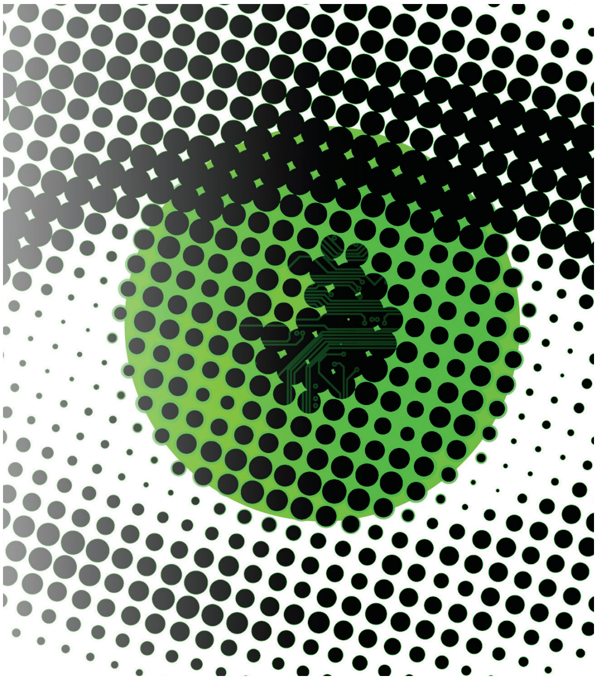

Tracking Mental Well-Being: Balancing Rich Sensing and Patient Needs

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Serious mental illnesses are among the most pressing public healthcare concerns. Continuous and unobtrusive sensing of social and physical functioning has tremendous potential to support lifelong health management by acting as an early warning system to detect changes in mental well-being, delivering context-aware micro-interventions to patients when and where they need them and significantly accelerating patient understanding of their illness.

Mental illnesses, like physical illnesses, can be disabling; they change how we feel, think, and behave. Their impacts are felt widely, with one-quarter of American adults suffering from a diagnosable mental disorder each year. People with a serious mental illness (SMI)—including major depression, schizophrenia, bipolar disorder, obsessive–compulsive disorder, and posttraumatic stress disorder—will, on average, die 25 years earlier than those unaffected.[1] The problems arising from mental illness are not limited to the individual sufferer: families, friends, and social networks can all be affected. SMIs are expensive as well: in the US, they are among the top five conditions for direct medical expenditure, with associated annual healthcare costs exceeding $30 billion.

Many SMIs require lifelong management. Individuals have to remain constantly vigilant for warning signs that might indicate a relapse. The standard practice for monitoring mental health is self-tracking. For a variety of reasons, this is difficult to maintain over an extended period. Manual and sporadic recording often fails to capture the finer, crucial details of behavior and temporal trends. Too frequently, the early indicators of decline and relapse are missed, and the healthcare system has to manage the devastating consequences.

The capacity to automatically track self-reported behaviors is expanding. There has been a marked rise in the use of personal sensing, as evidenced by the growing number of commercially available devices for automatically capturing behavior. An increasing number of studies demonstrate the ability of behavior-monitoring devices to assist in addressing the challenges of self-tracking.[2] We believe that mobile technologies not only have the potential to dramatically improve illness management, but could also do so in a cost-effective manner. Despite this clear potential, cutting-edge technology is conspicuously absent from mental health treatment.

When incorporating unobtrusive sensing technology into mental healthcare, there can be discrepancies between sensing capacity and patient acceptance. There might also be tensions between the requirements of healthcare providers, including clinicians and insurance companies, and those of patients. While it is vital that

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Table 1. Behavioral factors in serious mental illnesses than can be tracked with sensing.

Domain	Behaviors	Sensors/measurements	Example behavior-change goals
Physical activity	Sedentary versus nonsedentary activities (for example, walking, running, biking, stationary biking)	Accelerometer, GPS/location, gyroscope, barometer, compass	Increase physical activity, maintaining healthy weight/body mass index (BMI)
Social engagement	Social encounters, conversational turn taking, speech volume, speaking rate, intonation, speech affect, changes in geographic range	Microphone, accelerometer, GPS/ location	Increase frequency of social encounters; eliminate or modify factors leading to increased stress, anxiety, depressive symptoms, or distress linked with symptoms of psychosis
Sleep patterns	Disrupted versus continuous sleep, time of sleep	Microphone, accelerometer, GPS/ location, light, phone usage	Regulate sleep patterns, synchronize with internal body clock

patients as well as clinicians accept technological support, patient acceptance is paramount because low acceptance can lead to reduced adherence or nonuse. Acceptance is therefore a critical factor to consider when introducing sensing, particularly in the management of mental illnesses, which can carry significant stigma.

Effective solutions to the challenge of tracking mental well-being will require technical innovation as well as the central consideration of a positive patient experience. Here, we reflect on our previous and ongoing work to provide an outlook on the ways sensing can be used to detect the early onset of SMIs, the potential for passive sensing to support personalized treatment, and strategies that strike a balance between rich sensing and patient needs. We argue that behavioral sensing technologies, if developed closely with patients and their clinicians, will be accepted more widely in clinical practice and provide more effective management of SMIs.

TRACKING BEHAVIORAL INDICATORS OF MENTAL WELL-BEING

A significant amount of research links behavior to mental health.[3] Hence, inferring pertinent behaviors is key to assessing mental wellness. Decreased physical activity, emotional responsiveness, and social interactions are well-documented symptoms of depression. In schizophrenia, a reduction in social interactions coupled with anxious and depressed mood states could signal psychotic symptom exacerbation and relapse. Changes in speaking rate and speech volume are a behavioral indicator of manic and depressive states in bipolar disorder.

As Table 1 shows, passive sensing can be used to track symptomatic behavior for a range of SMIs. In our research, we focus on physical activity, social engagement, and sleep patterns, but there is rich potential for detecting many other behaviors.

Sensing physical activity

Accelerometer data on a smartphone is capable of characterizing the user's physical movements.[2] Distinct patterns within the data can be exploited to automatically recognize different activities such as running, walking, and standing. The combination of accelerometer data and a stream of location estimates from the GPS can recognize a user's mode of transportation—for example, riding a bike or driving a car. Other sensors in today's phones—including a barometer, gyroscope, and compass—along with the accelerometer make it easy to identify not only when someone is walking, but when he or she is climbing stairs and in which direction. Detecting physical activities using onboard phone sensors or external wearables such as Fitbit is becoming increasingly prevalent and can be mostly considered a solved research problem, especially for simpler activities.

Sensing social engagement

Continuously capturing social behaviors is still an active research challenge for the ubiquitous computing, computer vision, speech recognition, and machine learning communities. Our work has focused on capturing and analyzing social encounters in the physical world as well as the measurement of social functioning and affect based on speech and vocal patterns.[4] We have developed features and probabilistic models to robustly infer vocal patterns in noisy real-world scenarios without the use of close-talking microphones or rigid requirements on microphone placement as long as the signal is not completely occluded or muffled.

A growing body of evidence supports the use of acoustic properties to detect changes in emotional health. Detection of vocal affect by capturing characteristic speech signals associated with emotion holds promise as a tool that does not require the actual content of a conversation or the identification of a speaker[4] and makes the paralinguistic aspects of speech valuable in assessing mental health.[5] Using privacy-sensitive audio features and probabilistic inference techniques, we have shown that it is possible to reliably estimate the number of conversations an individual engages in, their duration, how much time an individual speaks, the speaking rate, and variations in pitch.[4] We have used these techniques to detect social isolation in older adults.[5]

Going beyond estimating nonverbal aspects of speech, we have utilized smartphone microphones as an optimal sensor for the unobtrusive identification of daily stress.[6] Stress is often a by-product of disruptive, unpleasant emotions and can be a contributing factor to SMIs such as major depression and bipolar disorder. Many physiological symptoms of stress can be measured via sensors—for example, through chemical analysis, skin conductance readings, electrocardiograms, and so on. However, such methods are inherently intrusive because they require direct interaction between users and sensors and are unlikely to be adopted by individuals over long periods of time. Consequently, we are exploring less intrusive methods to monitor stress.

Researchers widely acknowledge that stress influences human vocal production. Pitch, the most investigated acoustic feature for stress, is the fundamental frequency of vocal-cord vibration during speech production. Normally, the mean, standard deviation, and range of pitch increase with stress, while the jitter in voice usually decreases. More recently, studies on stress analysis have shown that features based on a nonlinear speech production model are very useful in stress detection.[7] We have developed techniques to passively detect stress episodes exclusively using smartphones and privacy-sensitive acoustic features, and to adapt models of stress to specific individuals even when the microphone's position relative to the speaker and the room is nonstatic.[6]

Sensing sleep patterns

Patients, especially those with an SMI, are unlikely to wear specialized sleep sensors for lengthy time periods. To ensure long-term adherence, approaches to monitoring sleep must minimize the burden placed on users. We and our colleagues have developed a smartphone-based sleep-sensing system using numerous phone features including stationary/nonstationary periods, a light sensor (for example, dark), acoustic features (for example, quiet), charging periods, and whether the phone is in use. A regression model correlates these features to estimate sleep duration.[8] Although this estimation has a larger margin of error than instrumenting the bed or requiring the user to wear a sensing device or place a smartphone on the bed, we believe this approach's unobtrusiveness will lead to more sustained use. If a user is more motivated, a more detailed record of sleep duration, interrupted sleep (for example, bathroom visits), and coarse sleep stages (for example, light/deep sleep) can be estimated by asking the user to place the phone next to his or her pillow while sleeping.

Smartphone apps such as Sleep Cycle, and wearables such as Fitbit and Nike+FuelBand, typically require the user to follow a specific protocol or manually mark the time when going to bed. Our aim is to make behavioral sensing effortless for the user. In our ongoing work, we are using low-level smartphone interactions such as screen-unlock events to infer sleep duration and sleep interruptions. Our unpublished experimental data from college students show that interaction patterns alone can be used to estimate sleep duration with about 85 percent accuracy.

Given the high usage of smartphones, particularly among youth and young adults, many behaviors, including sleep and sleeplessness, could be inferred from phone-usage patterns alone without relying on external or smartphone sensors. Furthermore, being able to understand these behavioral signals might help researchers reason about internal processes relevant to mental health—for example, an increased frequency of searching for information using the phone's browser might correspond to a relapse into a manic phase of bipolar disorder.

BEYOND BEHAVIORAL SENSING: GUIDING PATIENTS TO BETTER MENTAL HEALTH

While passive sensing holds tremendous promise for the early detection of relapse in a wide range of SMIs, there is potential to go beyond just detection. We believe that sensing could also significantly contribute to developing personalized evidence-based treatment strategies, providing patients with just-in-time tailored interventions outside of the clinic when they are most needed and rapidly increasing patients' learning about their illness.

Self-awareness and feedback

Patient self-monitoring of various well-being factors is central to many mental illness treatments. Mostly this data is for the clinician's benefit, providing a sense of the patient's progress since the last appointment. Smartphone sensing provides immediate possibilities to close the loop and provide patients with feedback outside the clinic. There are, however, important considerations in providing feedback to patients about their health when they are away from the clinic as there is no guarantee of their context and mental state. Such feedback must consist of easy-to-understand visualizations, maintain user privacy, and be appropriate to patients' current understanding of their illness.

One challenge is how to clearly include multiple feedback dimensions on one display. A promising approach is to provide feedback at different granularities so that users can easily absorb the information. In previous work, we developed BeWell, a smartphone app that presents an aggregate measure of physical activity, social engagement, and sleep patterns in an ambient display on the wallpaper.[9] As Figure 1 shows, BeWell maps these dimensions to the behavior of different aquatic species in an animated ecosystem. If the user wants to find out more information along a specific dimension, tapping on the relevant icon or species provides additional details.

Behavior-driven personalized interventions

Real-time sensing in patients' day-to-day lives creates the opportunity to deliver interventions closer to when they are needed. However, most smartphone apps for well-being prescribe one-size-fits-all suggestions or interventions to users. Although such systems provide useful health management advice, they often fail to relate to the users' specific context. Consequently, users often fall back on previous unhealthy behaviors. Context-aware algorithms can be used to intervene at appropriate times to support patients.

Figure 1. Screenshots from BeWell, a smartphone app that maps the user's overall well-being along three dimensions—physical activity, social engagement, and sleep patterns—to the behavior of different aquatic species in an animated ecosystem. The first two images show varying levels of social engagement: fewer fish far away implies low engagement, while many fish nearby represent high engagement. The third image shows analytic results of feedback from the previous day for all three dimensions.

Suggestions to users that consider personal characteristics and individual context are likely to be more engaging and effective than their generic counterparts. However, the creation of customized messages by medical professionals would impose an additional burden on an already overtaxed healthcare system. One way to tackle this challenge is to base such suggestions on past favorable actions that the user frequently completed.

Learning about one's mental illness is a central part of treatment and has been associated with increased treatment adherence.[10] Existing psycho-educational interventions range from patient handbooks to websites with rich media content such as videos to illustrate aspects of the illness. However, this uniform approach does not consider patient characteristics or context. There is thus considerable potential for sensor-supported patient learning derived from actual behavior. This approach might provide more meaningful and potentially more convincing lessons for patients, thereby leading to a deeper and more personalized understanding of their illness.

Sensing interventions grounded in SMI pathology

Pharmacological treatments for an SMI are necessarily grounded in its pathology. Similarly, psychosocial treatments are often centered on an evidence-based understanding of the illness. We argue that sensing systems should also consider each SMI's neural and behavioral characteristics. Such an approach could improve both relapse detection and treatment adherence. Bipolar disorder, for example, is associated with a dopamine dysregulation that results in increased sensitivity to rewards. This is most evident during a manic phase when people typically pursue numerous goal-directed activities, but it is also present during balanced periods. An early-warning relapse detection system could listen for an increase in technology-mediated goal-directed behavior, such as Google searches, while a treatment adherence system could incorporate behavioral rewards into an intervention.

RICH SENSING VERSUS PATIENT ACCEPTANCE

Passive smartphone sensing has the potential to seamlessly and continuously track nonreactive changes in behavior and thereby help patients change behavioral patterns for improved mental health. Yet the promise of rich sensing has not yet impacted clinical practice: the data collected via sensors has been limited almost exclusively to research studies. To be effective, sensing solutions must consider factors that affect patient adherence.

Addressing stigma

In the case of mental illness, several factors are strongly associated with nonadherence to treatment; the stigma associated with SMIs is one crucial factor. For example, while there is a long history of using some forms of sensing—physical activity and light exposure, for example—in bipolar disorder research, patient nonacceptance and consequent nonadherence to this technology can limit its effectiveness.[11] Many individuals with mental illness are understandably reluctant to use devices that cause them to stand out or feel different, and current clinical tools to measure physical activity and light exposure such as the Philips Actiwatch are purpose-built for research and hence conspicuous. Indeed, secrecy is a common strategy stigmatized people use to avoid stigmatization.

Unobtrusive sensing via smartphones offers the possibility of providing patients with higher levels of privacy.

Ensuring that user-facing aspects of the system visible to others, such as an ambient wallpaper display, obfuscate the underlying sensing purpose could further reduce the potential for stigma.

Gaining user confidence

A user's level of confidence in a behavioral sensing system can be influenced by its technological reliability as well as the accuracy of inferred activities. Most inference-based systems are probabilistic in nature and have associated uncertainty, which often is not reflected back to the user or others viewing captured information. When this data pertains to an SMI, it is critical to expose both the data's limitations and the system's uncertainty; otherwise, unresolvable tensions between the patient and clinician could emerge. The accuracy of probabilistic estimates can be made more precise by running sensing algorithms in conjunction with user self-reports for a designated training period, or asking users to confirm anomalous cases when they occur.

Sensing approaches often require users to adhere to protocols to ensure that sensed data is of the highest quality. For example, the Actiwatch requires users to wear the device at all times on their nondominant hand. Clinicians report that patients often fail to follow such protocols. A complicating factor is that many patients with SMI can at times have memory and cognitive deficits, and clinicians might have no way of knowing whether the sensed data is misrepresentative or if the patient is simply experiencing a period of reduced self-awareness.

Significantly reducing the number of these errors is an important step in creating a credible behavioral sensing system as well as in providing a means to correct errors close to when they occur and to support users' diagnosis or explanation of them. One solution is to request a patient to confirm sensed estimates and, when there is significant mismatch between a self-reported result and the inferred estimate, let clinicians delve into the contextual information. In the case of a discrepancy in sleep data, for example, this would entail exposing the noise and light levels and phone use to clinicians so they can gain more insight into the error's source.

Respecting user privacy

Collecting sensor data, especially from a microphone, involves recording people in unconstrained and unpredictable situations, both public and private. Thus, it is highly unlikely that users and those around them will ever be comfortable with raw audio recordings. To address this problem, we have developed a mobile behavior-tracking system that never records raw audio but instead destructively processes audio data on the fly to extract and store features that are useful to infer the presence and style of speech, but not sufficient to reconstruct the spoken words.[4] This approach has the added advantage of not needlessly complicating clinical decision-making by providing higher-than-necessary data resolution. The bottom line is that to establish user trust (as well as to increase adherence to sensing protocols and reduce stigma), sensing algorithms should only store as much raw sensed data as a user is comfortable sharing and as is clinically meaningful.

Providing control

Nonadherence to medication is very common in bipolar disorder (as high as 80 percent) and other SMIs, and can have serious consequences to patients as well as to society at large.[10] Given the associated side effects and cost of medication to treat mental illness, it is not surprising that medication adherence can be low. In a recent survey of individuals with bipolar disorder, respondents rated medications as the least effective and least popular compared to all other forms of treatment. The most effective and popular treatments—for example, a regimented sleep schedule, exercise, and mindfulness—all involve the person centrally in treatment.[12]

As we move from a top-down mental healthcare treatment toward a patient-centered approach, it is fitting that health systems support end-user autonomy and control over how the system functions. This should include being able to decide what is sensed and when, to delete data, and to mute sensing at certain times. Interestingly, the control of personal information is also a strategy people with an SMI use to combat stigma, indicating that providing patients with control over who can access their data is equally important. Giving patients an active role in their treatment is likely to increase feelings of self-efficacy, a significant factor in positive outcomes.

MOODRHYTHM: STRIKING A BALANCE BETWEEN SENSING AND ACCEPTANCE

To illustrate one approach to striking a balance between sensing capacity and patient acceptance, we focus on MoodRhythm (www.moodrhythm.com), a mobile app that uses passive sensing to support the long-term treatment of bipolar disorder. Bipolar disorder is a common illness that affects between 3 and 6 percent of the world's population in developing and industrialized countries, regardless of socioeconomic status or gender. The illness is associated with poor functional and clinical outcomes, high suicide rates, and huge societal costs.

System goals

Bipolar disorder is characterized by mood and sleep/wake instability. Maintaining a stable daily routine is a significant challenge for patients with bipolar disorder, and the absence of regularity in daily routines can lead to increased risk of new depressive and manic episodes.

Figure 2. MoodRhythm uses passive sensing to extend interpersonal social rhythm therapy (IPSRT) to support the long-term treatment of bipolar disorder. (a) Social rhythm metric (SRM) self-report screen. (b) Badge screen displays badges awarded for adherence to self-report tasks and for reaching therapeutic goals. (c) Home screen displays ambient bubbles that represent the activities users are trying to keep in balance.

Interpersonal social rhythm therapy (IPSRT) is a clinically validated behavioral treatment designed to regulate daily routines—specifically, physical activity patterns as well as sleep timing and duration. As part of IPSRT, patients use the *social rhythm metric* (SRM), a validated five-item self-assessment of the regularity of daily routines and moods. Increased regularity of routines, as reflected in SRM scores, has been shown to reduce the incidence of new episodes of bipolar illness.[13] MoodRhythm aims to build on IPSRT and extend its reach via sensing-driven tracking.

Daily rhythm sensing

Daily tracking of mood and physical activities helps bipolar disorder patients notice how changes in their routines affect how they feel. Clinicians can use this information to help patients stabilize their daily routines, improving their mood and reducing the risk of new episodes of mania and depression. However, self-reporting is taxing over long time periods and irregular when a patient is very symptomatic. Furthermore, self-ratings are unreliable during a manic episode, as patients often misjudge mood scores and levels of social interaction.

Smartphone sensing capabilities are uniquely suited to monitor key bipolar disorder parameters: the nature and frequency of social interaction, and sleep/wake activity. Figure 2a shows MoodRhythm's SRM screen. Initially, the system uses SRM data to construct a sensing model for a designated set of self-report tasks with therapeutic goals. Taking advantage of the reward-sensitive neural characteristic associated with bipolar disorder, MoodRhythm rewards users with virtual badges for completing these tasks and reaching the goals, as Figure 2b shows. This has the dual aim of motivating users to adhere to treatment and to provide labeled data.

Clinicians use levels of social activity, including how stimulating or stressful a patient finds social interactions, to assess the patient's mental health. MoodRhythm's sensing module computes the frequency and duration of face-to-face conversations that a patient has over the course of the day based on an analysis of audio data continuously collected using the smartphone's built-in microphone. It then uses output from this module to suggest completion times for some events on the SRM and to gauge patients' daily levels of social engagement.

Timing and duration of sleep are also important in assessing a patient's mental health; erratic sleep/wake cycles can both be causative and predictive factors of relapse. In MoodRhythm, we implemented a sleep module from prior research that uses an empirically validated weighting of inputs from audio, accelerometer, light-level, screen-unlock, and charging-state data sources to estimate the time that the user spent sleeping in a given 24-hour period with inference accuracies approaching 85 to 90 percent and with minimal user intervention.[8]

Beyond sensing

SRM data can be computed into a numerical metric using a simple algorithm: the higher the resulting score, the more stable the routine. MoodRhythm maps a running seven-day average of key daily behaviors—including sleep, meals, and social contact—to an ambient display on the app's homepage, as Figure 2c shows. A floating bubble represents a particular daily event; a clinically validated algorithm drives each bubble's movement. The more stable the routine, the less the bubble moves. The system uses color to denote which events are stable (green) or unstable (red), depending on whether or not the patient is meeting therapeutic targets.

The ambient display's goal is to raise patients' awareness about their routine's overall stability as well as to alert them to which aspects are out of kilter. By abstracting away the low-level sensor data to coarser-level representations, it highlights what is important in the context (away from the clinic) and emphasizes ease of comprehension.

IPSRT's rhythm-based interventions offer the potential to help stabilize patients' mood and well-being. A significant portion of a therapist's work is helping patients gain insights into connections between their daily routine and overall health. Therapists typically offer patients advice and educational support on how to stabilize their routines. We are currently exploring how sensed data can be used to personalize therapeutic suggestions and the timing of more involved educational modules that can be delivered via patients' smartphones.

Lessons learned

We worked closely with patients and clinicians for over a year to develop MoodRhythm, with the goal of balancing rich sensing and user needs. The resulting system was well accepted in a small pilot study involving three patients and three clinicians, who used the system for three to four weeks and provided both iterative and summative feedback.[14] In this study, patients' acceptance was closely associated with their understanding of how the sensing worked and whether the recorded data could help them or their clinician gain another perspective. For example, one patient was particularly keen on sensing levels of social interaction since "my perception … might be different than [the system's] perception. It would be interesting to hear how this works."

Building on a clinically validated treatment (IPSRT) and instrument (SRM) has both advantages and challenges. There is a well-identified clinical utility to adding sensing, and clinicians can readily integrate the technology into their practice. This is significant because technology is not currently used as part of IPSRT. On the other hand, integrating rich data from sensing into existing practice can be problematic. While passive sensing enables near-constant monitoring of daily rhythms, stressors, and levels of social interaction, clinicians are habituated to making decisions based on limited data from paper-based SRM forms. In the case of location data, for example, viewing a list of every location a person has visited would be overwhelming. Privacy is also a concern: patients would understandably be less than enthusiastic about sharing this level of data.

In addressing these challenges, MoodRhythm demonstrates that patient and clinician interests can sometimes align. By destructively processing location data into unique location IDs, devoid of actual geographical location, the system lets clinicians view changes in location and the number of locations visited but not where a person has been.

Serious mental illnesses are among the most pressing public healthcare concerns. Continuous and unobtrusive sensing of social and physical functioning has tremendous potential to support the lifelong management of SMIs by acting as an early warning system to detect changes in mental well-being, delivering context-aware micro-interventions to patients when and where they need them and significantly accelerating patient understanding of their illness.

Like any medical intervention, however, developing effective healthcare interventions is a complex task. To have a major impact on SMIs, mobile sensing technologies must address factors related to patient and clinician acceptance. This includes providing patients with control, being sensitive to the ways information and related uncertainty are shown to the user, recording only as much data as is needed to support both clinical decision-making and privacy, and ensuring robustness against potential sensing errors that could be more serious in mental health.

A consortium of leading researchers, advocates, and clinicians recently called for urgent action and investment to address mental illness globally.[15] We have presented a range of techniques from our previous and ongoing work to suggest how technologists can make significant advances in this area. While we are still shaping and evaluating these solutions, there is an opportunity for other researchers in our field to help ease the burden of SMIs by striking a balance between cutting-edge sensing and patient needs. This could empower patients by giving them a hand in their own treatment and ultimately lead to more effective, lower-cost treatment.

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