



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

Lianne Koinis<sup>1</sup>, Ralph Jasper Mobbs<sup>2,3</sup>, R. Dineth Fonseka<sup>2,3</sup>, Pragadesh Natarajan<sup>2,3</sup>

<sup>1</sup>Department of Psychology, University of New South Wales, Sydney, Australia; <sup>2</sup>Faculty of Medicine, University of New South Wales, Sydney, Australia; <sup>3</sup>Wearables and Gait Analysis Research Group (WAGAR), Sydney, Australia

Correspondence to: R. Dineth Fonseka. Faculty of Medicine, University of New South Wales, Sydney, Australia. Email: dineth.fonseka@gmail.com.

Submitted Nov 10, 2021. Accepted for publication Oct 22, 2022.

doi: 10.21037/atm-21-6016

View this article at: <https://dx.doi.org/10.21037/atm-21-6016>

## 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 ( $P\leq 0.031$ ) (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 difficult 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.

## Acknowledgments

The authors would like to thank the staff including Devon McCarthy, Collette Irvine and Catherine Ragy from NeuroSpine clinic for assisting with conduct of the project and provision of study materials.

*Funding:* None.

## Footnote

*Provenance and Peer Review:* This article was a standard submission to the journal. The article has undergone external peer review.

*Peer Review File:* Available at <https://atm.amegroups.com/article/view/10.21037/atm-21-6016/prf>

*Conflicts of Interest:* All authors have completed the ICMJE uniform disclosure form (available at <https://atm.amegroups.com/article/view/10.21037/atm-21-6016/coif>). The authors have no conflicts of interest to declare.

*Ethical Statement:* The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

*Open Access Statement:* This is an Open Access article distributed in accordance with the Creative Commons Attribution-NonCommercial-NoDerivs 4.0 International License (CC BY-NC-ND 4.0), which permits the non-commercial replication and distribution of the article with the strict proviso that no changes or edits are made and the original work is properly cited (including links to both the formal publication through the relevant DOI and the license). See: <https://creativecommons.org/licenses/by-nc-nd/4.0/>.

## References

1. Abdulla MA, Esmael AM. Providing information through smart platforms: an applied study on academic libraries in Saudi universities. *Journal of Education, Society and Behavioural Science* 2019;30:1-24.

2. Jin D, Adams H, Cocco AM, et al. Smartphones and wearable technology: benefits and concerns in cardiology. *Med J Aust* 2020;212:54-56.e1.
3. Cappon G, Acciaroli G, Vettoretti M, et al. Wearable Continuous Glucose Monitoring Sensors: A Revolution in Diabetes Treatment. *Electronics* 2017;6:65.
4. Brunier A. Investing in treatment for depression and anxiety leads to fourfold return: World Health Organisation; 2016. Available online: <http://www.who.int/news/item/13-04-2016-investing-in-treatment-for-depression-and-anxiety-leads-to-fourfold-return>
5. Bhugra D, Mastrogianni A. Globalisation and mental disorders. Overview with relation to depression. *Br J Psychiatry* 2004;184:10-20.
6. Jorm AF, Patten SB, Brugha TS, et al. Has increased provision of treatment reduced the prevalence of common mental disorders? Review of the evidence from four countries. *World Psychiatry* 2017;16:90-9.
7. Trull TJ, Ebner-Priemer U. The Role of Ambulatory Assessment in Psychological Science. *Curr Dir Psychol Sci* 2014;23:466-70.
8. Moons KG, Royston P, Vergouwe Y, et al. Prognosis and prognostic research: what, why, and how? *BMJ* 2009;338:b375.
9. Eloy NC, Patricia CM, Miranda-Duro MC. Technologies for Participatory Medicine and Health Promotion in the Elderly Population. *Multidisciplinary Digital Publishing Institute Proceedings* 2018;2:1198.
10. Insel TR. Digital phenotyping: a global tool for psychiatry. *World Psychiatry* 2018;17:276-7.
11. Betteridge C, Mobbs RJ, Ho D. Proposed objective scoring algorithm for walking performance, based on relevant gait metrics: the Simplified Mobility Score (SMoS<sup>TM</sup>)-observational study. *J Orthop Surg Res* 2021;16:419.
12. Dogan E, Sander C, Wagner X, et al. Smartphone-Based Monitoring of Objective and Subjective Data in Affective Disorders: Where Are We and Where Are We Going? Systematic Review. *J Med Internet Res* 2017;19:e262.
13. Mukhopadhyay SC. Wearable sensors for human activity monitoring: A review. *IEEE Sens J* 2014;15:1321-30.
14. Association AP. Diagnostic and Statistical Manual of Mental Disorders. Fifth edition. United States. 2013. Available online: <https://doi.org/10.1176/appi.books.9780890425596>
15. Saeb S, Lattie EG, Schueller SM, et al. The relationship between mobile phone location sensor data and depressive symptom severity. *PeerJ* 2016;4:e2537.
16. Kemp AH, Quintana DS, Gray MA, et al. Impact of depression and antidepressant treatment on heart rate variability: a review and meta-analysis. *Biol Psychiatry* 2010;67:1067-74.
17. Tazawa Y, Liang KC, Yoshimura M, et al. Evaluating depression with multimodal wristband-type wearable device: screening and assessing patient severity utilizing machine-learning. *Heliyon* 2020;6:e03274.
18. Currier D, Lindner R, Spittal MJ, et al. Physical activity and depression in men: Increased activity duration and intensity associated with lower likelihood of current depression. *J Affect Disord* 2020;260:426-31.
19. De Mello MT, Lemos Vde A, Antunes HK, et al. Relationship between physical activity and depression and anxiety symptoms: a population study. *J Affect Disord* 2013;149:241-6.
20. Teychenne M, Ball K, Salmon J. Associations between physical activity and depressive symptoms in women. *Int J Behav Nutr Phys Act* 2008;5:27.
21. Bell SL, Audrey S, Gunnell D, et al. The relationship between physical activity, mental wellbeing and symptoms of mental health disorder in adolescents: a cohort study. *Int J Behav Nutr Phys Act* 2019;16:138.
22. Helgadóttir B, Forsell Y, Ekblom Ö. Physical activity patterns of people affected by depressive and anxiety disorders as measured by accelerometers: a cross-sectional study. *PLoS One* 2015;10:e0115894.
23. Hagströmer M, Oja P, Sjöström M. Physical activity and inactivity in an adult population assessed by accelerometry. *Med Sci Sports Exerc* 2007;39:1502-8.
24. Winkler D, Pjrek E, Lanzenberger R, et al. Actigraphy in patients with treatment-resistant depression undergoing electroconvulsive therapy. *J Psychiatr Res* 2014;57:96-100.
25. Peis I, López-Morfiño JD, Pérez-Rodríguez MM, et al. Actigraphic recording of motor activity in depressed inpatients: a novel computational approach to prediction of clinical course and hospital discharge. *Sci Rep* 2020;10:17286.
26. Kuosmanen E, Wolling F, Vega J, et al. Smartphone-Based Monitoring of Parkinson Disease: Quasi-Experimental Study to Quantify Hand Tremor Severity and Medication Effectiveness. *JMIR Mhealth Uhealth* 2020;8:e21543.
27. Canzian L, Musolesi M. Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*; 2015.
28. Moshe I, Terhorst Y, Opoku Asare K, et al. Predicting

- Symptoms of Depression and Anxiety Using Smartphone and Wearable Data. *Front Psychiatry* 2021;12:625247.
29. Barnett I, Torous J, Staples P, et al. Relapse prediction in schizophrenia through digital phenotyping: a pilot study. *Neuropsychopharmacology* 2018;43:1660-6.
  30. Buck B, Scherer E, Brian R, et al. Relationships between smartphone social behavior and relapse in schizophrenia: A preliminary report. *Schizophr Res* 2019;208:167-72.
  31. Faurholt-Jepsen M, Vinberg M, Frost M, et al. Smartphone data as an electronic biomarker of illness activity in bipolar disorder. *Bipolar Disord* 2015;17:715-28.
  32. Walch O, Huang Y, Forger D, et al. Sleep stage prediction with raw acceleration and photoplethysmography heart rate data derived from a consumer wearable device. *Sleep* 2019;42:zsz180.
  33. Anderson KN, Bradley AJ. Sleep disturbance in mental health problems and neurodegenerative disease. *Nat Sci Sleep* 2013;5:61-75.
  34. Alvaro PK, Roberts RM, Harris JK. A Systematic Review Assessing Bidirectionality between Sleep Disturbances, Anxiety, and Depression. *Sleep* 2013;36:1059-68.
  35. Wen L, Cheng Q, Lan W, et al. An Objective Comparison of Light Intensity and Near-Visual Tasks Between Rural and Urban School Children in China by a Wearable Device Clouclip. *Transl Vis Sci Technol* 2019;8:15.
  36. Winkler D, Pjrek E, Praschak-Rieder N, et al. Actigraphy in patients with seasonal affective disorder and healthy control subjects treated with light therapy. *Biol Psychiatry* 2005;58:331-6.
  37. Islam Z, Hu H, Akter S, et al. Social jetlag is associated with an increased likelihood of having depressive symptoms among the Japanese working population: the Furukawa Nutrition and Health Study. *Sleep* 2020;43:zsz204.
  38. Zhang Z, Cajochen C, Khatami R. Social Jetlag and Chronotypes in the Chinese Population: Analysis of Data Recorded by Wearable Devices. *J Med Internet Res* 2019;21:e13482.
  39. de Looft P, Noordzij ML, Moerbeek M, et al. Changes in heart rate and skin conductance in the 30 min preceding aggressive behavior. *Psychophysiology* 2019;56:e13420.
  40. Yoon S, Sim JK, Cho YH. A Flexible and Wearable Human Stress Monitoring Patch. *Sci Rep* 2016;6:23468.
  41. Rausch JL, Johnson ME, Corley KM, et al. Depressed patients have higher body temperature: 5-HT transporter long promoter region effects. *Neuropsychobiology* 2003;47:120-7.
  42. Kemp AH, Quintana DS. The relationship between mental and physical health: insights from the study of heart rate variability. *Int J Psychophysiol* 2013;89:288-96.
  43. Scheffler M, Hirt E. Wearable devices for telemedicine applications. *J Telemed Telecare* 2005;11 Suppl 1:11-4.
  44. Gasperin D, Netuveli G, Dias-da-Costa JS, et al. Effect of psychological stress on blood pressure increase: a meta-analysis of cohort studies. *Cad Saude Publica* 2009;25:715-26.
  45. Kaufmann CN, Susukida R, Depp CA. Sleep apnea, psychopathology, and mental health care. *Sleep Health* 2017;3:244-9.
  46. Griffin B, Saunders KEA. Smartphones and Wearables as a Method for Understanding Symptom Mechanisms. *Front Psychiatry* 2019;10:949.
  47. Holmes EA, Ghaderi A, Harmer CJ, et al. The Lancet Psychiatry Commission on psychological treatments research in tomorrow's science. *Lancet Psychiatry* 2018;5:237-86.
  48. Byrne S, Kotze B, Ramos F, et al. Using a mobile health device to manage severe mental illness in the community: What is the potential and what are the challenges? *Aust N Z J Psychiatry* 2020;54:964-9.
  49. Torous J, Onnela JP, Keshavan M. New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. *Transl Psychiatry* 2017;7:e1053.
  50. Haghayegh S, Khoshnevis S, Smolensky MH, et al. Accuracy of Wristband Fitbit Models in Assessing Sleep: Systematic Review and Meta-Analysis. *J Med Internet Res* 2019;21:e16273.
  51. Althoff T, Sosič R, Hicks JL, et al. Large-scale physical activity data reveal worldwide activity inequality. *Nature* 2017;547:336-9.
  52. Hermard E, Coll C, Richalet JP, et al. Accuracy and Reliability of Pulse O<sub>2</sub> Saturation Measured by a Wrist-worn Oximeter. *Int J Sports Med* 2021;42:1268-73.
  53. Villatoro AP, Mays VM, Ponce NA, et al. Perceived Need for Mental Health Care: The Intersection of Race, Ethnicity, Gender, and Socioeconomic Status. *Soc Ment Health* 2018;8:1-24.
  54. Piccinini F, Martinelli G, Carbonaro A. Accuracy of Mobile Applications versus Wearable Devices in Long-Term Step Measurements. *Sensors (Basel)* 2020;20:6293.
  55. Ritterband LM, Thorndike FP, Cox DJ, et al. A behavior change model for internet interventions. *Ann Behav Med* 2009;38:18-27.
  56. Maugeri G, Castrogiovanni P, Battaglia G, et al. The impact of physical activity on psychological health during Covid-19 pandemic in Italy. *Heliyon* 2020;6:e04315.



57. Howell N, Chuang J, De Kosnik A, et al. Emotional biosensing: Exploring critical alternatives. *Proc ACM Hum Comput Interact* 2018;2:1-25.
58. Chandrashekar P. Do mental health mobile apps work: evidence and recommendations for designing high-efficacy mental health mobile apps. *Mhealth* 2018;4:6.
59. Bhugra D, Tasman A, Pathare S, et al. The Future of Psychiatry Commission - Authors' reply. *Lancet Psychiatry* 2018;5:17-8.
60. Shatte ABR, Hutchinson DM, Teague SJ. Machine learning in mental health: a scoping review of methods and applications. *Psychol Med* 2019;49:1426-48.

**Cite this article as:** Koinis L, Mobbs RJ, Fonseka RD, Natarajan P. A commentary on the potential of smartphones and other wearable devices to be used in the identification and monitoring of mental illness. *Ann Transl Med* 2022;10(24):1420. doi: 10.21037/atm-21-6016