

REVIEW

Digital technology and clinical decision making in depression treatment: Current findings and future opportunities

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Clinical decision making encompasses a broad set of processes that contribute to the effectiveness of depression treatments. There is emerging interest in using digital technologies to support effective and efficient clinical decision making. In this paper, we provide "snapshots" of research and current directions on ways that digital technologies can support clinical decision making in depression treatment. Practical facets of clinical decision making are reviewed, then research, design, and implementation opportunities where technology can potentially enhance clinical decision making are outlined. Discussions of these opportunities are organized around three established movements designed to enhance clinical decision making for depression treatment, including measurement-based care, integrated care, and personalized medicine. Research, design, and implementation efforts may support clinical decision making for depression by (1) improving tools to incorporate depression symptom data into existing electronic health record systems, (2) enhancing measurement of treatment fidelity and treatment processes, (3) harnessing smartphone and biosensor data to inform clinical decision making, (4) enhancing tools that support communication and care coordination between patients and providers and within provider teams, and (5) leveraging treatment and outcome data from electronic health record systems to support personalized depression treatment. The current climate of rapid changes in both health-care and digital technologies facilitates an urgent need for research, design, and implementation of digital technologies that explicitly support clinical decision making. Ensuring that such tools are efficient, effective, and usable in frontline treatment settings will be essential for their success and will require engagement of stakeholders from multiple domains.

KEYWORDS

computer/internet technology, empirically supported treatments, health services, internet, primary care, treatment

1 | INTRODUCTION

Depression is the leading cause of worldwide disability and a leading contributor to global healthcare costs (WHO, 2017). Efficacious depression treatments are available, including medications and behavioral treatments, yet a variety of clinical questions influence whether a patient receives effective treatment, including: What clinical concerns should be targeted in treatment? Is a patient likely to respond to a given treatment? What are the likelihoods of side effects? Is a given treatment approach working? When it is appropriate to change the type, dose, or frequency of treatment? These are common clinical questions that all providers who treat depression routinely address, and improving providers' capacities for making informed clinical decisions

around these questions will improve the effectiveness of depression treatment.

Digital technologies are growing rapidly and have the potential to shape the quality, scale, and method of depression care delivery (Clarke & Yarborough, 2013; Mohr, Burns, Schueller, Clarke, & Klinkman, 2013). Concurrently, healthcare systems are continuously adapting to new practice standards, scientific findings, and service and reimbursement models. As changes in technology and healthcare continue, there are growing opportunities to usher in technologies to support clinical decision making in depression treatment. Previous studies have reviewed how digital technologies can *deliver depression treatment* as stand-alone interventions (e.g., computer-, website-, and mobile app-based treatment; Donker et al., 2013; Huguet et al., 2016; Newman, Szkodny, Llera, & Przeworski, 2011); however, few studies have reviewed the ways digital technologies can *support clinical decision making*.

Our goal in this paper is to provide snapshots of current research findings, near-term challenges, and opportunities for digital technologies to support clinical decision making for providers who commonly treat depression (e.g., primary care providers, specialty mental health providers). We first provide an overview of clinical decision making, then discuss clinical challenges and opportunities for technology to support and enhance clinical decision making.

2 | DEPRESSION AND CLINICAL DECISION MAKING

Clinical decision making is a core element of practice. It is a multidimensional process that involves collecting, analyzing, and integrating multiple sources of data, corroborating those data with empirical research and clinical expertise, and producing actionable decisions (Croskerry & Nimo, 2011; Stacey, Légaré, & Kryworuchko, 2009). It is also a goal-driven activity geared toward achieving specific and measurable outcomes, such as symptom reduction or improvements in co-occurring issues (e.g., medical, behavioral, or quality of life problems). Depression treatment decisions often are made in collaboration with other health-care providers who span multiple disciplines.

Contemporary clinical decision-making models emphasize patient autonomy and shared decision making throughout the course of treatment (Elwin et al., 2012; Makoul & Clayman, 2006), which is associated with better treatment adherence, patient satisfaction, and clinical outcomes (Bauer et al., 2014; Clever et al., 2006; Loh et al., 2007). However, shared decision making can be challenging for many reasons, including a culture of provider-centered clinical decision making, limited time for patient-provider communication, differences in provider and patient goals, and a tendency for treatment goals to change over time as symptoms and circumstances change.

In sum, clinical decision making for depression treatment is a goal-directed process that is collaboratively formulated with patients and other professionals and based on the best-available information about a patient's predicted response. Three broad clinical movements can support these aspects of clinical decision making, including measurement-based care, integrated care, and personalized medicine. Current research findings, challenges, and opportunities for digital technologies within these clinical movements will be explored in the following sections.

3 | MEASUREMENT-BASED CARE

Measurement-based care (MBC) for depression refers to the systematic and routine administration, scoring, and reviewing of depression symptom rating scales to inform clinical decision making, and this practice is a fundamental component of many treatment modalities (Fortney et al., 2017; Trivedi & Daly, 2007). By routinely collecting standardized measures of depression severity, MBC helps providers identify response to treatment earlier than clinical judgment alone (Hatfield, McCullough, Frantz, & Krieger, 2010), yielding

larger, faster, and less costly improvements in mental health symptoms (Hawkins, Lambert, Vermeersch, Slade, & Tuttle, 2004; Knaup, Koester, Schoefer, Becker, & Puschner, 2009). MBC may also foster better patient-provider communication and help patients and providers navigate treatment goals and shared decision making (Scott & Lewis, 2016). Many practice organizations have called for systematic implementation of MBC, including the Institute of Medicine (IOM, 2006) and the American Psychiatric Association (Gelenberg et al., 2010).

Despite its clinical benefits, it is estimated that less than 1 in 5 psychiatrists and less than 1 in 9 psychologists routinely use MBC (Hatfield et al., 2010; Zimmerman & McGlinchey, 2008). The use of MBC in mental healthcare substantially lags its use for physical health conditions, often due to practical barriers. MBC for physical health problems typically relies on biometric values reported in the electronic health record systems (EHRs), whereas MBC for depression often relies on patient-reported outcomes, which are not routinely administered or entered into EHRs (Lyon & Lewis, 2016). Most MBC assessment tools do not measure treatment goals that are not directly reflected as symptoms of depression or other medical conditions, and most MBC tools only provide snapshots of symptoms at the time of clinical appointments with little or no information about patient outcomes between appointments. Despite consistent empirically demonstrated benefits, many providers view MBC as burdensome and unhelpful for guiding clinical decision making (Jensen-Doss & Hawley, 2010). Several technological opportunities may improve the implementation of MBC for depression, including enhanced integration with other EHRs, incorporating data on treatment process and quality with MBC data, and leveraging the potential of mobile and biosensor data to enrich MBC.

3.1 | Opportunity: Integrating patient-reported outcomes into electronic health records

Multiple systems exist for collecting, storing, and reviewing patient-reported outcomes for MBC, but most do not integrate with commonly used EHRs (Lyon, Lewis, Boyd, Hendrix, & Liu, 2016). Integrating tools that support MBC for depression with existing EHRs could greatly enhance the reach and efficiency of MBC while reducing provider burden (Gleacher et al., 2016; Steinfeld, Franklin, Mercer, Fraynt, & Simon, 2016).

Many administrative and technological barriers exist for integrating MBC and EHRs (Lyon & Lewis, 2016), including a limited presence of behavioral health elements in EHRs, limited interoperability and access to behavioral health data across different settings, and variability in EHRs and system requirements (Karakus, Ghose, Goldman, Moran, & Hogan, 2017). Implementation strategies will be necessary to better integrate patient-reported outcomes into EHRs, including studying key barriers and facilitators of integration, education on the benefits of MBC for different stakeholders, and obtaining stakeholder input across multiple domains (e.g., clinical, administrative, data management, software design, business), and throughout stages of development and implementation (Gleacher et al., 2016; Lyon, Wasse, et al., 2016).

There are several research and design opportunities to enhance the quality, usability, and clinical impact of tools that support MBC and

their integration into EHRs. Tools that automate or support aspects of provider workflows or that facilitate timely and goal-directed communication between patients and providers or within healthcare teams are likely to be more valued and therefore more successfully implemented in clinical practice. Recent research raises the concern that existing EHRs are an impediment to patient-provider communication, for example, with physicians spending up to twice as much time performing EHR-related tasks than making direct contact with patients (Sinsky et al., 2016). Shortages of time are common reasons that providers do not use MBC or shared decision-making processes (Légaré, Ratté, Gravel, & Graham, 2008), and there are considerable research opportunities to identify ways that providers can implement MBC to enhance both workflow efficiency and patient-provider communication. Usability and user-centered design studies could inform the development of tools that work toward these aims, identifying sources of and solutions to provider frustrations (e.g., “alert fatigue” from completing multiple clinical reminders; reduced clinical time due to increasing EHR-related tasks; Ash, Sittig, Campbell, Guappone, & Dykstra, 2007; Lyon, Wasse, et al., 2016), yielding tools that work in the service of their clinical needs without adding to their frustrations.

3.2 | Opportunity: Measuring treatments received

A major aim of MBC is to gauge the effectiveness of a given treatment in facilitating improved outcomes. Linking depression symptom data with depression treatment service data can simplify clinical judgments on whether and how much an existing treatment may be affecting symptoms (Chorpita, Daleiden, & Bernstein, 2016). Thus, there are opportunities to explore ways to integrate treatment process data with depression symptom data and to understand how that could inform clinical decision making.

Measuring the type, dose, and quality of treatment is itself a challenging feat with many research opportunities. For example, there are several mobile applications for tracking medication adherence (Dayer, Heldenbrand, Anderson, Gubbins, & Martin, 2013), although these tools are not widely used by patients and are currently unlikely to integrate with many EHRs. A simple tool that tracks real-time medication taking and summarizes this information with relevant alerts for providers could be a promising opportunity for digital tools to enhance MBC for depression.

Measuring the type and quality of psychotherapy is even more challenging. Psychotherapy quality can vary substantially, and providers are usually unable to assess their own level of skill or treatment adherence. Recent research has applied automated speech recognition, natural language processing, and machine learning methods to automatically and accurately assess psychotherapy quality metrics such as empathy and counselor reflections and questions within motivational interviewing (Atkins, Steyvers, Imel, & Smyth, 2014; Pace et al., 2016; Xiao et al., 2016; Xiao, Imel, Georgiou, Atkins, & Narayanan, 2015). NIMH, IOM, and the Affordable Care Act explicitly support assessment of psychotherapy quality on a large scale, noting the lack of this as a rate-limiting factor for large-scale delivery of effective psychosocial treatments. Research providing automated feedback to counselors for training, supervision, and quality assurance is just beginning, and future

research is needed to assess the impact of such technology on depression outcomes (Gibson et al., 2016).

3.3 | Opportunity: Harnessing mobile and biosensor data

Mobile devices (e.g., smartphones) and wearable biosensors (e.g., fitness bands) have the capacity to expand the quantity, quality, and temporal accuracy of data to inform MBC by capturing data “passively,” requiring minimal effort from the user and yielding data with minimal self-perception bias. Such devices can detect whether and when patients are engaging in various activities (e.g., sleeping, walking, running), physiological states (e.g., heart rate), geospatial locations, or communication patterns (e.g., texting, calling, emailing). Several small-sample studies suggest these data can predict mental health symptoms (e.g., Asselbergs et al., 2016; Ben-Zeev, Scherer, Wang, Xie, & Campbell, 2015; Faurholt-Jepsen et al., 2016); however, the robustness of these methods continues to be established.

Smartphones also have the capacity to collect self-reported depression symptom ratings on a much more frequent basis than most current MBC practices. Tools that support this form of self-monitoring may themselves provide therapeutic benefit (Poston & Hanson, 2010) by helping patients understand their symptoms better, and many patients report interest and willingness to use mobile devices for this (Torous, Friedman, & Keshavan, 2014).

At the same time, it is unclear whether greater volume of depression symptom data can improve clinical decision making or depression treatment outcomes. While patients may wish to share this type of data with their clinical providers, there are few tools that help providers access, integrate, and review the large volumes of data that can be collected through mobile devices (Chung, Cook, Bales, Zia, & Munson, 2015; Torous & Baker, 2016). Additional research is needed to identify methods for efficiently extracting actionable information from mobile data with minimal effort on behalf of providers, and to understand the extent to which these data impact clinical decision making and depression outcomes.

4 | INTEGRATED CARE

In addition to—and often in tandem with—MBC, there is growing interest and utilization of integrated care, in which medical and mental health treatment are provided jointly, often with multiple providers addressing multiple clinical issues concurrently. Integrated care is a flexible approach for coordinating care that can involve multiple formats (e.g., psychotherapy, medication management) to address medical and mental health conditions. The Collaborative Care Model is one of the most well-researched integrated care models with strong empirical support for improving clinical outcomes, reducing costs, and improving access to depression treatment (Archer et al., 2012; Coventry et al., 2014). Treatment decisions in the Collaborative Care Model are managed by teams of providers from different health disciplines, which allows each team member’s expertise to be matched with specific treatment-related tasks corresponding to their

clinical role (e.g., psychiatric consultation, patient outreach, care management). This team-based care efficiently leverages providers' specialized expertise to larger patient populations compared to direct specialty care by independent providers (Bower, Gilbody, Richards, Fletcher, & Sutton, 2006; Wagner, Austin, & Von Korff, 1996). Clinical registries serve as a critical center point for integrated care coordination and planning.

Integrated care models are increasingly being adopted as scientific, practice, and reimbursement models support these models of care (e.g., value-based care, medical home models; Kazak, Nash, Hiroto, & Kaslow, 2017). Digital technologies have the capacity to provide scaffolding that proactively supports the implementation and efficiency of integrated care team communication and coordination.

4.1 | Opportunity: Supporting treatment team communication and care coordination

Effective patient-provider and provider-provider communications are essential to the provision of integrated care. Yet, patient-provider communication has become increasingly limited in an era when a physician's office-based evaluation for depression may last fewer than 2 min (Tai-Seale, McGuire, Colenda, Rosen, & Cook, 2007). Likewise, high caseloads and lack of physical colocation between medical and mental health providers limits provider-provider communication. In their seminal work describing the Chronic Care model, Wagner et al. (1996) outlined the key role of technological infrastructure for supporting effective interactions between patients and care teams through shared care plans and clinical decision support tools, specifically emphasizing patient registries and reminder systems for ensuring proactive and consistent follow-ups.

Web-based registries for providers have emerged as key tools for facilitating effective Collaborative Care (Unützer, Choi, Cook, & Oishi, 2002). In parallel, electronic portals that give patients direct access to their medical records are a relatively new innovation. When integrated with provider-facing tools, such patient-facing tools have the potential to extend and streamline care coordination (Bauer, Thielke, Katon, Unützer, & Areán, 2014) by granting a central portal for accessing and modifying information on depression symptoms and treatment. Patients and providers are generally receptive toward tools that streamline integrated care, and most primary care patients are comfortable with sharing this information with healthcare provider teams via smartphone applications (Bauer, Iles-Shih, Ghomi, Grover, & Monsell, 2016; Bauer, Rue, & Munson, in press; Bruns, Hyde, Sather, Hook, & Lyon, 2016). Technologies that support communication with treatment providers outside of clinical sessions may promote patient engagement by helping patients feel connected and cared for by providers, even if communications are limited to standardized questionnaires to supplement brief or infrequent clinical visits. Well-designed healthcare portals could enhance patient engagement and provide a platform for clinical education around symptoms and treatments. There is considerable room for identifying ways to improve the effectiveness and efficiency with which providers can manage remote patient data in clinical registries and reach actionable decisions from them (Office of the National Coordinator for Health Information Technology, 2015).

5 | PERSONALIZED MEDICINE

Finally, there is increasing interest in information and tools that support the delivery of mental healthcare that is tailored to individual patients, pinpointing *which treatments* provide the optimal benefit for *which patients* at the *right time* (e.g., Insel et al., 2010). Research suggests that individual patient characteristics can predict responses to different depression treatments (DeRubeis et al., 2014); however, developing more personalized depression treatments will likely require "big data" on clinical outcomes across large combinations depression treatment approaches, crossed with the multitude of genetic, biomedical, behavioral, environmental, and demographic patient characteristics that could predict different responses to different treatments. While randomized clinical trials (RCTs) have typically been the gold standard for testing treatment efficacy, RCTs cannot provide all the necessary data to identify optimal treatments across all patient characteristics (Trivedi, Fava, Marangell, Oser, & Shelton, 2006). The NIH's precision medicine initiative (Precision Medicine Initiative Working Group, 2015) aims to support these efforts by enrolling one million patients into a single, large-scale study of health. Existing, large-scale datasets in EHRs may also inform these efforts.

5.1 | Opportunity: Supporting discovery in personalized medicine

"Big data" in EHRs could provide a useful source for informing areas where RCT data are insufficient in identifying who is more likely to respond to different treatments and at which times (Kessler et al., 2017). EHR databases can provide valuable, real-world, practice-based evidence to support better models of predicting which patients are at risk for a specific disorder or outcome (e.g., suicide; McCarthy et al., 2015) or which treatments may be most effective for a particular patient. The ability to alert providers to conduct targeted screens (e.g., for suicidality) and consider delivering personalized interventions (e.g., via electronic clinical decision-support tools for addressing suicide), may be particularly appealing in primary care, where providers often have limited capacity to conduct numerous clinical screens or personalize depression treatments during brief appointments (Kurian et al., 2004).

6 | CONCLUSION

Changes in healthcare and technology are increasing the opportunities to design, test, and implement tools that can support more effective and efficient clinical decision making. The opportunities discussed here focus on using technology to provide "scaffolding" to support clinical decision-making approaches with already established empirical support (e.g., MBC, integrated care). Several of these opportunities are summarized in Table 1.

Successfully integrating clinical, scientific, and technological frameworks to support clinical decision making will require substantial efforts in clinical science, technology design, data science,

TABLE 1 Example clinical decision-making questions and supporting technologies in depression treatment

Measurement-Based Care	
Is my patient getting better with their current treatment regimen, or should I change the treatment?	<i>Current technology:</i> Standardized depression rating scales are completed at time of clinical sessions, possibly entered into electronic health record systems, and possibly graphed or summarized to monitor treatment progress. <i>Potential technology:</i> Behavioral and psychological indicators of depression are assessed remotely through standardized rating scales and passive mobile and biosensor data. Patient-reported outcomes are integrated with other data on treatment service delivery and quality (e.g., treatments administered, treatment fidelity, patient adherence) with graphical or summary feedback to help assess impact of treatment on patient outcomes.
Collaborative Care	
How do I know which patients are "falling through the cracks"?	<i>Current technology:</i> Providers develop and maintain a patient registry with all patients in need of depression care. The registry includes data on patient visits, outreach efforts, and clinical outcome measures. Patients who are not engaged in care are flagged, triggering reminders for clinicians to provide outreach. <i>Potential technology:</i> A patient registry is automatically populated by the electronic health record and patient-generated data. An algorithm identifies patients who are not engaged in care or not responding to treatment, triggering automated outreach based on patients' preference for communication (e.g., primary language, and preferred contact method, such as interactive voice response, SMS, or mobile app). Providers are alerted when automated efforts are unsuccessful and additional clinical action is needed. Providers are notified in advance if the patient visits primary care or another service (e.g., dental service, nutrition, etc.) and can attempt an in-person outreach to reengage the patient in depression care.
How can patients and provider teams communicate effectively and efficiently to facilitate care coordination?	<i>Current technology:</i> Providers access clinical registries that track patients' depression data and care plans. Medical and mental health data may be integrated and accessible to all treatment providers, or in some settings mental health records may be stored separately and accessible only to a limited set of providers. Patient outreach and communication are usually handled through face-to-face contact, telephone outreach, and electronic messaging. <i>Potential technology:</i> Patients and provider teams access shared electronic health record system where patients and all team members easily access and review depression data (e.g., via clinic computers or mobile devices). Patients and provider teams may use this system to coordinate and edit treatment goals and plans, address questions, and provide education with the goal of enhancing patient and team engagement in decision making, often remotely and between clinical sessions.
Precision Medicine	
How can I identify which of my patients are at risk for serious clinical events (e.g., psychotic episode, suicide attempt) and select an appropriate intervention strategy?	<i>Current technology:</i> Electronic reminders prompt providers to screen patients for specific issues (e.g., suicide risk), either universally or in response to other individual data points (e.g., responses in other screening tools or patient diagnoses). Clinical note templates or order sets may help structure and document a corresponding treatment plan. <i>Potential technology:</i> Prediction algorithms identify levels of risk for whole patient populations based on all electronic health record and patient-generated data and suggest appropriate, possibly patient-matched, interventions. Patient registry data are likewise used to help improve future iterations of prediction algorithms that can help identify clinical risks in the same or other healthcare settings.

Note. Current technologies reflect designs of some existing technologies for supporting clinical decision making; however, there is considerable variability in whether and how such tools are implemented and designed in practice. Potential technologies reflect ideas for design improvements that could help support more effective and efficient clinical decision making.

implementation science, and other fields. Utilizing implementation strategies (e.g., stakeholder engagement) throughout the process of developing and testing these technologies will likely facilitate more successful downstream implementation (Bruns et al., 2016).

It is important to note that clinical decision making is a broad and complex process. There are undoubtedly additional aspects of clinical decision making that may be improved through technology but were not discussed here, and additional technological opportunities will continue to grow. For example, micro-RCTs and just-in-time adaptive interventions are two emerging methodologies that hold promise for enhancing fine-grained treatment decisions to deliver more optimal treatments that are patient tailored and timed for optimal effectiveness (Ben-Zeev et al., 2014; Nahum-Shani et al., 2014).

Technology can rapidly revolutionize the ways we communicate and access information, for example, the iPhone was first released in 2007

and personal communication has evolved drastically over the decade since that time. In the coming decade, it is possible that thoughtfully designed, clinically integrated technologies can similarly help usher in innovations in clinical decision making for depression and other mental illnesses.

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CONFLICT OF INTEREST

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