**Integrating Smartwatches in Community Mental Health Services for Severe Mental Illness: A Case Series**

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**Author Contributions**

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The authors have declared that no competing interests exist.

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**Ethics Statement**

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**Patient Consent**

All patients included in our study provided informed consent.

**Abstract**

**Objective:** This case series explored the integration of smartwatches in a community mental health service to support severe mental illness (SMI) management and intervention. We examined whether biometric data provided by smartwatches could help to predict relapse and inform treatment decisions.

**Method:** Four SMI patients were selected from a prior study. Clinicians accessed patients' biometric data (activity, sleep, heart rate, and electrodermal activity) through smartwatches.

**Results:** Changes in circadian rhythm and electrodermal activity preceded hospitalization in two cases. Additionally, smartwatch data was effectively used to guide targeted interventions, improving patient treatment outcomes.

**Conclusion:** Integrating smartwatches in community mental health services offers promise as adjunct tools for severe mental illness management. However, ethical considerations on data privacy and technology reliance require further evaluation.

**Background**

Severe mental illness (SMI), characterized as a chronic relapsing condition with profound impact on the individual, family, and society [2], is estimated to affect 5% of the population [1]. Since the 1960s, there has been a worldwide trend in treating SMI from hospital settings to a more community-focused approached [3]. In community settings in Australia, multi-disciplinary teams provide intensive case management of patients, including a range of treatment and support services [4]. Clinicians within these services face several challenges, from patient level to systemic issues. Technological innovations may offer a means to overcome substantial challenges clinicians face within this space.

Smartwatches are devices with the ability to capture key indicators of health including a person’s activity level, sleep, heart rate, and electrodermal activity (EDA) [5]. Such markers have been shown to be useful predictors of mental health; predictive of relapse [6], treatment efficacy [7], and diagnostically useful in identifying circadian disruptions [8]. For clinicians, smartwatches may be an appealing prospect both for monitoring and treating patients. They are generally unobtrusive, affordable, and can provide a comprehensive analysis of a patient’s overall health [5]. Importantly, these devices have high levels of community acceptance, even among people with SMI [9].

Our case series illustrates the integration of a smartwatch device within a community mental health service. Patients were asked to wear the mHealth Empatica Embrace2 device on their wrists for 6 months as part of a randomised controlled trial (the unWIRED study) [10]. This device has a biosensor that captures, stores, and transmits EDA and motion data, and can detect autonomic events and categorise changes across the sleep-wakefulness cycle (see Table 1). Case managers were able to observe patient data through a dedicated website. Our case series of four participants who enrolled in the study is highlights the potential utility of integrating technology within existing services.

**Predictive Utility of Deterioration**

**Case Study 1: Riley**

Riley was a 19-year-old female with a history of psychosis. She was previously scheduled as an involuntary patient when she acted on her persecutory delusions. Riley was placed on a Community Treatment Order (CTO) and had been prescribed 25mg Risperdal, 2.5-5mg diazepam, and 2mg risperidone. Nine months post admission, Riley decided to participate in the unWIRED study. Two weeks later (6th January), Riley contacted the mental health line reporting a ‘mild crisis’, then two days later was scheduled as an inpatient on the background of an increase in persecutory delusions.

**Sleep.** A significant decline was observed 3 days prior to her call to the crisis service, with the average amount of sleep decreased from 8.97 (*SD* = 0.96) to 3.57 (*SD* = 1.39) hours per night (Figure 1).

*Figure 1.* Riley’s (case study 1) sleep data from 28/12/2021 to 07/01/2023. Note: SRI = Sleep Regularity Index.

**Physical Activity.** Riley’s physical activity displayed the opposite trajectory to her sleep patten (Figure 2). Prior to the 4th of January, Riley averaged 5,551 (*SD* = 4,611) steps per day which increased to an average of 10,200 (*SD* =2,871) across the next three days.

*Figure 2.* Riley’s (case study 1) daily step count from28/12/2021 to 07/01/2023.

**EDA.** The most substantial changes noted in her EDA were observed during her wake period, with less autonomic activity detected in the days prior to her admission compared to the week prior (Figure 3).

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Figure 3.Riley’s (case study 1) electrodermal activity from 30/12/21 3AM to 04/01/22 9AM.

**Case Study 2: Sinclair**

Sinclair was 18-year-old trans-male with a diagnosis of borderline personality disorder and gender dysphoria. In the year prior to their enrolment in the trial, Sinclair had four presentations to the emergency department (ED). Sinclair was seeing their psychologist on a weekly basis and was prescribed fluvoxamine 100 mg; Quetiapine 300 mg oral modified release tablet. A relapse occurred whilst Sinclair was part of the trial. Sinclair attended the ED with somatic complaints, absconded, then presented the next day with evidence of self-harm and was discharged three days later.

**Sleep.** Across the initial part of the trial, Sinclair was on average sleeping 7.19 hours per night (*SD* = 0.69) Two days prior to attendance at the ED Sinclair was sleeping 7.39 hours per night (*SD* = 0.52).

**Physical Activity.** On the day of the initial presentation to ED there was a substantial change in the level of activity (Figure 4). Prior to this point, they were on average taking 11,380 (*SD* = 4,769.33) but on the 9th this increased to 23,340 steps in a day.

*Figure 4.* Sinclair’s (case study 2) daily step count from02/12/2021 to 09/12/2021.

**EDA.** An inspection of Sinclair’s EDA levels highlighted the degree of affective instability (Figure 5). There is marked variability and high levels of activity which occur independent of the amount of activity. Interestingly in the days prior to their presentation at the ED there was a pronounced lack of activity during their sleep relative to the week prior.

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Figure 5.Sinclair’s (case study 2) electrodermal activity from 03/12/21 3AM to 09/12/21 9PM.

**Utility in Treatment**

**Case Study 3: Jasmine**

Jasmine was a 24-year-old female with a primary diagnosis of bipolar affective disorder. In 2021 Jasmine was admitted to an inpatient unit and placed on a CTO after experiencing mania, delusions, suicidality, and auditory hallucinations. Jasmine was prescribed aripiprazole 400mg IM monthly, Chlorpromazine 75mg nocte, and Lithium 900mg nocte. Following her admission, Jasmine was referred to a community treatment team and was seeing an occupational therapist on a weekly basis.

Initially, Jasmine’s therapy goals were primarily focused on making friends, however Jasmine’s smartwatch data revealed that at the time of beginning the trial she was on average sleeping between 2:29AM-4:06PM (*M* = 14.43 *SD* = 1.12) and was on average walking 333 steps per day [*SD* = 186.10]. This additional data allowed for significant insight into the extent of Jasmine’s problem (i.e., issues with sleep and activity) but also a focus for intervention. The clinician initially implemented a behavioural modification program that sought to increase Jasmine’s engagement in outside activities and improve their sleep schedule. The clinician monitored the level of activity and used this to provide feedback and encouragement. Five months into the intervention, Jasmine’s step count reflected a 325.8% increase in her level of activity. Jasmine’s sleep cycle also progressively changed to sleeping between 10:42PM-11:44AM (*M* = 12.86, *SD* = 1.17).

An interestingly finding was the normalisation and decrease of Jasmine’s EDA which occurred during the intervention (Figure 6). Notably, Jasmine’s EDA was still more pronounced during her sleep as opposed to her wake period, highlighting further work is required to increase her level of activity during the day.

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Figure 6.Jasmine’s (case study 3) electrodermal activity from 21/12/21 11AM to 07/01/22 9PM.

**Case Study 4: Krystal**

Krystal was a 22-year-old female with diagnosis of agoraphobia, social and generalized anxiety. These issues onset at age 17, resulting in school refusal and an inability to leave the house. Since this time, Krystal has been housebound. At the time of enrolling in the study Krystal was prescribed 250mg of sertraline and 25mcg of clonidine.

Krystal was having weekly sessions with her community health clinician focusing on treating her agoraphobia and social anxiety. Krystal’s clinician utilised the smartwatch to monitor the exposure protocol that was being implemented, specifically exposure to unfamiliar locations and a weekly social event run at the service. Krystal’s EDA was then explored in parallel with Krystal’s subjective ratings.

Figure 7 highlights the changes in EDA across time when Krystal would attend a social event organised by the service (from 12:30PM-2:00PM). During the first visit Krystal showed unremarkable EDA, however following the visit, Krystal experienced a panic attack at approximately 4:30PM that same day. The clinician hypothesised that Krystal’s utilisation of safety behaviours inhibited her arousal, delaying the onset of panic symptoms. A behavioural experiment was then performed during the next exposure involving ‘dropping’ the safety behaviours. This was mirrored in the EDA where there was an increase in activity during exposure. No panic attack was experienced after exposure, which was also reflected in the EDA. The exposure protocol continued with a focus on safety behaviours until the third exposure, where there was little change from baseline EDA, suggestive of the effectiveness of the intervention.

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Figure 7.Krystal’s (case study 4) electrodermal activity from each instance of exposure to the social event organised by the mental health service.

**Discussion**

Our case series illustrates how wearable technology could be integrated into community health services including the potential utility of predicting relapse and supporting monitoring and treatment of symptoms of SMI. Notably, clinicians in community health settings are consistently faced with difficult decisions when it comes to managing risk and planning future care. Clinicians are reliant on conducting risk assessments whose predictive properties are notoriously poor. For example, the strongest discriminator of suicide risk is a current or recent psychiatric hospital patient, yet this represents the majority of clients seen in community mental health services in Australia [11]. Clinicians therefore are being placed in precarious positions where the tools at their disposal to inform clinical decision making is severely limited.

In our case series, we presented two instances where biometric indicators preceded the eventual admission to an inpatient unit. In both instances there appeared to be changes in circadian rhythm represented by changes in sleep patterns or changes in EDA. At this stage of the study, it is difficult to know whether these signals are predictive or whether post-hoc reasoning has influenced our interpretation. What is apparent is that understanding an individual's unique digital footprint offers clinicians the ability to utilise dynamic risk factors to inform their decision making. Future research may therefore wish to explore the potential utility of using these devices on people post-admission where the incidence of relapse is substantially higher.

Presently, the methods through which treatment effects are measured in community services is largely reliant on patient self-report. The second two case studies illustrate how integrating smartwatches into a service can introduce objective data for the clinician to use to inform treatment decisions. In case study 3, the clinician became aware of how poor the patient’s sleep and activity levels were, and then implemented a targeted treatment to address this. In this example, the use of technology was able to overcome the significant lack of patient insight. Further, the patient’s experience was especially positive, given they requested ongoing use of the device after the trial period finished.

In case study 4, the clinician was able to monitor the implementation of their exposure protocol. To our knowledge, this has never been performed nor published in this manner. Cognitive models explain agoraphobia with recurrent panic attacks as stemming from exaggerated beliefs that anxiety and bodily sensations will result in physical or mental catastrophe [12]. Remission of symptoms occurs when there is adoption of a more benign and realistic alternative explanations, achieved through repeated behavioural experiments. Whilst there was a reduction in the level of physiological arousal the effects did not generalise beyond the specific event. As noted by the clinician, the generalisation of the improvement will be the ongoing focus of treatment.

There are several ethical and practical concerns which need to be considered. The wearable devices used collect highly personal data, however currently this is limited to activity, sleep, and EDA. With increasing technological innovation comes increasing potential to capture more data from a person, however it’s benefit must constantly be evaluated. In a high-risk population, there is forever the delicate balance between an individual’s freedom and safety, and it may be easy to justify the usage of these devices in lieu of the evidence to support its use. This will continue to be an ongoing area of debate.

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Table 1.

*Metrics and method of calculation of motion and electrodermal activity data acquired from the mHealth Empatica Embrace2 device*

|  |  |  |
| --- | --- | --- |
|  | Metric | Method of Calculation |
| Sleep | Restful | Proprietary algorithm which detects wrist movements consistent with motion utilising accelerometer and temperature sensors |
| Non-Restful |
| Sleep Regularity Index | Calculated through a three-day rolling average of the degree of consistency of sleep and wake times. |
| Activity Levels | Steps | Proprietary algorithm which detects wrist movements consistent with motion utilising 3-axis accelerometer (sampled at 32Hz) |
| Stress | Electrodermal Activity (EDA) | Measures variations of the electrical conductance of the skin (sampling rate is 4Hz) |