focussed on collecting vital signs, with wearable devices acting as electrocardiograms (such as the Holter monitor and its derivations) and glucose monitoring systems (through the electrochemical analysis of sweat in patients with diabetes mellitus) (2,3). Recently, research interest in wearable devices has expanded towards mental health outcomes—a field that has historically lacked quantifiable biological indicators of health.

Mental health is a key indicator of overall wellbeing but is unfortunately the leading cause of disability worldwide. Common mental illnesses including depression, anxiety disorders (e.g., generalised anxiety disorder, social anxiety disorder and panic disorder), obsessive-compulsive disorder (OCD) and post-traumatic stress disorder (PTSD) are experienced by approximately 8% of world's population (4). These can manifest physically (such as with panic attacks, restlessness, sleep changes, weight changes), psychologically (such as with excessive fear, catastrophizing, thoughts of worthlessness and hopelessness) and behavioural symptoms (such as with withdrawal from social situations, difficulty concentrating) (5). The projected cost of anxiety and depression alone is expected reach approximately $147 billion by 2030 (4). This trajectory emphasises the importance of effective identification and monitoring of mental illness.

The early identification and monitoring of mental illness is difficult. In the 2007 National Survey of Mental Health and Wellbeing in Australia, the estimated population treatment rate for people with mental disorders was only 35% (4), with most of this deficit being attributed to people not being willing to seek health care resources for their mental disorder. This prevents the early identification of and timely intervention against mental disorders before deterioration. Individuals that do present to health services to undertake mental health assessments often do so once symptoms become severe, when intervention is substantially less effective (6). Furthermore, the identification of symptoms typically relies on clinician-reported or patient-reported assessment measures such as the Patient Health Questionnaire, Hamilton Rating Scale for Depression, and Hamilton Anxiety Rating Scale. These forms of assessment are limited by their heavy reliance on recall, constituting a source of bias. In addition, questionnaires are administered at sporadic timepoints, failing to capture continuous and ongoing changes in symptomology (7). Given the gravity of mental illness, and its potential contribution to impairment, disability and mortality, there is an urgent demand to enhance clinicians' capacity to recognise and monitor patient symptoms, as well as identify individual indicators of relapse (8).

Smartphones and other wearable devices (such as the Fitbit, Oura Ring, and Garmin watch) may enhance the early identification and monitoring of mental disorders by providing data associated with a patient's mental health. These data can include device use time, social interaction via messaging services, voice data (speech rate and tone), environmental factors (such as ambient light exposure and weather), contextual data (such as number of phone calls) and global positioning system (GPS) traces (9). Together, these metrics form the "digital phenotype" of the individual, which refers to the behaviour and characteristics of an individual as inferred by their interaction with digital devices (10). Moreover, contrary to traditional single timepoint based assessments such as patient-reported outcomes, wearable-based metrics can be collected continuously (for as long as the device is worn), allowing dynamic changes in disease status over time to be captured (11-13). Although currently not directly corresponding with diagnosable mental illnesses identified in the *Diagnostic and Statistical Manual of Mental Disorders*, *Fifth Edition* and although digital phenotyping may be redundant in some cases due to the diagnosis being obvious, a deterioration in these metrics may enable the early identification of mental illness and the progression of these metrics may correspond with disease severity. Furthermore, individuals who are at risk of mental illness such as those with previous mental illness could be monitored allowing for the early identification of disease onset or relapse (14). For instance, GPS data such as changes in location, percentage of time at home, and consistency of movement over a 24-hour period were associated with severity of depression and anxiety symptomology (15). In addition, decreased smartphone use and social interaction may indicate a low mood. Meanwhile, increased physical activity levels captured using inbuilt inertial measurement units (which document acceleration patterns) signified by high step counts and high caloric expenditure are negatively correlated with depression (12). Even changes in skin conductance and reduced HRV can serve as biomarkers for depression (16).

However, the adoption of wearable technology in mainstream health care for the monitoring and identification of mental illness has been slow relative to its widespread intrusion into modern-day life. This reluctance may be attributed to service providers' limited knowledge, low familiarity with these devices, and a lack of interdisciplinary dialogue among practitioners, app designers and individual users (17).

This review aims to summarise and comment on the literature surrounding the use of smartphones and other wearable devices to identify and monitor symptoms of mental illness and propose avenues of future research.

Wearable devices and mobile health for the identification and monitoring of mental illness

Wearable sensors can act as a clinical adjunct and provide objective data capture that can provide insight into a person's mental health. This data can be classified as being related to either physical activity, GPS tracing, social behaviour, sleep patterns, or some others (such as skin temperature, skin conductance, and heart rate variability).

Physical activity

Wearable devices can measure metrics such as step count, distance travelled, and body posture. It is well established that people with depression and anxiety exhibit altered levels of physical activity (18-20). This can be objectively measured using wearable inertial measurement units (17,21,22) to identify at-risk individuals, with Helgadóttir, Forsell & Ekblom (2015) finding that people with depression were sedentary during waking hours for an average time of 546 minutes per day, significantly higher than the population average of 459 minutes found by Hagstromer, Oja & Sjostrom (2007) ($P<0.05$) (22,23). In addition, physical activity can serve as an objective outcome pre- and post-intervention, as shown by Winkler *et al.* (2014) where patients with depression who were able to obtain remission with electroconvulsive therapy had consistently higher activity scores (of approximately 50 points, measured as the number of wrist movements per minute) throughout the day than those who did not obtain remission (24). This suggests that changes in physical activity can be measured as a proxy of treatment efficacy. Further supporting this claim, Peis (2020) demonstrated that activity levels of inpatients with depression could be used to predict discharge date (activity levels on day 7 of admission predicted discharge date with a mean error of 0.23 days) (25). Finally, wearable devices containing inertial measurement units have even been shown to measure hand tremors (26). This may be useful in monitoring adverse effects of medications commonly used to treat mental disorders, and further research is warranted in this area.

GPS location

GPS tracing can be used to identify a person's most visited locations, the periodicity of movement between these locations (termed circadian movement), and the variability of time typically spent at each location (termed entropy) (15). Movement patterns are most insightful when analysed on non-workdays which have heavy reliance on the individual's motivational state, as opposed to workdays where movement patterns may be determined by social roles and expectations. Both circadian movement and entropy were significantly correlated with scores on the Patient-Health-Questionnaire-9 (circadian movement, r=−0.51; entropy, r=−0.55; where r = linear correlation coefficient) in a study by Saeb (2016) using a dataset of college students in a small town (15). This implies that patients with depression move less variably between their most-visited locations and spend a similar amount of time at each location when they do, together reflecting a state of isolation and psychomotor retardation. Similar findings were published by the same author group using a different dataset (adults from a large city, Chicago), and by a separate independent group (27), suggesting high external validity. However, a recent study by Moshe (2021) contradicts this research by finding no significant relationship between smartphone parameters (including GPS tracing) and mental health symptoms (28). Nonetheless, this finding is likely impacted by lockdown restrictions amidst the present COVID-19 pandemic, preventing free movement. The clinical utility of GPS tracing is likely to be hindered by privacy concerns, and future research can be directed towards clinical integration within appropriate privacy-preserving guidelines.

Social behaviour

Smartphones can be used to obtain information about a person's call and text logs (such as call time, call duration, the length and content of messages, screen time, and application use), providing insight into a person's baseline sociability. Barnett (2018) investigated sociability features such as call duration, missed call count, and number of text messages in schizophrenia patients (29). It was found that, of subjects who experienced relapse, the rate of anomaly detection in sociability features in the 2 weeks prior to relapse was 71% higher than the rate of anomalies detected in dates further away from relapse. Similarly, Buck *et al.* (2019) found that the number and duration of outgoing calls and the total frequency of text messages was significantly correlated with schizophrenia relapse (P≤0.031) (30). These findings suggest that data from smartphones could be used to predict relapse of mental disorders before they occur enabling possibilities of prevention. Furthermore, Faurholt-Jepson (2015) found that patients in the manic phase of bipolar disorder (as determined using the Young Mania Rating Scale) showed significantly higher number of incoming calls per day than did asymptomatic patients (adjusted B =0.97, P=0.029) (31). Hence, sociability measured with smartphones could be used to track different stages of disease progression. Sociability may also be used to objectively quantify disease severity, with daily call duration, daily SMS counts, and daily screen usage being significantly (P<0.05) correlated with scores on the Hamilton Rating Scale for Depression. However, again, monitoring an individual's social interactions poses privacy concerns. Solutions include data anonymization algorithms which could combine individual sociability metrics into an overall sociability mental health score without exposing the specifics of an individual's sociability patterns—future research could be directed towards this.

Sleep patterns

Wearable sensors can measure sleep parameters such as total sleep duration time, rapid eye movement sleep duration time, and night-time awakenings (32). Sleep disturbance is a symptom in many mental disorders, including anxiety, major depressive disorder, bipolar disorder, and primary sleep disorders such as insomnia (33). A systematic review found that the best available evidence suggests that sleep disorders are bidirectionally related to anxiety and depression; that is, that sleep disorders can predict the onset of anxiety or depression, and that anxiety and depression predict the onset of a sleep disorder (34). This indicates that sleep disturbances identified by wearable sensors may identify individuals who are at risk of developing mental disorders, allowing for the provision of timely preventative intervention. Moreover, the development of sleep disorders in people with mental disorders may be an objective marker of disease severity, though more research is required before abnormal sleep parameters (such as the deviation of total sleep time from normative values) can be stratified according to disease severity. Meanwhile, in bipolar disorder, alterations in sleep patterns may follow the course of the disorder, with manic episodes being associated with reduced sleep, and depressive episodes associated with either insomnia or hypersomnia (14).

Alongside this, smartphones can collect data regarding a person's light exposure, providing insight into their circadian rhythm (35). This is a relevant metric that can track post-intervention improvement in patients with seasonal affective disorder, whose circadian rhythms can return to normalcy after receiving bright light therapy (36). Light exposure may also provide an indication of the ratio of indoor to outdoor time a person spends. This may be useful in assessing psychomotor retardation in patients with depression, and further research could explore this possibility.

Interestingly, social jetlag has also been proposed as another sleep-related metric associated with mental health. For example, Islam *et al.* found that greater social jetlag was associated with an increased likelihood of having depressive symptoms where Japanese employees with at least two hours of social jetlag (defined as the difference in sleep timing between work days and non-work days) were 2.14 times more likely to demonstrate depressive symptoms (P=0.01) (37). Social jetlag can be measured on a population scale, as shown by Zhang, Cajochen & Khatami (2019) who monitored social jetlag in 71,176 participants (38). In this way, the monitoring of social jetlag on a large scale may contribute to population screening for mental illness, allowing for targeted early intervention. Clearly, paucity of research in this area represents a clear avenue for future research.

Other relevant metrics

Additional physiological data collected from wearable devices include skin conductance (a measure of electrodermal activity) (39), skin temperature, and heart rate variability (40). Patients with depression were found to have a significantly higher body temperature compared to healthy controls (98.38 *vs.* 98.13 °F, P=0.03) (41). Meanwhile, increased skin conductance has a positive correlation with aggressive incidences in psychiatric mental health institutions (P=0.04), and therefore can be used for the early detection and prevention of aggression to improve both staff and patient safety (39). Furthermore, Kemp and Quintana (2013) reported that HRV may be a transdiagnostic sign of mental illness, given its indication of autonomic dysregulation, and therefore may act as a non-specific screening test of mental distress (42). Further research is warranted to clarify the impact of additional, unmeasured variables on this relationship.

Future considerations in the wearable-based monitoring of mental illness

Novel wearable-based metrics in mental health monitoring

Beyond the metrics already covered by this commentary, the authors speculate that blood pressure and oxygen saturation may also be useful in mental health monitoring. These can be captured by wearable sensors but, to the authors' knowledge, have not yet been explored in the context of identifying and monitoring mental illness (43). Interestingly, it is well established that psychological stress is associated with increased blood pressure. A meta-analysis by Gasperin *et al.* (2009) demonstrated that subjects who had stronger responses to psychologically stressful tasks were 21% more likely to develop an increase in blood pressure compared to those with weaker responses (P<0.001) (44). Meanwhile, oxygen saturation is relevant in the monitoring of sleep apnoea, which itself is linked to mental health disease such as anxiety and suicide ideation – Kaufmann *et al.* (2017) found that past year sleep apnoea was associated with a 3.11 (95% CI: 2.77–3.50) times increase in the odds of reporting depression in the past year (45). Therefore, wearable-based continuous blood pressure and oxygen saturation monitoring should be explored by future authors as novel methods of mental health monitoring.

Combining objective data streams to evaluate patients with mental disorders

Profiling variations in mental illness symptomology over time can be improved by combining multiple objective data streams to form a more detailed picture of a person's mental health (46). For example, while decreased smartphone use and social interaction alone may indicate a low mood, concurrent findings of high physical activity in an outdoor park on a sunny day may instead suggest that this individual is not depressed and is immersed in another activity (12). Yet, the influx of several complex objective data streams may be different to interpret simultaneously, and clinicians may benefit from easily interpretable summary scores. This has been done in the field of objective gait analysis, with the Simplified Mobility Score combining walking speed and daily step count to provide a score out of 100 (0= no mobility, 100= excellent mobility) reflecting a person's walking health (11). In the same way, future studies may aim to construct summary scores for the assessment of mental disorders; for example, with a sociability summary score combining objective information from call and text logs. Although summary scores may oversimplify metrics and lack nuance associated with, in an example pertaining to call metrics, the purpose of each call and the identity of the caller, they may still be useful in broadly categorising patients into varying levels of disease severity. In addition, the widespread use of smartphones and consumer grade wearable devices have led to the generation of large-scale data that can be analysed using machine learning. We envision a future where objective data from smartphones and wearable sensors can be combined by machine learning algorithms to generate probable diagnoses that can supplement clinical decision making. In addition, objective data and their summary scores could be streamed real-time to health care providers from a remote location, allowing for continuous measurements instead of discrete timepoint questionnaires.

Barriers to clinical implementation

Despite the exciting possibilities of wearable devices in the detection and monitoring of mental illness, many barriers to clinical implementation exist. For example, given that it is not feasible to screen for mental illness indiscriminately, it is unclear how individuals should be selectively screened to allow for the early detection of mental illness. One approach is to screen individuals who are at risk of developing mental illness. While this may be possible in individuals who have had prior mental illness with access to a mental health professional, it is unlikely that members of the community can be identified as appropriate candidates for wearable-based monitoring with their consent before they present to a mental health professional of their own accord, additional studies should include larger sample sizes over longer durations to explore the potential of data-phenotyping to identify individualised early warning signs and predict symptom changes over time (47). Disparities can exist between what an individual experiences and reports, and what a clinician observes. Given the heterogeneity of mental illness symptoms, even among patients with the same diagnosis (48), this data has the potential to assist health clinicians to better-tailor interventions to their patient, based on greater, more accurate sources of data regarding the effectiveness of treatments for certain objective symptoms. Additionally, it may offer insight into causal mechanisms (e.g., loneliness, severe stress, physical condition), and therefore promote a personalised treatment focus relating to each individual's specific symptom patterns (49).

Thus far, data derived from smartphones and wearables does not directly correlate with specific diagnoses. These technologies would allow for the detection of aberrancies from baseline patterns, which could function to provide feedback to the individual and clinician, and act as an early warning system for mental illness. Larger, more comprehensive studies may allow for the determination of which specific data clusters correspond with which particular clinical diagnosis. By integrating these devices into psychiatric intervention plans, decisions by health providers would be better guided by constantly up-to-date information regarding their patient, consequentially optimising treatment success.

Other barriers to clinical implementation include device validation and the lack of sufficient normative data for various health metrics. For example, in a meta-analysis by Haghayegh *et al.* it was found that, compared to the gold-standard polysomnography, Fitbit models had poor specificity (0.10–0.52) in correctly identifying sleep epochs (50). Advancements in wearable technology accuracy must take place before these devices can be recommended for clinical use. In addition, health metrics obtained from patients must be compared against population norms. While this is possible for some metrics such as daily step count where there exist large databases organised by sex and age (51), a normative range for other metrics such as social jetlag has not been defined. Additional work is required to gather normative values for a larger range of psychology-related metrics before wearable-based monitoring of mental illness can be applied in clinical settings. Moreover, some metrics may not yet be collected with sufficient accuracy with the current state of wearable technology. Haghayegh *et al.* (2019) performed a systematic review and found that the wrist-based Fitbit had poor specificity (0.58–0.69) when detecting sleep epochs (50). Similarly, Hermand, Coll, Richalet & Lhuissier (2021) found that the Garmin Forerunner (a wrist-based oximeter) had a >50% error rate when reporting oxygen saturation ($P<0.001$) (52). Before widespread clinical uptake can be expected, wearable devices need to demonstrate improved accuracy.

Limitations

Several limitations of the current review should be considered. There is sample bias amongst the studies discussed towards people owning smartphones where findings cannot yet be extrapolated to low-income environments. Given that mental illness varies across socioeconomic status, race and education, it can be presumed this bias may have impacted prognosis (53). Combining several studies, including those with participants of more diverse backgrounds and across smartphone platforms, may overcome this limitation by minimising the impact of any potentially biased research. Additionally, heterogeneity between samples and measures across studies pose challenges when attempting to compare results. Accuracy of data may vary across sensors (e.g., over- and under-estimation), and these devices generally do not provide professional grade monitoring (54).

The existing literature around the use of wearables and smartphones to identify and monitor symptoms of mental illness is limited. Future research utilizing comparable devices with a larger, more diverse sample may promote an understanding as to which individual factors shape the acceptability of continuous data tracking via smartphones and wearables. This may include cognitive traits, beliefs and demographics (55). Such findings would allow researchers to detect which groups digital phenotyping may pose the greatest effectiveness for. It must be noted that due to the recent effects of COVID-19, movement patterns can be expected to be relatively minimal, relative to studies conducted in prior years (56). Therefore, a holistic approach when combining data from wearable devices and smartphones, to identify and monitor symptoms of mental illness, is warranted.

Nevertheless, the present review demonstrates that data obtained from smartphones and wearable sensors can be useful to identify and monitor individuals at-risk of experiencing or currently experiencing a mental illness. It is recommended that future studies focus on determining whether additional data, such as bio-sensing (57) and app usage (58), could improve the accuracy of predictions (59,60). Future research should also assess the impact of extraneous variables on symptomology and oscillating variances of data across measurement devices.

Conclusions

Although still in its infancy, the current literature shows that smartphones and other wearable sensors can be used to provide objective data related to a person's mental health. Together, these metrics can be used to assist in the early identification and monitoring of mental disorders. Future possibilities involving machine learning could also generate probable diagnoses based on a person's objective data streams to assist in clinical decision-making.

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