Sensing Technologies for Monitoring Serious Mental Illnesses

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Mental health is an urgent global issue. Around 450 million people suffer from serious mental illnesses worldwide, which results in devastating personal outcomes and huge societal burden. Effective symptom monitoring and personalized interventions can significantly improve mental health care across different populations. However, traditional clinical methods often fall short when it comes to real-time monitoring of symptoms. Sensing technologies can address these issues by enabling granular tracking of behavioral, physiological, and social signals relevant to mental health. In this article, we describe how sensing technologies can be used to diagnose and monitor patient states for numerous serious mental illnesses. We also identify current limitations and potential future directions. We believe that the multimedia community can build on sensing technologies to enable efficient clinical decision-making in mental health care. Specifically, innovative multimedia systems can help identify and visualize personalized early-warning signs from complex multimodal signals, which could lead to effective intervention strategies and better preemptive care.

Mental health is an urgent global issue. Around 450 million people worldwide suffer from mental illnesses.[1] According to the World Health Organization, serious mental illnesses are among the leading causes of disability.[2] People with mental illnesses have a mortality rate 2.22 times higher than the general population; approximately 8 million deaths each year are attributed to mental disorder.[3] Suicide is one of the top ten causes of death in the US—44,193 individuals committed suicide in 2015 alone.[4] Mental illnesses also cause huge economic burden resulting from both direct cost of care and indirect cost, such as lost productivity and income, and support for chronic disability beginning early in life. The resulting financial cost associated with mental disorders was at least $467 billion in the US in 2012.[5] Bloom et al.[6] estimate that the global cost

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associated with mental illness was $2.5 trillion in 2010, and it is projected to be $6 trillion by 2030.

Serious mental illnesses often don't have life-long cures; however, appropriate intervention and management can ensure long-term patient well-being. Effective illness management requires granular symptom monitoring. Specifically, identifying early-warning signs in patients can result in timely clinical interventions and, thus, prevent relapse onset and hospitalization.[7]

However, existing clinical tools for monitoring illness trajectory are inadequate. Traditionally, clinicians use face-to-face interactions for assessment and diagnosis. However, these clinic-centered services can pose a number of logistical challenges. For monitoring illness trajectory, patients are required to travel frequently to a clinical center within its limited hours of operation. This can be difficult for patients with serious mental illnesses. Also, these methods are highly resource-intensive because they require one-to-one interactions with a trained clinician, and, thus, their large-scale dissemination is challenging. The accessibility and scalability issues inherent in these methods result in significant barriers to patient care.

Effective illness management requires granular symptom monitoring.

To address these issues, clinicians have developed and employed survey-based methods. For example, PHQ-9 is a widely used self-assessment survey for diagnosing and assessing severity of depression.[8] However, self-assessment surveys at most can capture infrequent snapshots of patient states. As such, survey data might fail to track crucial details about illness trajectory. Moreover, data from self-assessment surveys can be unreliable due to memory limitation and recall issues.[9] This is particularly problematic for patients with serious mental illnesses—accurate recall can be challenging for patients in certain stages of illness. Given these limiting factors of existing methods, there is an explicit need for better ways to monitor illness symptoms and trajectory in mental health care.

This is where technology can help. In recent years, sensing abilities of phone and wearables have increased significantly. These devices can be used to monitor behavioral and contextual signals relevant to mental health issues. There has also been a dramatic growth in the ownership of these devices. Today, around 3.9 billion people own phones, and this number is estimated to increase to 6.8 billion people by 2022.[10] This trend of using phones is also true for patients with serious mental illnesses. Based on a large study, Dror et al.[11] reported that 72 percent of individuals with serious mental illness own phones. Robotham et al.[12] also found that technology use is on the rise among patients with mental illness. As such, sensing technologies based on these devices can potentially reach a global population far beyond the capability of current clinic-based services. The multimedia community can further leverage these devices' abilities by identifying actionable insights from data and visualizing patterns in complex signals, thus enabling shared and efficient clinical decision-making. Bridging the gap between sensing technologies and traditional treatment steps will be essential in ushering currently reactive mental health care into a new preemptive era.

In this article, we aim to describe the current landscape of sensing technologies for monitoring mental health issues. Specifically, we describe technologies that can be used for tracking behavioral, physiological, and social signals relevant to serious mental illnesses. We mainly focus on scalable technologies that leverage widely available consumer devices. We also point out limitations of these technologies and their potential future directions.

BACKGROUND

For diagnosis of mental disorders, the Diagnostic and Statistical Manual of Mental Disorders (DSM)[13] is the most widely used resource. The DSM is maintained and published by the American Psychiatric Association; the fifth edition (DSM-5) is the most recent one. It provides a set of criteria for classification and diagnosis of numerous mental disorders. For example, the DSM-5 lists nine criteria (such as daily depressed mood, weight loss, and insomnia) for Major Depressive Disorder (MDD). Experiencing five out of these nine criteria within a two-week period might indicate onset of MDD.

While the DSM provides a standardized set of criteria, diagnosing mental disorders remains difficult. Large variations in symptom onset in mental illnesses can make it difficult to fit any standardized profile. For example, when considering symptom combinations for MDD, there are 1,497 different possibilities.[14] These symptoms can also change over time for a patient. Moreover, serious mental illness tends to have several other comorbidities. For example, panic disorder, substance abuse, and depression are often comorbid with schizophrenia.[15] The presence of multiple comorbidities can further complicate subjective diagnosis of mental disorders. Zimmerman et al.[16] reported that a substantial fraction of psychiatrist and non-psychiatrist clinicians often don't use DSM criteria for diagnosis.

Identifying objective markers of mental illnesses can address these issues. Changes in illness states often are reflected in behavioral, psychological, and social signals. For example, decreased social interaction[17] and mobility[18] can indicate deteriorating conditions in depression. Thus, granular monitoring of these signals can provide unique insights into illness trajectory. These signals can further help identify individualized markers of illness onset, which in turn could be used to design personalized treatment steps. This could significantly improve clinical feedback and therapeutic outcomes for a patient.

In the following sections, we will describe sensing technologies that can be used for tracking signals relevant to mental health states. Specifically, we will focus on technologies that leverage widely available consumer devices for sensing behavioral, physiological, and social signals (see Table 1). We will also discuss their limitations and how these limitations can be addressed in future work.

Table 1. Sensing technologies for capturing behavioral, physiological, and social data relevant to serious mental illnesses.

Signal Type	Data	Technology	Example Data Features	Relevance to Mental Illnesses
Behavioral signals	Location and mobility	GPS, Bluetooth, and Wi-Fi	Total distance travelled, circadian movement, radius of gyration, routine index, and location cluster	Depression, bipolar disorder, schizophrenia, and anxiety disorder
	Speech patterns	Microphone in phone and smartwatch	Voice features (MFCC), speaking cues, and conversation frequency and duration	Bipolar disorder, schizophrenia, depression, and suicidal ideations
	Technology use	Phone	Duration and frequency of phone and app use	Bipolar disorder, schizophrenia, and depression
	Activity	Accelerometer and gyroscope in phone and smartwatch	Sedentary duration, activity types (such as running and walking), and activity duration	Bipolar disorder, schizophrenia, and depression

Physiolog-ical signals	Facial expression	Camera in phone and computer	Facial Action Units (AUs) and facial expressivity	Schizophrenia, suicidal ideation, and depression
	Heart rate variability (HRV)	Smartwatch	Anomaly and reduced variability in heart rate	Schizophrenia, bipolar disorder, PTSD, and anxiety disorder
	Eye movement	Camera in phone and computer	Blinking and oculomotor performances	Schizophrenia, depression, and dementia
	Electroder-mal activity (EDA)	Smartwatch	Amplitude, rising time, and habituation rate	Schizophrenia, mood disorder, and suicide risk
Social signals	Social interaction	Bluetooth and Wi-Fi in phone	Proximity and co-location	Bipolar disorder and schizophrenia
	Communica-tion patterns	Phone	Calls and SMS	Bipolar disorder, schizophrenia, and depression
	Social media	Twitter and Instagram	Textual and image content, and engagement	Depression and PTSD

BEHAVIORAL SIGNALS

Location and Mobility

Our daily behaviors are characterized by repetitive patterns of mobility and location traces. Location patterns can also be a good indicator of our social activities. As such, signals from mobility and location data can provide unique insights into one's mental states. For example, Babak et al.[18] associated sedentary lifestyle with depression.

Location can be tracked continuously using the GPS sensor in a phone. In a recent work, Canzian et al.[19] used mobility traces from GPS data from phones to monitor depression severity. They defined mobility traces as a sequence of stops and movements, where a stop is defined as a participant staying in a place for a certain interval of time. From this data, they calculated different matrices that represent various aspects of user mobility such as total distance traveled, radius of gyration, and routine index. They reported that mobility traces show significant correlation with severity of depression as calculated using PHQ-8 scores.[19] Similarly, Saeb et al.[20] used GPS data to calculate mobility features, including circadian movement, entropy, and variance. They also found that these features are strongly correlated with depression severity.

Similar location-based features have been used for monitoring other mental illnesses, as well. In our own work, we used GPS data from patients with bipolar disorder to calculate daily distance traveled and number of location clusters.[21] We found that the location features are the most important ones in our model for predicting stability in bipolar disorder. In a later work focusing on schizophrenia, we computed a rich set of location and mobility features using GPS data (such as total distance traveled, maximum displacement from the home, location entropy, and location routine index).[22] A number of these location features were strongly correlated with disease symptoms in patients with schizophrenia. Chow et al.[23] used similar features from GPS data for monitoring social anxiety symptoms.

Speech Patterns

Speech characteristics can be an important indicator of mental health. Individuals with depression tend to have a lower fundamental frequency range,[24] as well as a slower rate of speech and relatively monotone delivery compared to the healthy population.[25] Ozdas et al.[26] also found that vocal jitter—short-time fluctuations in the fundamental frequency—is less prominent in high-risk suicidal patients.

As such, voice features can potentially be used for diagnosing mental illness. For example, Alghowinem et al.[27] reported that Mel-Frequency Cepstral Coefficients (MFCC), intensity, and energy features from speech data are useful in identifying depressive states. Similarly, a number of recent studies have used prosodic, articulatory, and acoustic features for diagnosing depression and suicidality (see Cummins et al.[28] for a detailed review).

However, most of these studies are done in the controlled lab environment. For continuous and passive monitoring, it is important to collect and analyze speech data "in the wild." Microphones in smartphones can collect audio data in real time. Lu et al.[29] developed StressSense to collect audio data for monitoring stress in daily life. Muaremi et al.[30] used phone call conversation data to identify manic and depressive states in bipolar disorder. They computed three different types of features: phone call statistics (such as frequency and duration of phone calls), speaking cues (such as number of speaker turns), and voice features (such as MFCC and kurtosis energy per frame). They then used data from 12 patients with bipolar disorder to train Random Forest models for classification. Their models show high accuracy with an average F1 score of 81 percent. Faurholt-Jepsen et al.[31] also collected voice features from phone calls and found that these features can be used to determine phases in bipolar disorder.

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Beyond phone calls, social interactions are often marked by engagement in conversations. As such, conversation information can provide important cues about illness trajectory and mental health states. In our previous work, we developed a smartphone framework for continuously collecting audio data to infer presence of human voice and conversation.[32] For privacy reasons, the framework doesn't store audio recordings, but rather processes data "on the fly" to compute features such as spectral regularity and energy. These features can then be used to detect the presence of a human voice, but don't contain adequate information to reconstruct speech content,[33] mitigating privacy concerns.

This framework enabled us to collect conversation information—an important marker of social engagement. We have deployed this framework among patients with bipolar disorder[21] and schizophrenia.[22] Conversation frequency was strongly correlated with self-assessed energy scores from patients with bipolar disorder.[21] We also found that daily conversation features are useful in predicting state changes in patients with schizophrenia.[22]

Technology Use

Our daily behaviors are often mediated through technology. As such, patterns of technology use can provide behavioral and contextual information relevant to mental health. In particular, phone use patterns have been associated with sleep onset and wake-up behaviors. In our prior work, we developed an algorithm that only uses screen on and off information from smartphones to accurately model sleep behavior.[34] Tracking sleep behavior can provide important insights into a range of mental illnesses.[35]

Changes in illness states can also manifest in technology use patterns. From a survey with 84 patients, Mark et al.[36] reported that technology use changes across different states of bipolar disorder. They also concluded that such changes in technology use patterns can be leveraged as early-warning signals of mood episodes. Alvarez-Lozano et al.[37] found that phone app use correlates with mood and stress levels of patients with bipolar disorder—higher use of social apps correlates with lower stress, and increased use of entertainment apps is associated with higher mood level. Rui et al.[22] also reported a similar association with entertainment apps and illness states in schizophrenia (for example, worrying about being harmed was associated with lower use of entertainment apps).

Screen on and off data can be used to infer duration and frequency of phone use over a given period of time. Frost et al.[38] found these features to be highly correlated with mood in bipolar disorder. Saeb et al.[20] reported that a higher level of phone use (increased duration and frequency) is associated with increased depressive symptom severity. On the other hand, Rui et al.[22] reported that negative symptoms in patients with schizophrenia are associated with less phone use.

Activity

Level of physical activity can be indicative of mental health status. For example, in bipolar disorder, mania is marked by overactivity, while activity level significantly reduces during depression.[39] Reduced level of physical activity is also a marker of increased symptom severity in patients with schizophrenia.[40] To assess levels of activity, most of these studies used actigraph—a wrist-worn device that uses accelerometer data to infer frequency, intensity, and duration of physical activities.[41]

Smartphones also have accelerometer and gyroscope sensors, which can be used to continuously monitor the activity level of a user. Wanmin et al.[42] used accelerometer and gyroscope data to accurately classify sedentary and physical activity behaviors such as sitting, walking, and jogging. Recent studies have used physical activity data collected by smartphone sensors to associate states in bipolar disorder,[43,44] depression,[19] and schizophrenia.[22] The wide adoption of smartwatches could further enable granular data collection about activities in patients with mental illnesses.

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PHYSIOLOGICAL SIGNALS

Facial Expression

Facial expressions play a major role in conveying one's emotional states. As such, facial expressions and activities can be useful in diagnosing mental illnesses. For example, patients with schizophrenia tend to show reduced facial expressivity ("flat affect").[45] A number of recent studies have developed systems for classifying mental health states using facial features. For example, Tron et al.[46] used 3D structured light cameras for tracking facial Action Units (AUs) in patients with schizophrenia. Using these features, their classification algorithm achieved high accuracy in differentiating patients from control participants. Laksana et al.[47] have also used facial expression data to detect suicidal ideation. For feature generation, they used AUs from facial expressions along with smile information (such as intensity and frequency), frowning behavior, eyebrow raises, and head movement. Valstar et al.[48] have proposed using facial features along with audio cues for detecting levels of symptom severity in patients with depression. These studies mostly use data recorded in the controlled lab environment. However, given the recent rise of ubiquitous devices with cameras, we believe that facial expression signals could play a major role in diagnosing mental illness. For example, Rui et al.[49] developed a system that opportunistically captures one's facial expressions throughout the day by using the front camera of a phone. Given the availability of smartphones, such a system can potentially be used to diagnose and monitor mental health issues on a global scale.

Heart Rate Variability (HRV)

Heart rate variability (HRV) can provide useful insights into mental health states. Patients with mental illness have a much higher risk of cardiovascular morbidity compared to the general population. Coronary heart disease is the primary cause of premature mortality among patients with schizophrenia.[50] Cardiovascular mortality is also significantly higher in patients with bipolar disorder[51] and depression[52].

Kemp et al.[53] argued that the relationship between increased cardiac mortality and mental illness could result from the reduction in HRV. Patients with depression consistently have reduced HRV.[53] Quintana et al.[54] reported reduced HRV in patients with bipolar disorder and schizophrenia, as well. Veterans with post-traumatic stress disorder (PTSD) also show lower HRV.[55] Anxiety disorders have been associated with reduced HRV, as well.[56] As such, HRV and other measurements of cardiac functioning could be used as effective biomarkers for tracking states in mental illness.

HRV is usually measured by electrocardiogram (ECG) data. Traditional ECG devices can be quite bulky and, as such, are not appropriate for continuous measurement. However, given the capabilities of smartwatches, this might be less of an issue in the future. For example, Apple Watch now has the ability to continuously track heart rate.[57] Using this data stream, it's possible to identify anomalies in HRV patterns that might indicate symptom onset in patients with mental illnesses.

Eye Movement

Subtle changes in eye movement can provide useful information about mental illness issues. Indeed, eye-tracking dysfunction is a consistent trait among patients with schizophrenia.[58] Patients with melancholic depression show different saccadic eye movement compared to control populations.[59] Alghowinem et al.[60] used eye movement and blinking features to detect depression. They used video data from 30 patients with severe depression and 30 healthy control subjects to train their models. These models achieved 70 percent accuracy in identifying patients with depression.

There has been some recent work focusing on collecting eye-tracking data in the real world. In particular, wearable Electrooculography (EOG) glasses[61] can be used for detecting eye movement and blinking. These methods can potentially be used for diagnosing mental illnesses at scale. In a recent work, Cano et al.[62] proposed using web cameras for assessing oculomotor performance. Such a method could be used to detect the early stage of dementia onset.

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Electrodermal Activity (EDA)

Electrodermal activity (EDA) refers to changes in electrical properties of the skin. EDA can reflect cognitive and emotional processing within the central nervous system.[63] As such, it has been widely used in both clinical and non-clinical settings. For example, Schell et al.[64] reported that heightened electrodermal activities predict negative symptoms and poor functional outcomes in patients with schizophrenia. Lanata et al.[65] used EDA signals to classify different mood states (such as depression, hypomania, and euthymia) in patients with bipolar disorder. Similarly, Greco et al.[66] reported that variations in EDA signals can be used to discriminate mood states in bipolar disorder. EDA data has been used as a risk marker for suicide, as well. Using data from patients with Major Depressive Disorder, Jandl et al.[67] found that patients who have attempted suicide have significantly lower levels of EDA habituation rate. Thorell et al.[68] also concluded that EDA signals can indicate suicide propensity in patients with depression.

Therefore, EDA can be a useful biomarker for both diagnosing and monitoring patients with mental illnesses. A number of recent projects have developed wearable devices that can be used for tracking EDA signals over a longitudinal period of time. For example, Gravenhorst et al.[69] developed a system that participants wear around their ankles and feet for collecting EDA data. They also developed a custom Android app for uploading and storing EDA data. Empatica[70] has developed a number of commercially available wristband devices for continuous and real-time monitoring of EDA signals. Data from these devices can help us better understand the relationship between physiological signals and illness trajectory in patients with mental illnesses.

SOCIAL SIGNALS

Social engagement can indicate one's psychological well-being. Social isolation, for example, has been associated with depressive symptoms.[71] Cannon et al.[72] also found that psychosis onset in patients with bipolar disorder and schizophrenia is preceded by poor social functioning. Monitoring social behavior can be useful for identifying early-warning signs of relapse onset.

Social Interaction

Sensing technologies can be used to unobtrusively collect data about social interactions. Bluetooth, Near Field Communication (NFC), and Wi-Fi access point data can indicate proximity and co-location. These signals have been used as a proxy for quantifying social relationships and interactions in the general population.[73] Dror et al.[74] used Bluetooth beacons to capture movement and activities of acutely ill hospitalized inpatients with schizophrenia.

Communication Patterns

Our social behavior often is dispersed through communication technologies. As such, data about the use of these communication technologies can indicate one's level of social engagement. A number of studies have looked into communication patterns for inferring states in serious mental illnesses. Beiwinkel et al.[44] used outgoing calls and SMS data for monitoring social communication in patients with bipolar disorder. They found that depressive symptoms are associated with a decrease in outgoing SMS, while the manic phase resulted in increased phone calls. Similar findings in patients with bipolar disorder have been reported in other studies, as well.[75] These communication patterns can also be useful for tracking symptom states in schizophrenia. In our study, we found that phone call and SMS activities (such as frequency and duration) can indicate positive and negative states in patients with schizophrenia.[22]

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Social Media

Social media platforms have revolutionized our social engagement and communication behaviors. People use social media platforms to share their activities and thoughts. Data from these platforms can provide unique insights into behaviors and contexts relevant to one's overall well-being. Specifically, social media data can be useful in determining social engagement, social network characteristics, mood, and emotion. These features can lead to predictive models for monitoring mental health issues. For example, Munmun et al.[76] were able to predict depression onset with 70 percent accuracy using textual content and network properties of Twitter data. Similarly, Reece et al.[77] reported that Twitter data can be used to predict the onset of depression and PTSD.

Social media posts also contain images and videos. While it is computationally more challenging, recent studies have focused on collecting and extracting useful signals from such non-textual content in social media. In our work, we developed an image analysis framework to detect faces and smiles from social media images.[78] We found that the resultant "smile index" correlates with public mood and external events. Moving beyond general sentiment analysis, Reece et al.[79] reported that features from Instagram photos can be used to predict depression. These findings show that signals from social media data—both textual and multimedia content—can be useful in long-term and scalable mental health tracking.

NEXT STEPS

In previous sections, we described the current landscape of sensing technologies in the context of mental health. As these studies show, granularly tracking behavioral, physiological, and social signals has great potential for reshaping mental health care. However, there is still much to do before such transformational changes in health care can be fully achieved. In this section, we will point out the limitations of current sensing technologies and how the multimedia community can help address them.

Extending Clinical Evidence

While recent studies show the clear potential of sensing technologies in mental health care, there is still a lack of clinical evidence regarding the efficacy of these systems. Findings from these studies are often limited due to their small sample size, mostly non-clinical population, and the short duration of the deployment. In other words, the findings from these studies are often based on underpowered pilot data. Also, given the continuously evolving nature of sensing technologies, it can be challenging to systematically ensure validity of a particular method over a long period of time. The relatively short iteration period in technology development can result in abruptly making an existing technology and associated clinical evidence obsolete. Moreover, since the sensing technologies are relatively new, sometimes there is no appropriate theory or ground-truth yet. This makes comparing the outcomes from these methods and establishing clinical evidence difficult.

Overall, there is a serious need to broaden the clinical evidence supporting the efficacy of sensing technologies in the context of mental health. To address this "evidence gap," it is important to ensure high-quality study design, reliability of data collection, and the replicability of the data analysis process. In particular, it is important to consider what would constitute sufficient evidence during the early design phase of the study and to plan accordingly. Going beyond pilot studies would require a consistent focus on collecting quality data over a long period of time from a large pool of participants with a given clinical condition. These steps can help extend the much-needed clinical evidence base for emerging sensing technologies.

Integration of diverse signals would be particularly useful for identifying individualized early-warning signs.

Better Integration of Diverse Data Streams

These studies have looked into individual sources of sensor data and its association with mental illnesses. However, only a few of these methods have focused on the fusion of behavioral, psychological, and social signals. Better integration of multimodal data streams can potentially improve classifier accuracy. It can also be used as an additional check for internal validity. For example, if the state of a patient inferred from different sources of data—behavioral, physiological, and social signals—is consistent, then a system can be more confident about its validity. Integration of diverse signals would be particularly useful for identifying individualized early-warning signs. Patients with serious mental illnesses often have a number of other comorbidities. As a result, symptom onset and illness profiles can be very different even across patients with a similar diagnosis. For example, social cues might be more informative for some patients, while changes in behavioral signals might indicate relapse onset for others. Moreover, indicators of relapse onset can also be dynamic, changing over time. Integration of diverse data streams can help better adapt to such individualized and dynamic changes.

However, integration of different data streams poses a number of computational challenges. In particular, the sample frequency across different data streams varies a lot—an accelerometer can produce more than 60 samples per second, while only a few social media data points are generated over a day. While there has been some recent work on effective fusion of data streams with different temporal resolution, there is still much to do.

Privacy and Confidentiality

These sensing technologies collect an enormous amount of personal and potentially sensitive data. For example, location data can divulge one's home and social interactions. Moreover, some of these technologies might end up capturing data for non-participants, as well. For example, the audio sensing technologies might pick up conversations from non-participants, extending the privacy risks. As such, it is essential to consider privacy and confidentiality implications when developing and deploying these technologies.

Researchers should identify potentially sensitive data items and come up with a data management strategy that covers data transmission, storage, and analysis. They can also significantly lower risks by adopting privacy-preserving data processing. For example, our audio module processes speech data in real time only to store features for later analysis.[32] By deciding to not store any speech content, it significantly reduces privacy risks for both participants and non-participants. Similarly, GPS data can be aggregated so that it still retains useful information while not being granular enough to identify a patient's home location. Balancing the need for privacy while keeping the accuracy of the sensing technologies can be difficult. However, the question of privacy and confidentiality is important for engendering trust in users.

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User Engagement

While sensing technologies often collect data in a passive manner, user engagement can be crucial for ensuring data quality over a long period of time. For example, technologies that use smartphone sensors need to make sure that a user carries her phone and charges it regularly. Long-term user adherence is also critical for collecting ground-truth data. However, most recent studies on sensor technologies do not focus on user engagement and adherence. As a result, large-scale deployment of these technologies in the real world might face some serious challenges. For example, a recent study found that around 53 percent of users stop engaging with a given mHealth app after 30 days.[80] Strategies for long-term user engagement and adherence are essential for successful deployment of sensing technologies.

CONCLUSION

In this article, we provide a brief overview of sensing technologies for monitoring trajectories of mental illnesses. We focus on technologies that can leverage widely used commercial devices and, thus, are easily scalable. As evidenced by recent studies, sensing technologies can be used to collect granular behavioral, physiological, and social signals relevant to a diverse range of mental illnesses. This can lead to personalized early-warning signs and effective clinical feedback for patients with serious mental illnesses.

However, there is still much to be done before these technologies can be fully integrated into existing healthcare infrastructure. We must address numerous key challenges, including the lack of clinical evidence, integration of multimodal data streams, privacy issues, and long-term user engagement. Successful integration of sensing technologies has the potential to reshape mental health care—making it preemptive, patient-centered, and cost-effective while extending its reach to a global population. The multimedia community can play an important role in this transformation by developing innovative methods for identifying actionable insights from complex signals, and then effectively communicating those insights to clinicians, patients, and caregivers.

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