

Mobile technology for mental health assessment

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Introduction

Diagnosis, case formulation, and outcome monitoring are critical to the delivery of evidence-based mental health treatment.¹ Unlike other areas of health care, there is no blood test or other diagnostic assay to determine a diagnosis or explain a client's symptoms.² Until recently, mental health clinicians have had to rely solely on clinical judgment and client self-reported symptoms to assign a diagnosis and elect the optimal treatment. Despite decades of research improving and refining clinical observation and self-report measures, these methods remain problematic, as they depend on retrospective recollection of symptoms and functioning during clinical interviews that occur outside the client's typical milieu; reports of this nature are known to be biased and inaccurate.³

Ecological momentary assessment (EMA) holds promise as a method for capturing more accurate accounts of a client's emotions, functioning, and activity.^{4,6} Examples of EMA commonly used are daily diary methods, signal-dependent reporting, and event-dependent reporting. Daily diaries require the client to report on events and mood at the end of the day and are thus

Assessment and outcome monitoring are critical for the effective detection and treatment of mental illness. Traditional methods of capturing social, functional, and behavioral data are limited to the information that patients report back to their health care provider at selected points in time. As a result, these data are not accurate accounts of day-to-day functioning, as they are often influenced by biases in self-report. Mobile technology (mobile applications on smartphones, activity bracelets) has the potential to overcome such problems with traditional assessment and provide information about patient symptoms, behavior, and functioning in real time. Although the use of sensors and apps are widespread, several questions remain in the field regarding the reliability of off-the-shelf apps and sensors, use of these tools by consumers, and provider use of these data in clinical decision-making.

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Clinical research

still subject to some recollection bias. Signal-dependent reporting involves the client reporting on symptoms at random intervals during the day in response to an alarm. Event-dependent reporting has the client report on symptoms after predetermined interpersonal or challenging events during the day. Of the three, signal- and event-dependent reports are the most accurate; however, they are burdensome and demand a level of engagement and motivation often not encountered in many psychiatric illnesses.⁷ Personal mobile technology, such as smartphones and wearable sensors, has the potential to capture a more accurate picture of a client's symptoms in real time, with far less burden and greater adherence than traditional EMA methods. Momentary assessment through technology gives clinicians an opportunity to look at how one's symptoms and disability vary over time, and could give us insights into how these symptoms vary between different social contexts (work versus home).^{8,9} Current technologies can capture many different kinds of behavior, and with the right analytical tools, it is possible to identify behavioral profiles or phenotypes that predict illness trajectories and differential responsive to treatment over time. As an example, the global positioning system (GPS) and accelerometer technologies in smartphones can be used to calculate physical and spatial activity, which are known to be good measures of disability associated with depression and anxiety.^{10,11}

Clearly, there is great potential for technology to enhance prediction and assessment of psychiatric problems. But are we there yet? Which technologies are useful and which are still in development? What does the client consider acceptable in terms of remote data collection in this manner? Are providers prepared or willing to utilize this data? What are the ethical ramifications of the different types of data collection? In this paper, we review the state of the art in mobile, momentary assessment; the potential avenues that require further research; as well as client and clinician readiness for this form of data collection and, finally, the ethical ramifications of mobile assessment.

Technology-based assessment methods

The ownership of feature phones, smartphones, and wearable sensors rises dramatically from year to year. In 2013, 1.31 billion people around the world owned a smartphone, and by 2016, that number is expected to in-

crease to 2.19 billion.^{12,13} A recent Nielsen poll and the Pew Hispanic Trust found that mobile device ownership is pervasive across ethnic and income groups, and people from these groups are more likely to purchase a smartphone than to purchase a computer.^{14,15} Low- and middle-income countries are experiencing large increases in cell- and smartphone ownership, owing to the declining costs of devices and wireless services.¹⁶ Smartphone owners are more likely to use their phones for Internet-based activities than to use, or own, laptop and desktop computers.¹⁷ Although electronic actigraphs, pedometers, and wearable GPS units have been in existence for a decade or more, smart versions of these tools—those that have Bluetooth connections to phones (eg, smart watches)—are relatively new and, although less is known about who buys these devices and for what purpose, most sensors are marketed as fitness tools. In a 2013 survey of US adults, 40% said they were interested in purchasing a smart watch, and of those who expressed interest in purchasing, 48% said they intended to use these tools for health and fitness purposes.¹⁸

Because of their ubiquitous nature, smartphones and wearable sensors have the potential to collect a warehouse full of physiological, social, emotional, and behavioral data in real time with limited burden on the client. Data of this nature is important in informing decisions about treatment options, as well as in monitoring response over time. Physical activity, social connection, cognitive function, and symptom burden are important targets for most therapeutic interventions, and changes in these functions are indicators of treatment success or failure. The four following types of data can be collected: (i) those that require responses from the client, such as electronic self-reporting of symptoms (self-report); (ii) those that require clients to engage in a task to assess cognition (performance measures); (iii) those that can be collected from sensors from the phones or wearable sensors (sensor data); and (iv) data collected by phone and Internet activity (social media data).³ These data are processed through mobile software applications (apps), and then are arranged and presented to the user, be it the clinician or client, in a way that could be used to inform treatment decisions.

Self-report

These tools are the oldest methods of technology-based data collection and consist largely of the delivery

of standardized mood and disability questions over a mobile platform. Although feedback from the 9- and 2-question Patient Health Questionnaires (PHQ-9 and PHQ-2) is collected on a number of available depression apps, the consensus among mobile app designers is that more efficient assessment methods, such as daily mood scales, have greater potential for adherence among clients. Recent studies find that daily, Likert-style mood ratings conducted over text messaging or as survey apps are as reliable at measuring mood over time as weekly paper-and-pencil self-report measures.⁷ Apps that track self-reported symptoms are often customizable. A common example of this is the T2 Mood Tracker, which provides an array of surveys and symptoms that clients can elect to monitor, as well as customize how often and when to send prompts and reminders to track the selected symptoms. The use of customizable symptom tracking enhances client engagement in treatment and daily monitoring by giving real-time feedback about how the client is improving over time.¹⁹

Performance data

Performance data consists of asking clients to engage in a task delivered over an app and collecting data on how they perform on that task. In mental health, the most common performance-based assessment apps are those that deliver cognitive assessments over a game-like platform. Tests commonly used to measure attention, concentration, and working memory are redesigned to mimic video games. As the clients use the game, data is collected on the number of errors, reaction time, and other task-based measures of performance. The data are generally processed using an adaptive algorithm to minimize floor, ceiling, and practice effects that are common measurement problems with traditional, paper-and-pencil versions of the tasks. The use of these algorithms theoretically can make assessment of cognitive function more accurate and reduce the need for repeated assessment trials.²⁰ The data on the reliability of these tools currently is mixed. Some commercially available tools do not have sufficient data to demonstrate that they accurately detect the cognitive burdens associated with mental health problems, yet research-based apps are demonstrating promise in mobile assessment of cognition.²¹⁻²³ Given the recent research on the association between poor executive and attentional function and poor response to certain antidepressants,²⁴

these tools could be useful in the selection of treatment options for given disorders.

Sensor data

Sensors embedded in smartphones can measure important functional behaviors, such as physical activity and physical location. Wearable sensors can also detect physiological data, such as blood pressure, galvanic skin response, heart rate, and respiration, and some sensors claim to collect electroencephalogram (EEG) measures. In terms of reliability in the assessment of mental health functioning, these sensors are still in the early phases of development but hold promise. A recent study demonstrated that data on changes in daily physical activity collected with smartphone GPS and accelerometer technology were predictive of mood states before clients reported changes in mood.²⁵ Data of this nature could serve as an early alert to clinicians and result in expedient delivery of an intervention before a client experiences a relapse. Another recent study found that the microphone on smart devices that collects ambient noise is useful as a means of measuring activities of daily living.²⁶ Likewise, the use of the smartphone microphone to collect vocal data has been shown to detect risk for the onset of depression and other serious mental illnesses.²⁷ Vocal data, such as speech fluency, prosody, hesitations, and word errors, are known to be indicators of cognitive burden²⁸⁻³⁰ and mood.³¹ Although these studies are small proof-of-concept trials, they demonstrate the potential for unobtrusively collected data to serve as predictors of changing mood states.

Physiological measures of mental health collected via smartphones and wearable devices have not been well studied. However, the potential to record heart rate and blood pressure changes over the course of the day, coupled with geolocation sensors, for clients with anxiety disorders and other affect-regulation difficulties could be useful in understanding the situations that are most problematic for the client. The clinical utility of these measures, however, is still an open question.

Social media data

Social data collected from smartphones include a combination of incoming and outgoing call and text frequency, length of texts and calls, and number of people contacted, as well as the content of public messages sent

Clinical research

via social media (eg, Twitter). These data can serve as a proxy for social connectivity. Given the tendency of smartphone owners to use these devices for Internet searches, keywords entered into a search could also serve as indicators of psychopathology. The use of this data is controversial, given the inherent risks for violating client privacy. However, there is growing evidence that data gleaned from social media use and communication patterns could serve as passive monitors for depression and changes in psychopathology. One study demonstrated that Twitter posts can predict suicidal ideation³² and onset of depression.^{33,34} Internet-search behavior has also been found to be predictive of suicidal ideation.³⁵ Even the type of apps downloaded could serve as a marker for psychopathology.³

Case example

The advantages to the collection of mood and behavioral data from smartphones and wearable sensors are many, and it is likely that one day we will have enough data from these devices to create algorithms to accurately predict who is at risk for developing a mental illness and how clients are responding to treatment. Below, we provide an example of existing technology that could be used for this purpose.

Ms X is a 25-year-old woman who is 3 months pregnant and beginning her prenatal care with Dr Z. At her first visit, Ms X is given a smart tablet to complete her medical history and intake information. As she types in answers to questions about her health and well-being, she is asked to type in a message to Dr Z about her main questions and concerns. As she is typing, an app runs in the background, collecting information on how long it takes to complete the questionnaire and the number of corrections she makes to her answers. This information is fed into an algorithm that compares her errors and response latency to women in her stage of pregnancy, age, and educational background, and calculates an estimate of cognitive performance. Natural language processing algorithms also survey the content of her text to determine if any significant psychosocial issues are mentioned, such as personal or family history of mental illness. This information is used to alert Dr Z to any psychosocial risk factors for prenatal depression that should be addressed during the visit.

After Ms X completes the survey, a nurse collects biological and vital signs and escorts her to the exami-

nation room to wait for Dr Z. In the meantime, Ms X is asked to complete a few more surveys while waiting privately in the office. On the smart tablet, a computer avatar pops up and it asks Ms X a series of routine questions about her sleep, appetite, concentration, and positive aspects of her day, collecting a 2-minute vocal sample. This vocal sample will be used both as a baseline measure of her vocal expression and as a means of screening for depression, anxiety, and mania—the data collected here include not only the content of her answer, but also data on prosody, fluency, latency, hesitations, inflection, and clarity. The avatar then directs Ms X to a video game that she plays for 10 minutes. This game collects information on her concentration, attention biases, and psychomotor ability.

Dr Z reviews the history and the physical and emotional data and sees that Ms X is at risk for developing prenatal depression. Dr Z, on the basis of her clinical judgment and recommendations generated from the assessment app, gives Ms X a prevention plan that includes 30 minutes of physical activity a day, suggestions for increasing her social support, and strategies for improving sleep during pregnancy. Additionally, Dr Z helps Ms X download an in-home wellness-check app that contains the same tools as the assessment app used for the intake screening. This app also collects continuous passive data on physical activity from the phone's accelerometer and GPS, uses the GPS to measure Ms X's activity space (a measure of social activity), and measures social connectedness gleaned from the information on the number of texts sent, calls made, and number of texts and calls ignored. To measure sleep quality, as well as stress levels, Dr Z recommends that Ms X use one of the commonly available smartwatches. These devices can estimate the level of emotional stress through skin conductance and heart rate. They can estimate sleep—even the stages of sleep, on the basis of heart rate— O_2 , and motion detection. In case Ms X does not have the income to purchase these devices, the app she downloaded on her phone can estimate sleep quality from ambient sound, provided the phone is on and near Ms X while she sleeps.

Once a week, Ms X is prompted to complete her in-home wellness check by her app. Throughout the week, data is collected through her app and health band on her physical activity, social activity, and sleep, and the data is monitored for changes that suggest risk for depression; when risk is detected, suggestions for brief

therapeutic techniques are given to Ms X through the app. She is also given a therapeutic video game to improve cognition. The weekly wellness check includes information on cognitive performance, vocal analytics, and a brief self-report-based mood thermometer; as in the intake app, Ms X is asked questions about her week in order to collect vocal data and is asked to send a brief email to her doctor. During a brief brain game, her cognitive performance is documented. This data is processed and made available to Dr Z before Ms X's prenatal visits or alerts Dr Z and her office staff if Ms X needs to be seen earlier for aggressive intervention. If more extensive intervention is given (antidepressants), the data from the app and health band will serve as a means for measuring symptom improvement on a continuous basis.

Acceptance of digital assessment by clients and clinicians

As the case example above illustrates, mobile technologies produce a wealth of information about a client's quality of life, function, and mood. The number of health and mental health apps is growing exponentially, with 165 000 health apps³⁶ and 30 000 mental health apps available for free or for purchase through the iTunes or Play stores.³⁷ Some are designed to be completely client-centered, whereas others have clinician portals to access client data. The actual reach these apps have and the ability and willingness of users to fully engage in the apps' protocols remain untested. Of particular concern for clients and providers is the fact that less than 2% of the existing apps integrate with electronic medical records, making the process of accessing these data by clinicians onerous. Furthermore, clients and clinicians have very little guidance as to what apps are most accurate in assessing mental health problems.³⁶ The ethical issues related to mobile assessment still require attention. It remains unclear which apps retain data securely and which have protections in place to guard against data breaches. Although clients may be comfortable tweeting about their mood and daily activities, it is unknown how comfortable they would feel having that data compiled for the purposes of psychiatric surveillance. Central to these ethical dilemmas is how informed clients are about the risks to their confidentiality when they download a mental health app. One potential method for ensuring clients are informed is the use of consent

quizzes before downloading an app. Rather than relying solely on agreement to terms and conditions, clients could answer a few questions demonstrating that they understand the potential risk to their personal information. A final concern rests in the fact that many apps are self-guided apps. These are tools for which there is no clinician or service monitoring patient symptom severity to provide feedback or advice based on how one responds to high-risk questions, such as thoughts of suicide, putting the onus of seeking care squarely on the patient's shoulders. Because most apps do not provide guidance about what to do when someone endorses suicidality, providers recommending mood-tracking apps should instruct and remind their patients that most mood-tracking apps do not send alerts to anyone and that if patients are feeling suicidal they must seek help immediately. Patients should also be reminded that very few apps link to health records. A solution to this problem is to recommend only those apps that provide communication back to the clinician or that provide advice and feedback when items that indicate risk are endorsed. A study in Australia is currently investigating the utility of a suicide-prevention app that tracks adolescent risk for suicide using social media traces and other behavioral indicators and that provides self-guided interventions based on mindfulness approaches to help teens modulate their affect.^{38,39} Although data is still being collected and the effects of proactive apps of this nature remain unknown, apps that provide feedback to users and their clinicians proactively could be a safer option than simple mood trackers.

Future directions and conclusions

The future of psychiatric assessment is closer than we think, and will no doubt include the collection of client mood and behavioral data in real time. Mobile data collection can lead to more efficient and expedient care. Rather than asking clients about their week, clinicians will be able to review a client's progress using information collected in real time. A number of studies and projects are well underway to demonstrate the utility of combined mobile data collection to improve treatment and our understanding of psychopathology. ICT-4Depression, a European 7th Framework Program for Research and Technological Development (FP7) project, is currently collecting EMA through a combination of mobile phone and Web-based self-report assessment,

Clinical research

monitoring of activities by wearable sensors, as well recording of electrophysiological measures. The project is also using algorithmic computation of the data to predict a client's current and future mental health states, which is integrated into a monitoring program that provides ongoing and real-time support to clients through smartphones and the Internet.⁴⁰ It is also likely that EMA data collected electronically and on a large scale could help refine our understanding of mental illnesses and if tied to electronic health records, enhance our knowledge regarding who responds to some treat-

ments and who responds best to others. Some technologies are ready to be used, such as those that monitor physical activity and those enabling self-report of mood and function. Others require more development and more research into their reliability, usability, and overall clinical utility. Privacy and ethical problems of this form of assessment will need to be resolved before such data are widely collected. Finally, as these tools are improved, developers will need to seriously consider the interoperability of their assessment tool with electronic health records. □

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La tecnología móvil para la evaluación en salud mental

La evaluación y la supervisión de los resultados son esenciales para la detección efectiva y el tratamiento de la enfermedad mental. Los métodos tradicionales de captación de datos sociales, funcionales y conductuales están limitados a la información que los pacientes reportan retrospectivamente a sus proveedores de atención de salud en momentos seleccionados en el tiempo. Como resultado, esta información no constituye datos precisos del funcionamiento día a día, ya que a menudo están influenciados por sesgos en el auto-informe. La tecnología móvil (como aplicaciones móviles en teléfonos inteligentes, bracelets de actividad) tiene el potencial de superar los problemas de la evaluación tradicional y aporta información acerca de los síntomas, conductas y funcionamiento de los pacientes en tiempo real. Aunque el empleo de estos sensores y aplicaciones está muy extendido, aun persisten algunas preguntas en este campo en cuanto a la fiabilidad de las aplicaciones y sensores comerciales, el uso de estas herramientas por los consumidores y el empleo por los proveedores de esta información en la toma de decisiones clínicas.

La technologie mobile au service de l'évaluation de la santé mentale

L'évaluation et la surveillance de l'évolution sont essentielles pour un diagnostic et un traitement efficaces de la maladie mentale. Les méthodes traditionnellement utilisées pour recueillir les données comportementales, fonctionnelles et sociales sont limitées aux informations rapportées ponctuellement par les patients à leur médecin traitant. Ces données ne reflètent donc pas exactement le fonctionnement quotidien car elles sont souvent biaisées par l'auto-évaluation. La technologie mobile (applications pour smartphones, bracelets de contrôle d'activité) est capable de surmonter ces difficultés de l'évaluation traditionnelle et de fournir en temps réel des informations sur les symptômes des patients, leur comportement et leur fonctionnement. L'utilisation de capteurs et d'applications est répandue mais plusieurs questions restent en suspens en ce qui concerne la fiabilité des applications et capteurs standard, leur utilisation par les consommateurs et l'usage de ces données dans la prise de décision médicale.

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