Chapter 17
Informatics Technologies in the Diagnosis and Treatment of Mental Health Conditions

Wendy Marie Ingram, Rahul Khanna, and Cody Weston

Abstract Mental health conditions, unlike most other illnesses and disorders today, remain bereft of objective and conclusive physiological diagnostic tests. Classically, mental disorders are diagnosed, and treatment plans determined, based on extended interviews to collect patient reported symptoms and histories, careful evaluation by well-trained clinicians, and an often Odyssean journey to reach a satisfactory treatment plan. Mental health informatics technologies may change that. Both consumer and clinician facing technologies hold promise to revolutionize the detection and diagnosis, the prevention and treatment, and the coordination and continuity of care for those with mental health conditions. In this chapter we introduce and discuss the current state of informatics technologies as it relates to the diagnosis and treatment of mental health conditions. We also highlight outstanding issues and challenges.

Keywords Telehealth · Wearables · Smartphone based assessment · mHealth Mobile applications · Computerized psychometric assessment

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17.1 Introduction

Mental disorders are typically diagnosed by first ruling out physical causes of symptoms through physical exams and laboratory testing, then performing in-depth psychological examination. The Diagnostic and Statistical Manual of Mental Disorders – 5 (DSM-5) is the most recent revision of the most widely accepted diagnostic criteria for psychological examination of mental illnesses [1]. It is used as part of a case formulation assessment that leads to a fully informed treatment plan for each patient. The DSM-5 is made up of three sections: I. Basics, II. Diagnostic Criteria and Codes, and III. Emerging Measures and Models. Within the second section lies the core of contemporarily defined and accepted mental disorders parsed into 22 different categories including Neurodevelopmental Disorders, Depressive Disorders, Feeding and Eating Disorders, and Personality Disorders, just to name a few. Trained mental health professionals such as social workers, psychologists, and psychiatrists can employ the Structured Clinical Interview for DSM-5 (SCID-5) in order to make systematic diagnoses for both clinical and research purposes [2, 3]. These semi-structured diagnostic interviews are available in a number of versions differing in detail and design, tailored for specific uses including clinical trials or research. SCID-5 interviews are thorough and typically take 30 to 90 minutes to complete, depending on the diagnosis being tested and the complexity of the patient's case. It is of note, however, that SCID-5 interviews are rarely used in non-research-related clinical practice [4, 5].

Despite the utilization of the methodical SCID-5 framework, there are many reasons that lead to inadequate care for patients with mental health conditions. Patients will often wait years after the onset of symptoms to seek treatment due in part to social stigma, restricted access to behavioral health specialists, and the complex nature of mental illnesses themselves [6]. Once a patient is seen, it is quite common for mental health clinicians to require multiple visits with a patient before determining a primary diagnosis and an appropriate treatment plan. The majority of symptoms of a mental health condition occur outside of office visits and may be masked within the clinical environment, intentionally or otherwise. In addition, epidemiological research has revealed that many "discrete" DSM-5 diagnoses co-occur in the same person (e.g. depression and anxiety, or attention deficit hyperactivity disorder and conduct disorder [7]). The complexity of mental health conditions, the diversity of presentation, and the severe shortage of mental health providers all contribute to many patients receiving shifting primary diagnoses over time as they interact with the health care system and are seen by increasingly specialized practitioners and/or as their condition worsens. For example, a diagnosis of bipolar disorder (BD), a serious mental illness, is often preceded by a diagnosis of depression, with a mean delay of 8.7 years [8–11]. Additionally, many mental health conditions are chronic and/or episodic in nature. Once a correct diagnosis is reached and an adequate treatment plan determined, many patients with mental illnesses will experience periods of remission where regular clinical observation is not required. During these times, continuity of care may lapse and it falls on the patient and their

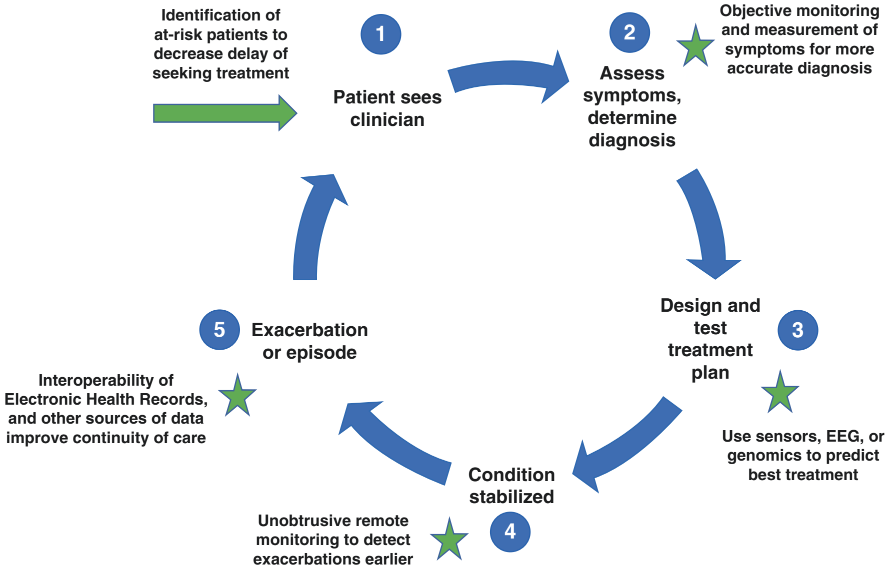

Fig. 17.1 Classical mental health treatment cycle and informatics technologies improvements. The classical mental health treatment cycle may be improved or augmented in many ways by informatics technologies. The blue arrows indicated the classical treatment cycle beginning with 1. Patient sees clinician and cycling through steps 2 through 5. Exacerbation or episode. The green arrow and stars indicate a selection of informatics technologies that could improve these steps in the process

personal support system to detect an exacerbation and reinitiate care [12]. When considered together, the above-mentioned issues lead to major challenges in detecting, diagnosing, preventing, treating, and coordinating continuity of care of mental health conditions. Fortunately, as depicted in Fig. 17.1 and described below, advances in mental health informatics may help address many of these issues through new research and application of informatics technologies [13].

17.2 Detection and Diagnosis

Arguably the largest problem in mental health is the delay of detection and accurate diagnosis of mental illness. In 2004, it was estimated that 80% of people with a lifetime DSM disorder had over a decade of delay between the onset of symptoms and initial contact with a mental health professional [14]. There now exist a multitude of both consumer and provider facing technologies that are helping to close that gap (Fig. 17.1, step 1). Consumers have direct access to several platforms and technologies that produce extensive amounts of data which can be leveraged using informatics methodologies to assist in early detection and more accurate diagnosis of mental health conditions (Fig. 17.2).

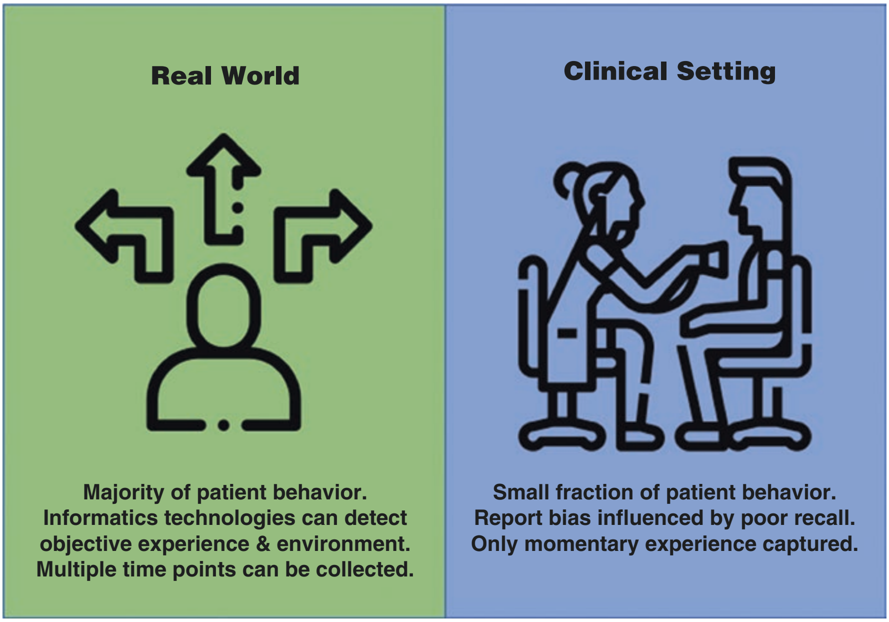

Fig. 17.2 Clinical Setting versus Real World. The clinical setting is limited by how much information can be gathered and how reliable that data is. Only a small fraction of patient behavior and experience can be assessed during clinical visit and is often influenced by problems with patient recall, especially when their mental health condition affects their cognitive ability or memory. The majority of patient experience occurs as the patient moves through the real world where informatics technologies such as wearables and smartphone applications can collect and synthesize objective behavioral and environmental information longitudinally

17.2.1 Consumer Facing Technologies

17.2.1.1 Wearable Devices

The most evident method of capturing behavioral data on free-moving, natural acting individuals involves wearable fitness trackers which contain accelerometers, global positioning system (GPS), and other types of data gathering equipment. These collect actigraphy data (or level of activity, including sleep patterns), location data and more. Direct to consumer and research grade actigraphy devices, most typically worn on the wrist, have been used to study sleep, activity, and movement disorders in ever more impressive detail [15–23]. Less well known are other wireless and wearable devices such as patches and clothing that allow for measurement and electronic transmittal of a variety of biometrics ranging from heartrate to interstitial fluid molecule monitoring [24–28]. Using wearable technology allows real-time objective assessment of patient behavior including sleep quality, eating and drinking behaviors, activity levels and psychomotor activity which can enhance and refine the detection and diagnosis of mental illnesses, likely a significant improvement over current methods involving predominantly patient reported experiences [29–31].

17.2.1.2 Smartphone Based Assessment

In addition to wearable technology, mobile phones allow for unprecedented measurement and analysis of activity, environment, mood state, and behavior at the individual level. These advancements offer enormous potential for better characterizing symptoms and mechanisms of psychiatric disorders, as well as predicting clinical severity and treatment response [30]. Presently it is estimated that 65% of US adults have a smartphone allowing for the development and deployment of applications capable of targeted or longitudinal psychiatric data collection. Global activity can be tracked with GPS transmitters which have already been used to study social behavior [32, 33] and food seeking [34, 35].

There are now over 10,000 smartphone-based applications providing various mental health services with growing acceptability [36–40]. Many include validated instruments for screening and symptom tracking, including the depression screener Patient Health Questionnaire (PHQ-9) or the Generalized Anxiety Disorder 7-item scale (GAD-7), while other mobile applications present screeners and resources for self-evaluation and personal tracking such as the Center for Epidemiologic Studies Depression Scale Revised (CESD-R) and Mood 24/7. In addition to measured or reported information about individuals collected by smartphones, digital environmental sensors are also on the rise and allow the collection of data on noise, chemicals, light, and weather-related environmental exposures [41–44]. The combination of momentary or periodic assessments with passively collected smartphone-based data holds even more promise to assist in detecting and monitoring psychiatric symptomology. In the case of schizophrenia spectrum disorder, the metrics of distance traveled, time spent alone and time sitting still all were associated with increased persecutory ideation (the delusion that includes the belief that they are being or will be intentionally harmed) [45].

17.2.1.3 Social Media

One of the most data-rich sources for detecting mental health concerns is also one of the most challenging: social media. For social, technical and ethical reasons, social media data such as that derived from platforms like Twitter, Facebook, Reddit, Weibo and Instagram have been found to be both promising and difficult to harness [46, 47] (and see Chap. 13). Depression and suicidality have been preferentially studied leading to insights into sentiment, circadian signals, and pronoun usage being linked to experience of mood disorder disturbance [48–59]. However studies of other disorders such as autism, substance use disorder and eating disorders have demonstrated correlations with detectable signal in certain platforms and features in their data [60–63].

Utilization of social media text mining has also been employed to survey populations for concerning mental health deterioration following disasters [64]. There are significant differences in social media usage between patients based on the severity of their mental illness, however, which may affect studies employing this data to detect and diagnose individuals [54]. Despite the promise of leveraging social media data to detect and diagnose mental illnesses, it should also be noted that the use of these platforms may be contributing to mental distress or disorders themselves [65–69].

17.2.1.4 Implications for Mental Health Conditions

Thus far, individual-level moment-by-moment mood monitoring data has advanced our understanding of the temporal associations of different symptoms within mental disorders such as bipolar disorder, post-traumatic stress disorder, and anxiety disorders [70]. For example, a mood monitoring study of individuals with bipolar disorder found that chronic mood instability was more common than the diagnostic criteria of discrete episodes of mood variation [71]. Passive data from mobile phones can also increase our understanding of psychiatric disorders. Number and length of outgoing phone calls and text messages have been shown to be correlated with manic symptoms among individuals with bipolar disorder [72].

Complimentary studies using wearables in addition to self-reported mood data have elucidated potential underlying mechanisms of psychiatric disorders (Fig. 17.1, step 2). Individuals with borderline personality disorder demonstrated significant changes in diurnal physiology (i.e. sleep, activity and heart rate), which may exacerbate symptomatology and could prove to be useful targets for intervention [73]. Emotional processing has been shown to mediate the effects of antidepressants on mood, and early decrease in negative affective bias is considered an early marker of antidepressant efficacy [74]. In addition to the great wealth in knowledge generation about the diseases themselves through research, a crucial application of these consumer facing technologies is to improve detection and accurate diagnosis of disease (Fig. 17.3).

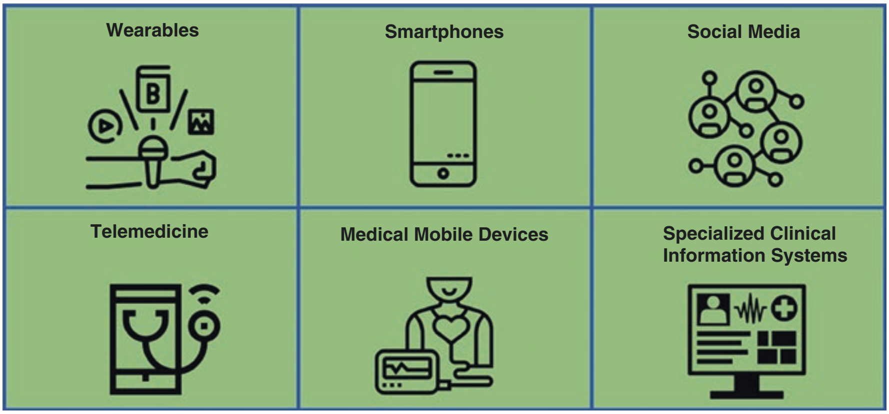

Fig. 17.3 Detection and diagnosis with informatics technologies. Wearables, smart phones, social media, telemedicine, medical mobile devices, specialized clinical information systems

17.2.2 *Provider Facing Technologies*

17.2.2.1 Computerized Psychometric Assessment

Recently, extensive research has been devoted to determining validity and reliability of web- and application-based psychometric assessments comparing against existing paper and in-person administered scales. Computerized psychometric assessments have generally been found equivalent to currently used methodologies, ranging from adolescent to geriatric populations [75–77]. These include psychometric assessments for mental illnesses and associated features such as anxiety, depression, schizophrenia, OCD, suicidal ideation, post-traumatic stress disorder, emotional disorders, cognitive disorders, and more [76, 78–88]. The benefits of utilizing validated computerized psychometric assessment are multifold. They save time for both clinicians and patients by being completed in a variety of settings, including by the patient in the comfort of their own home, before even scheduling an appointment. They can improve access to care for patients in settings that have behavioral health clinician shortages by effectively triaging patients, prioritizing patients with more severe or emergent conditions. In addition, it has been found that computerized adaptive testing, where each item is dynamically selected from a pool of items until a pre-specified measurement precision is reached, can actually improve the efficiency of testing while not losing reliability or validity [89–91].

17.2.2.2 Telemedicine

Access to specialized mental health clinicians that can reliably diagnose and treat mental health conditions is limited by both time and location. Telemedicine, the remote access to clinicians through digital technology, is particularly well suited to improve this aspect of the mental health field. Second only to radiologists, psychiatrists in 2019 were the most likely specialty to employ telemedicine to provide care to their patients (27.8%) [92]. Because psychiatrists rarely need to conduct physical exams of their patients in an outpatient setting, two-way video telemedicine allows for increased access to care that may not otherwise be possible, especially for populations in rural, underserved, and developing nations' communities [93–103]. Establishing a telemedicine practice, however, is not trivial and includes legal, technological, regulatory and billing issues that vary from state to state in the United States and from country to country worldwide [104, 105]. One of the barriers to the adoption of telemedicine is the resistance of clinicians themselves due to concern over developing trust and rapport with their patients as well as concerns over safety, security, and legal issues [105].

The 2019 novel coronavirus (COVID-19) global pandemic has played a transformative role in accelerating necessary rapid adoption of telepsychiatry resulting in both positive and negative consequences [106–115]. The pandemic itself has seriously and negatively impacted a large proportion of individuals' mental health [111, 116, 117]. Those with pre-existing mental health conditions were potentially impacted by not being able to be seen in person in order to refill prescriptions or address exacerbations in a timely manner, especially at the outset of the pandemic. The expansion of telepsychiatry was not instantaneous. It took a bit of time for rules to be suspended, allowing practitioners licensed in other states to provide services in areas that were in desperate need, and for practitioners and clinical systems to set up and adjust to the necessary infrastructure. However, following the growing pains of this sudden transition, clinicians that were previously reticent are now realizing unexpected benefits of telepsychiatry [118]. For example, outpatient psychiatry services at Johns Hopkins School of Medicine have reported that their no-show rates have dropped precipitously, and more patients can be seen each day per physician. Other psychiatric service lines, however, continue to be negatively impacted by the pandemic. Some inpatient units now require each patient to have their own room, essentially halving the number of beds available. Brain stimulation services including electroconvulsive therapy (ECT) and transcranial magnetic stimulation (TMS), are being delayed or rescheduled due to fear of contracting COVID-19. Altogether, it seems that the pandemic has one bright side in that the widespread adoption of telepsychiatry and reduced problematic regulation between states in the US may be here to stay, resulting in much needed improvements in access to care and reduced burden due to other disparities.

17.2.2.3 Mobile Medical Devices

Technological advances have led to the possibility of gathering even more sophisticated types of data that are relevant to mental health [119]. While not used in conventional diagnostic work ups of most mental disorders, research has demonstrated that many conditions are accompanied by clinically meaningful differences in brain structure and activity. Portable brain mapping is migrating from dedicated imaging facilities to the bedside and now into the community with mobile point-of-care MRI head and neck scanners, now FDA approved (example: hyperfine.io) [120]. Functional near infrared spectroscopy [121–124], portable EEG and telemetry applications [125–134], ultrasound imaging [135–137], and optical tomography [138–141] have all seen vast improvements in cost, portability, and accuracy. With increased portability and affordability, mobile medical devices will likely usher in a new era in biometric-based detection, diagnostics, and personalized care for mental health conditions (Fig. 17.1, step 3).

17.2.2.4 Specialized Clinical Information Systems

At the core of mental health informatics is the recognized value in collecting, storing, analyzing, and using specialized information. The collection of this information and its processing leads to improved understanding of community needs, prevalence, treatment response, and other beneficial insights valuable for planning and efficient detection. In 2005 the World Health Organization published a Mental Health Policy and Service Guidance Package specifically covering Mental Health Information Systems [142]. In this report, the authors conclude that general health information systems often fail to capture the data necessary for mental health purposes due to lack of adequate understanding of this branch of medicine. It was perhaps too early at that point, but a major missing piece in their report is the inclusion of mobile applications as a means of providing this specialized information systems for mental health [143]. Connecting primary and secondary care for mental health conditions, knowing when and where to refer patients, and efficiently diagnosing disorders may be fundamentally enhanced by informatics technology driven by mobile applications.

While still challenging, it is now easier than ever to securely connect smartphone based informatics systems to traditional electronic health records allowing for improved monitoring, management, and diagnosis of mental disorders [144–147]. Both electronic health records and smartphone-based applications are not without their challenges and concerns, however. Although there are thousands of mental health applications currently available, almost none provide scientific evidence that their systems properly diagnosis or improve outcomes among users [148–151], and there is evidence that consumers will largely not continue to use the apps when not enrolled in a clinical trial [152, 153]. Furthermore, patient perspectives on the privacy of their mental health information are complex and dynamic, requiring ardent patient engagement in the further development of mental health information systems and how they are used [154].

17.3 Prevention and Treatment

Informatics technology has applicability in prevention, treatment development, and therapeutic response prediction [70]. Individual-level digital monitoring, mental health information systems, and blending of these data are critically useful for the development of predictive algorithms that will allow for better prevention and treatment of mental health conditions, with increasing sensitivity to personalized medicine approaches (Fig. 17.4).

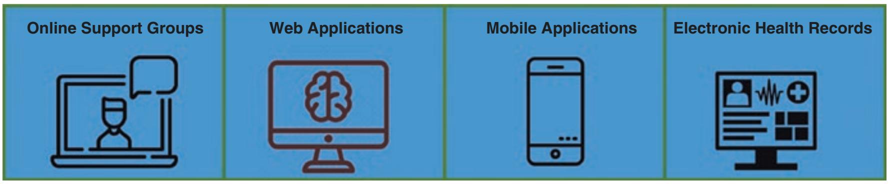

Fig. 17.4 Prevention and treatment. Online Support Groups, Web Apps, Mobile Apps, Electronic Health Records

17.3.1 Consumer and Provider Facing Technologies

17.3.1.1 Online Support Groups

As epidemiological studies reveal an increase in mental health conditions worldwide [155], the shortage of specialized clinicians and limited access to behavioral health care is driving many people to seek support online through disorder specific support groups [156]. International surveys have repeatedly demonstrated that an increasing number of people are seeking help through online support groups [157–161]. Interviews and content analysis reveal that people predominantly seek online support to avoid stigma and to gain immediate, compassionate emotional support, especially when in-person care is unavailable or inconvenient [162–171]. These groups have been used effectively by patients with many disorders, including postpartum depression, schizophrenia, eating disorders, and OCD. Many online support programs and groups are not designed, directed, or evaluated by clinical experts and thus may vary tremendously in their efficacy and safety for those using this modality in exclusion of professional psychiatric and/or psychological support. However, there are examples of clinically designed and distributed online support systems such as the recent Australian site "Moderated online social therapy for youth mental health." [172]

17.3.1.2 Web Based and Mobile Applications

The advent of smartphones and the near ubiquitous availability of internet access in modern times have allowed people unprecedented access to means of daily mental health monitoring and convenient access to resources and remote care. The ability to self-monitor and have applications alert health care providers allows for earlier detection of exacerbations, episodes, or deterioration in individuals which in turn allows for earlier and more effective intervention. Both consumer and provider facing web-based and mobile applications are already available and have been shown to be effective for conditions such as OCD [173, 174] and predicting antidepressant response [175]. A number of web-based and mobile application mental healthcare programs have emerged to meet the need for prevention, early detection, remote therapy, and medication management as well [39, 40, 176–180]. These hold promise for extending the reach of scarce providers into underserved areas and for reaching patients who are reluctant or unable to reach providers in traditional settings. In addition to stand-alone mobile treatment, smartphone based cognitive behavioral therapy (CBT) may also accelerate or support pharmacotherapy for illnesses like depression [181]. Given the time-intensive nature of traditional in-person CBT, this could greatly extend the reach of this intervention in areas with a limited supply of psychotherapists (Fig. 17.1, step 4).

Mobile app-based programs are increasingly available as force-multipliers for teaching wellness skills such as mindfulness and self-compassion and were effective at reducing psychological distress and improving mental well-being among various populations worldwide [182–184]. In addition to the use of self-report measures, smartphone-based applications have the advantage of collecting other forms of data (keystroke rate, activity data, vocal patterns) that can be used to better understand a person's day-to-day mental status. This can be especially useful in tracking symptoms in affective disorders, particularly bipolar disorder [39]. Prediction of future psychiatric manifestations is challenging with current tools, and accurate assessment could prevent significant harm in the form of risk-taking and suicidal behaviors if interventions were offered early. Despite the potential cost- and time-savings associated with adoption of mobile health technologies, psychiatric and psychological practices remain reluctant to adopt them due to lack of specific interest, challenges learning and deploying the technologies, and patient-reported difficulties using the tools [185]. Because mobile mental health applications are still relatively young as a field, there is limited regulatory oversight to differentiate safe and evidence-based interventions from others. This presents a significant barrier to adoption, as clear guidelines could confer legitimacy to rigorously developed applications and increase provider confidence [186] and clearly identify applications and programs that do not have an evidence base [187, 188]. While some efforts are being made to evaluate apps [189], there remains a need for more rigorous and widely accepted oversight and validation.

17.3.1.3 Coordination and Continuity of Care

Mental healthcare suffers from a severe lack of coordinated continuity of care [190–193]. Many studies suggest that patient outcomes would improve dramatically if coordination and continuity of care were enhanced [190–193]. Informatics technology could be the driving force behind such improvements [194] and yet continue to prove difficult to implement and bring to scale [195, 196]. Electronic health records (EHRs), sensors, digital technology and applications on wearable devices or smartphones have been tested in a variety of mental health conditions and shown promising results. However, interoperability issues and high initiation costs of these informatics technologies slow their adoption and deployment. An increase in implementation research may be useful in driving this domain forward (Fig. 17.1, step 5).

17.4 Ongoing Issues and Challenges

As is the case with any rapidly developing field, informatics technologies in the diagnosis and treatment of mental health conditions face several ongoing challenges. Some of these are conceptual and others practical. The conceptual issues relate to the nature and limits of psychiatric diagnoses themselves. Further, practical issues relate to clinician and patient acceptance, the latter of which raises equity and access challenges.

17.4.1 Contemporary Psychiatric Diagnostics

To understand the challenges and opportunities of informatics in mental health diagnostics and treatment, we must understand the status quo and its limits. Although structured and validated interviews and rating scales are common in research settings, contemporary clinicians primarily diagnose mental illnesses through information gained through patient self-report and observations made during the clinical interview [197]. This information is then considered in light of the operationalized diagnostic criteria as outlined in the Diagnostics and Statistical Manual (DSM, currently version 5) published by the American Psychiatric Association (APA) or from the International Classification of Diseases (ICD, current version 11, though the US still largely uses ICD-10) published by the World Health Organization. The two documents, both consensus-based, share substantial overlap in their approach to categorizing psychiatric illnesses based on observable symptom clusters. They have been purposefully agnostic regarding etiology since DSM-III (1980) and primarily aimed to increase inter-clinician diagnostic reliability. The DSM-5 'recognize[s] that the current diagnostic criteria for any single disorder will not necessarily identify a homogeneous group…available evidence shows that… validators [e.g. biomarkers] cross existing diagnostic boundaries but tend to congregate more frequently within and across adjacent DSM-5 chapter groups.' [198] As such, practical questions of utility remain the explicit primary aim of these documents [199]. Despite this limited aim, lacking a clear alternative, these manuals have come to be the basis of everything from treatment research to compensation and remuneration schemes. The disorder categories they describe have therefore becoming rarified in a way not originally intended.

The implications of this background for the application of informatics solutions for diagnosis and treatment are manifold. Firstly, machine learning techniques common for analyzing the dense data provided by novel tools expect a valid 'ground truth' to train on. If that ground truth is flawed, our conclusions risk being even more flawed. So just collecting more accurate, refined data using more sophisticated tools within the same paradigm risks making the current approach more entrenched, adding to the mass of signs and symptoms that can be sliced and diced into more diagnostic categories. It may provide more phenotypes, but we will not have any more insight into which phenotypes represent a clinically meaningful class of disorders (i.e., disorders with common etiologies that can be precisely targeted).

Further, although the informatics techniques described above may give a more accurate window into an illness state than retrospective self-report to a clinician, the latter is what most of the extant evidence base stands on. In fact, there is evidence that patients' everyday experience or physiological state and retrospective evaluation of mental states are distinct [200]. We therefore risk conflating distinct (if overlapping) illness states, adding to confusion and possibly hindering rather than helping to accurately and efficiently diagnose patients. To present an example, studies have correlated actigraphy profiles with a depressive episode [33]. Although exciting, it would not be correct to say that a person diagnosed in this way will have an identical clinical trajectory or treatment response to one diagnosed on classic self-report. The question of what the clinician should then do to intervene with such a patient remains open. The issue is akin to the proverbial 'incidentaloma' in physical medicine, where a lesion is detected incidentally on a scan, but the patient is otherwise asymptomatic. The classic case is that of the pituitary incidentaloma, where pituitary masses are being detected in large quantities in patients having a brain scan for other reasons. The extant literature may for example suggest that 80% of said lesions are fatal without treatment, however this is based on symptomatic patients. Several years, surgeries and active surveillance later, doctors now know most of these lesions follow a benign course and intervention was unnecessary or worse, detrimental [201].

We present these caveats not to discourage further advancement in this field but to prompt informed clinicians and informaticians to fully appreciate both the risks and potentials for emerging tools and analytic approaches. Rather than aiming to diagnose within existing paradigms, we must remember that diagnoses are not aims in themselves but are ultimately the means to making predictions about outcomes, specifically treatment outcomes. This broader aim does not necessarily need to travel the circuitous path of a DSM-5 diagnosis. Rather, purely objective data-driven analytics can be embedded within clinical trials alongside classic diagnostic and treatment approaches and aim to predict the ultimate outcomes directly. Doing so will not only help validate emerging technologies but also enhance clinician acceptance.

17.4.2 Clinician Acceptance

The issue of clinician acceptance is a challenge not restricted to informatics. Medicine is a conservative industry with good reason. The infamous startup mantra of 'move fast and break things' is ill-suited to high risk organizations, where 'first, do no harm' has held sway (in theory if not always in practice) for millennia. This conservatism however can sometimes have deadly consequences and several studies suggest the gap between research and widespread implementation in healthcare is seventeen years [202]. Demographic shifts alone, however, make the status quo untenable. By 2030, there is expected to be a worldwide shortage of 15 million health workers [203]. It is therefore crucial that informaticians and clinicians partner effectively to implement practical models of care.

Contemporary EHRs have been described by clinicians as an intruder between patient and clinician which slow workflows [204] and compromise rapport [205]. Clinicians who are involved in the development and customizing of the software are however more likely to be satisfied users [206]. Intuitive and customized interfaces are necessary yet insufficient. The technologies we describe in this chapter depend on large volume and high-quality data, yet data quality can only improve if informaticians can show value to the clinicians and patients entering the data. So although informatics has great potential for improved business intelligence [207] and resultant improvements in efficiency, revenue and reporting, such potential can only be realized by simultaneously bringing clinical value and cultivating stakeholder buy in.

Another barrier to clinician acceptance is a lack of training and remuneration [208, 209]. The ability to utilize consumer-grade technologies for diagnosis are a double-edged sword. On the one hand, this greatly expands the scale of diagnosis and intervention. On the other hand, it leaves clinical uses dependent on the whims of commercial actors which have a different set of priorities and regulation. Externalities like the Cambridge Analytica scandal of 2018 or the 2019 USA trade ban with Huawei, then the second largest smartphone manufacturer globally, are but two recent examples of events that can cause shifts in data availability for health analytics. Such events affect platform owners' policies around access, individual willingness to share their data and regulations that cover data and technology transfer [210]. Meanwhile, commercial incentives discourage open reporting of consumer device accuracy, making external validation crucial. A recent comparison of a range of consumer wearables with sleep diaries and research grade equipment showed both the steady improvements in accuracy but also wide divergence between devices [211]. For example, when examining their ability to distinguish lying in bed awake from sleep, mean percent error ranged from 11.6% to 31.6%. Further, proprietary software often does not allow extraction of raw data and manufacturers are not obligated to share any data pre-processing changes that may occur even between different firmware versions of the same device. Furthermore, at the clinician level, there also exists a lag in the appropriate remuneration for the use of emerging technologies in mental healthcare. To facilitate clinician adoption of new informatics technologies, training and education are required and cost precious time and money, often out of limited continuing education funds. Companies developing these technologies often target administrators within health care systems to purchase their products or license their software. Without proper training and onboarding of healthcare workers themselves [212], with appropriate compensation for their time, implementation and adoption are going to be impeded. In contrast to companies, researchers producing cutting edge developments in informatics technology generally lack the funding or infrastructure to translate scientific and algorithmic innovation to user-ready applications. Clinicians cannot be expected to invest their own time into incorporating informatics research innovations into their practice without extensive support. Additional focus on and funding for translation of informatics research to the clinical setting is required for these breakthroughs to reach patients and clinicians and realize their promised benefits [213].

17.4.3 Patient Acceptance, Access and Equity

Superficially, the popularity and volume of web-based treatments described above implies a high level of acceptance in the population. However, once the high global prevalence of mental illness is accounted for, these numbers still represent a small segment of those in need. Further, up to 94% of those downloading popular mental health apps stop using them within two weeks [153]. This suggests work is needed to provide value and enhance engagement. Co-development and living laboratory approaches, where multiple stakeholders including patients, clinicians, funders and developers work together, are one potential path forward [214].

Bringing informatics technologies for diagnosis and treatment to individuals with mental health conditions also raises several specific access challenges. There is a bidirectional relationship between poverty and mental illness [215], so patient-access to devices and the internet may be limited. In Australia, despite having the 10th highest average wage in the world, a study of schizophrenia sufferers published in 2020 showed that only 58% owned a smartphone and 30% had never accessed the internet from any device [216]. Both clinician- and patient-facing limits to access require resolution and often lie outside the boundaries of health departments or organizations. Further, specific symptoms like paranoid delusions may also impact patients' willingness to use informatics tools for diagnosis or treatment.

17.5 Summary and Conclusion

As we can see, informatics technologies have made great strides in bringing innovative approaches to mental health diagnoses and treatment. Some, like telemedicine and computerized psychometric testing, digitize existing validated approaches. Others, such as wearables and mobile medical devices, can provide insights hitherto impossible. These may allow us eventually to entirely leapfrog the extant diagnostic paradigms and help predict treatment outcomes and prognoses directly.

Though not insurmountable, several challenges remain before promising research outcomes can be translated to everyday care. One impediment is the uncertain validity of the current diagnoses as described in the DSM and ICD, an understanding of which is crucial for deriving useful insights from these novel tools. Beyond this, several clinician and patient-side factors must be addressed. On the clinician side, enhanced training, remuneration and transparency from technology vendors could enhance acceptance. Some of these may require regulatory changes to overcome proprietary concerns and encourage validation studies. For patients, more needs to be done to address limited engagement and the ethical and practical access and equity issues. A focus on co-development and re-thinking funding approaches may be helpful. Properly managed, the future for such technologies for diagnosis and treatment remains bright.

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