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Ecological momentary interventions for depression and anxiety

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Ecological momentary interventions (EMIs) are becoming more popular and more powerful resources for the treatment and prevention of depression and anxiety due to advances in technological capacity and analytic sophistication. Previous work has demonstrated that EMIs can be effective at reducing symptoms of depression and anxiety as well as related outcomes of stress and at increasing positive psychological functioning. In this review, we highlight the differences between EMIs and other forms of treatment due to the nature of EMIs to be deeply integrated into the fabric of people's day-to-day lives. EMIs require unique considerations in their design, deployment, and evaluation. Furthermore, given that EMIs have been advanced by changes in technologies and that the use of behavioral intervention technologies for mental health has been increasing, we discuss how technologies and analytics might usher in a new era of EMIs. Future EMIs might reduce user burden and increase intervention personalization and sophistication by leveraging digital sensors and advances in natural language processing and machine learning. Thus, although current EMIs are effective, the EMIs of the future might be more engaging, responsive, and adaptable to different people and different contexts.

KEYWORDS
anxiety/anxiety disorders, CBT/cognitive–behavioral therapy, computer/Internet technology', depression, treatment

1 | INTRODUCTION

The use of digital technologies for the treatment of depression and anxiety has the potential to revolutionize treatment practices in several ways. One revolution would be to move treatments from clinical settings and therapists' offices and into people's daily lives. Although ecological momentary assessment (EMA) has long helped move the window of observation from the laboratory and into people's homes and lives, ecological momentary interventions (EMIs) are increasingly being developed to move the window of intervention into new contexts. EMIs refer to "momentary health treatments provided via hand-held mobile technologies that deliver psychological interventions while people are engaged in their typical routines in their everyday life" (Heron & Smyth, 2010).

The development of EMIs has been increasing in recent years due to the expansion of technologies such as smartphones and wearables. Early EMIs used platforms such as palmtop computers (Newman, Przeworski, Consoli, & Taylor, 2014) or mobile phones (Burns et al., 2011) that lacked both the penetration and features of current devices. This reduced the widespread use of EMIs and limited enthusiasm for their ability to make a large public health impact. Now, however, smartphones are much more pervasive, with membership in the United States increasing from 35% in 2011 to 72% in 2016 (and higher in those under age 35 at 92%) (Poushter, 2016). People tend to keep their phones with them constantly. More than 90% of owners report having their phones charged, turned on, and constantly within arm's reach (Rainie & Zickuhr, 2015). Current smartphones are also extremely powerful. In fact, the computing power of a current smartphone is several times more powerful than Cray-2 supercomputer, which was the fastest computer in the world in the 1980s (Processing power compared, 2017). Furthermore, they contain an increasingly large complement of embedded sensors and can connect to various external devices that can power deeply personalized EMIs. Early EMI research provided proof-of-concept that EMIs could work, but powered by current devices, more recent research is demonstrating increased potential of such interventions.

EMIs differ from traditional face-to-face treatments, as well as other digital treatments such as Internet treatments, in several ways including the design of such treatments and the evaluation of their efficacy. We highlight these differences in this review. We begin with an overview of the design of EMIs, discuss past work conducted in using EMIs for depression and anxiety, highlight issues of evaluation in EMI work, and conclude with future directions for the field.

2 | DESIGN OF EMIS

The goal of EMIs is to provide relevant, useful intervention strategies in the context of people's daily lives. As such, EMIs consist of a combination of intervention options and decision rules that specify when and why those interventions will be deployed. In this section, we discuss the components of EMIs and how they combine to produce an overall treatment experience. The behavioral intervention technology (BIT) model (Mohr, Schueller, Montague, Burns, & Rashidi, 2014) is one framework that can help understand the components of EMIs. The model makes a distinction between BIT "treatments" and BIT "interventions." A BIT intervention refers to a specific single interaction between a user and an element of the technology. In the context of an EMI, this could be a single push notification or text message. A BIT treatment refers to the sum of these interactions that unfold over time. Interventions are evaluated by their impact on proximal outcomes. Proximal outcomes include intermediate measures of a distal outcome such as momentary mood or stress instead of depressive symptoms as well as mechanisms of action through which one believes that interventions will ultimately lead to long-term benefits such as reading a notification or following instructions to enact a coping skill, or aspects that might impact use such as usability. BIT treatments are evaluated by their impact on distal outcomes. Distal outcomes refer to the ultimate goal of the BIT treatment. In the case of depression and anxiety, this would usually be a gold standard measure such as the Patient Health Questionnaire-9 (Kroenke, Spitzer, & Williams, 2001), Beck Depression Inventory (Beck, Steer, & Garbin, 1988), Generalized Anxiety Disorder-7 (Spitzer, Kroenke, Williams, & Lowe, 2006), or change in diagnostic status. In mental health, distal outcomes often change slowly or have a period of time associated with their evaluation (e.g., past 2 weeks for a major depressive episode). Proximal outcomes can change more rapidly, sometimes in direct response to a specific intervention. Identifying proximal and distal outcomes is important not only for the evaluation of EMIs, which will be discussed in more detail later, but also for personalizing EMIs to individuals or contexts.

Within an EMI, decision rules are workflow characteristics that define when a specific intervention will be deployed. Interventions can be triggered using time-based rules that deploy at particular or random times throughout the day to task completion or event-based rules that deploy in response to contextual or user variables. Decision rules are a critical, yet often overlooked, aspect of EMIs. One reason they are overlooked is that it is difficult to translate clinical guidelines or empirical findings from traditional interventions into decision rules for EMIs because EMIs are more dynamic and complex than traditional treatments. EMIs are deployed in people's real lives and as such often require a great deal of data collection to inform their deployment and evaluation. Information can draw on both actively and passively collected data. Active data collection requires some action on the part of the user such as completing a survey. Passive data collection requires no action on the part of the user and may come from embedded phone sensors (e.g., GPS, phone activity, screen state) or other devices (such as smartwatches that may provide heartrate, accelerometer, etc.).

One way to differentiate EMIs among each other is based on the level of complexity defined as the relationship between the user and the intervention (Carter, Day, Cinciripini, & Wetter, 2007). In "low" levels of complexity, interventions do not change for each user, but are merely static information that can be "pulled" as needed when the user requests it. For example, an app that has self-help content that can be accessed as needed. For example, within the PTSD Coach app (Owen, Kuhn, Makin-Byrd, Ramsey, & Hoffman, 2015), a popular mental health app for the treatment of PTSD, users can select from one of many tools and receive a tip in the moment such as "Remind yourself where you are, what today's date is, when you were born, what you did yesterday" corresponding to the grounding tool. In the second level of complexity, "interactive" EMIs change interventions in response to user information. For example, before receiving a tip within PTSD Coach, one is required to rate their current level of distress on a 1–10 scale. If different tips were provided at different levels of distress, this would be an "interactive" EMI. The highest level of complexity is referred to as "integrative" in which a learning system evolves over time, continuously improving its responses to a user's pattern of responses and interactions with the system. After receiving a tip with PTSD Coach, users again rate their distress. An integrative system would start to display only the tips it predicts would be most useful based on these past ratings. Integrative EMIs share many characteristics with "just-in-time adaptive interventions" (JITAIs), in that they work to deploy right intervention, at the right time, for that particular person (Nahum-Shani et al., 2016).

As advances in technology are powering the evolution of more complex EMIs, a special class of EMIs, referred to as "just-in-time adaptive interventions," are becoming more prevalent for mental health applications. JITAIs refer to treatments that adapt overtime to provide the most beneficial interventions for a particular person often by using information about that person or their environment. For example, a JITAI might encourage a person with an elevator phobia to do an exposure exercise when they walk past a high rise building or provide a reminder to go to sleep if past information suggests that his or her depressive symptoms are elevated on days when they go to bed after that particular time. JITAIs have many of the same elements of other EMIs, a set of intervention options, decision points as to when those interventions can be potentially provided to a user, tailoring variables such as information about the user or the context, decision rules that link tailoring variables to intervention options. JITAIs differ from other EMIs in that they use statistical methods, such as algorithms, to optimize individual interventions on the basis of proximal outcomes, thus adaptively improving and tailoring the interventions overtime for a given individual.

3 | EMIS FOR DEPRESSION

Several examples of EMIs to reduce depression have been created and evaluated. In this section, we review evidence on the efficacy of such treatments and key findings that highlight open questions in their use. EMIs intended to reduce depression do so through

interventions aimed at various proximal outcomes such as engagement in pleasurable activities (Ly et al., 2014), increasing positive emotions (Tugade & du Pont, 2014), or other pathways. EMIs for depression have also made use of diverse conceptual treatment strategies including acceptance and commitment therapy (Ahtinen et al., 2013; Lappalainen et al., 2013; Ly, Dahl, Carlbring, & Andersson, 2012) and interpersonal therapy (Dagoo et al., 2014), but the majority have been cognitive–behavioral in focus including cognitive–behavioral therapy (CBT), behavioral activation (Burns et al., 2011), relaxation (Grassi, Preziosa, Villani, & Riva, 2007), and self-monitoring (Agyapong, Ahern, McLoughlin, & Farren, 2012). A recent meta-analysis of EMI studies reviewed those targeting symptoms of depression as well as other mental health outcomes including anxiety, perceived stressed, and positive psychological functioning (Versluis, Verkuil, Spinhoven, van der Ploeg, & Brosschot, 2016). This analysis identified 33 studies, 17 of which included a measure of depression as an outcome with levels ranging from mild symptoms to those meeting criteria for major depressive disorder. EMIs had a small-to-medium effect on within-person change in depressive symptoms of Hedge's $g = .48$ (95% confidence interval [CI] 0.34–0.61). Analysis revealed one significant moderator, which was additional support, which is consistent with findings in other areas of BITs in which supported interventions tend to be more efficacious than unsupported interventions. Supported EMIs had larger effect sizes ($g = .73$), suggesting that larger or more consistent results can be obtained with some amount of human support compared with stand-alone EMIs ($g = .45$) and stand-alone EMIs provided in combination with care as usual ($g = .38$). Importantly, the overall quality rating for the studies analyzed was low, with an average of 2.29 on a six-point scale. This is perhaps unsurprising, given that EMI methodology is still in its infancy; however, it suggests that results might be interpreted with caution.

It is interesting that this review found that stand-alone EMIs provided along with care as usual are not more effective than stand-alone EMIs themselves (Mohr et al., in press). Although, of course, this is based on meta-analytic comparisons and not experimental studies, it is worth considering whether such a difference provides design implications for EMIs. One possibility is that the addition of a EMI to care as usual does not provide additional benefit above and beyond that treatment. However, a recent study of a coach-supported app program for depression and anxiety found no differences in benefits between those receiving concurrent treatment with psychotherapy or pharmacotherapy and those receiving the app program alone, suggesting that those receiving usual care can benefit as much as those who are not (Mohr et al., in press). EMI are likely more effective when they complement and extend the treatment rather than serving as a separate and disjointed adjunct. If a provider does not or is not skillful at integrating it into treatment, as might be the case in usual care, the EMI might not be as effective as a more integrated program. In this way, EMI might be like other material intended for outside the session, like homework. The strongest predictor of compliance and benefit from assigned homework tends to be therapist factors such as reviewing assignments and general therapeutic skill (Bryant, Simons, & Thase, 1999). EMIs might have similar considerations and providers should reference EMI material and EMI material should reflect session activities to reinforce and complement care and increase the benefit.

Indeed, EMIs have been used as an adjunct to therapy to increase homework adherence and reinforce therapeutic concepts in real-world settings. One example comes from a project examining the use of EMI text messages inquiring about mood and reinforcing the specific CBT topics (i.e., thoughts, activities, social contacts, and physical well-being) in manualized group CBT (Aguilera & Munoz, 2011). Results from this project have demonstrated that one-item daily mood questions are useful proxies for longer clinical assessment measure (i.e., the PHQ-9) (Aguilera, Schueller, & Leykin, 2015), that mood scores predict attendance in group sessions (Bruehlman-Senecal, Aguilera, & Schueller, in press), and that receiving this text messaging adjunct increases attendance. All of these benefits either provide additional information for or increase the dosage of in-session interactions. Finding effective ways to integrate EMIs with human provided therapeutic support may ultimately yield the most efficient and effective intervention method.

4 | EMIS FOR ANXIETY

EMIs for anxiety share a lot of similarity to those for depression. They have similar conceptual diversity and similar efficacy. In this section, we present an overview of these findings and highlight potential features that might yield important advances in such treatments. In the previous review discussed, 15 studies examined anxiety symptoms as an outcome and found a within-person pre–post effect size of $g = .47$ (95% CI 0.32–0.63), which was nearly identical to that found for studies with depression as an outcome (Versluis et al., 2016). Levels of anxiety again ranged from mild to clinical ranges of anxiety. Another systematic review of EMIs for anxiety disorders explored reduction in generalized anxiety (Gee, Griffiths, & Gulliver, 2016). This review identified seven studies which produced a small pooled effect size of $d = .32$ (95% CI 0.12–0.53) favoring the EMIs over comparison or control conditions (Gee et al., 2016). Mixed results were found for the other anxiety disorders, but only three studies investigated these (two for panic disorder and one for social anxiety). EMIs targeting stress, however, were significantly superior to comparison conditions. Stress might be more responsive to EMI interventions because it can function better as a proximal outcome than symptoms of anxiety, which are usually evaluated over longer periods. An analysis of the features that were included in the EMIs found that only two studies used automated sensors (Gorini et al., 2010; Repetto et al., 2009). This is despite significant technical work advancing the use of sensors to detect anxious states, which opens the possibility of triggering and tailoring interventions using passive data collection, which reduces the burden on the user (Huang et al., 2016; Miranda, Calderon, & Favela, 2014; Rennert & Karapanos, 2013). Thus, it remains possible that future EMIs that better leverage the unique affordances of technology might be able to create more personal and powerful treatments. We will now turn to a discussion on evaluation methodologies, starting with those that address unique considerations of the personalized nature of EMIs.

5 | EVALUATION OF EMIS

EMIs, by their nature, aim to provide contextualized, personalized, and impactful experiences to each user. As such, evaluations methods for EMIs aim to optimize the individual experience and to determine the benefit each person gains from individual interventions and the overall EMI treatment. In this section, we discuss methodological and analytic strategies that are particularly well-suited to investigate these questions and promote early development work for EMIs. One particularly promising methodology to understand the benefit for each individual is the use of microrandomized trials (MRTs). An MRT is a sequential factorial design that randomly assigns an intervention component to each individual at relevant time points (Klasnja et al., 2015). Thus, within an MRT, each individual is randomized multiple times in order to better understand the time-varying and dynamic nature of interventions and how their effectiveness corresponds to various contextual factors. For example, an MRT including three decision points each day would randomized each individual at each decision point to receive a specific intervention (or no intervention). MRTs are often initially conducted as single-arm trials, as the focus is to optimize the treatment through the refinement of decision rules and to compare interventions to each other and to no intervention. MRTs determine the immediate (proximal outcomes) and long-term (distal outcomes) effects of a particular intervention component, how those effects change over time, and which variables indicate when and how to intervene most effectively. This design is extremely helpful, as information gained from randomized controlled trials (RCTs) might tell us what treatments are beneficial, but often do not provide sufficient information of what intervention to provide when and how much. Furthermore, behavior change theories, guided by findings from RCTs, are insufficient to guide such decisions, as most do not account for highly interactive interventions, high levels of intra-individual tailoring, and high frequency longitudinal data (Riley et al., 2011). Microrandomization is also useful within a n-of-1 trial. In such a case, randomization repeatedly occurs overtime as a single-patient cross-over design to evaluate the effectiveness for that particular patient (Chen et al., 2014).

Advances in analytics, such as data mining and machine learning, are also increasing the ability to adapt and understand EMIs at the individual level. Simple EMIs use static decision rules to provide interventions to people, but more complex EMIs often use algorithms to optimize and personalize systems overtime. One example, is a bandit algorithm that changes the likelihood of the presentation of a particular intervention overtime based on the impact of that intervention in the past on proximal outcomes (Rabbi et al., 2016). For example, if two potential interventions exist within an EMI, instructions for deep breathing and progressive muscle relaxation, they might start with randomization odds of .50. But if deep breathing proves to reduce anxiety for a given user, overtime those randomization odds can be shifted to preference deep breathing. This allows for adjustment of decision rules overtime for each individual based on empirical data. One challenge with such approaches is that multiple variables (e.g., time of day, recent stressors, previous practice of skills) likely contribute to the impact of any given intervention. Such variables can be included in these algorithms to contribute to predictions; however, the more variables included, the

more instances are needed for the presentation of each intervention to estimate the effect. Passively collected data streams also have variable data quality or might introduce complications such as energy consumption demands or the need for an external device, which might negatively impact their use in EMIs.

This approach poses an interesting challenge to the evaluation of EMIs. When EMIs include learning models, then no single treatment is given to all individuals. Instead, treatments represent a collection of intervention interactions aimed to optimize outcome for each given individual. As such, evaluation methods focus on generating knowledge at the individual level first and then move to generalize to the population level. This is different than RCTs that make inferences on means (i.e., group-level analyses) first before conducting within-person or moderator analyses that might attempt to make recommendations to individuals. For algorithmic development, one can make group models (using data from all users to improve prediction for each individual user) or individual models (using data from a single user to improve prediction for that user), or can couple such models to work in tandem. Decisions between individual-level and group-level models are often accompanied with several tradeoffs. For example, individual-level models require experience with a specific user before predictions can be made but are more accurate once data are gathered. Group-level models can work from the start for a new user but may ultimately be less accurate.

It is worth noting that on a group level what is being evaluated for an EMI is the sum of the interventions, tailoring variables, decision variables, and decision rules. The fact that sum of these aspects may evolve over the course of a trial (e.g., the decision rules may be updated based on new information gained) means that traditional RCTs may be a poor fit for early stages of EMI development. RCTs may play an important role in determining if an EMI works in comparison to some other types of intervention (e.g., a nonindividualized EMI), but such evaluations should take place only after EMIs have been investigated and optimized through other methods.

6 | FUTURE DIRECTIONS

Current evidence supports that EMIs can be beneficial to reduce depression and anxiety and associated aspects of mental health such as stress, acceptance, and quality of life (Gee et al., 2016; Versluis et al., 2016). However, many current EMIs are somewhat limited. Many require some initiation by the user either in the form of a request or assessment and interventions can be somewhat clunky usually pulling from a prepopulated option created without knowledge of each user and each context. Highly integrative and deeply personalized EMIs may be possible, however, through leveraging several advances in technologies. First, EMIs should make greater use of the ability to understand people's mental health state through passive detection derived from sensors. Several small studies have demonstrated proof-of-concept that sensors can be used to predict aspects of people's mental health (Mohr, Zhang, & Schueller, 2017). The EMIs of the future might not need to ask people what they need, but be able to tell them based

on their ability to collect and process passive data. Second, although machine learning and algorithms can provide deeply personalized decision rules, EMIs could provide deeply personalized interventions created in the moment for user. This has already been made possible through the use of peer networks to create content on demand and in nearly real-time based on each person's need (Morris, Schueller, & Picard, 2015). Advances in natural language processing and machine learning are likely to automate this process (Hirschberg & Manning, 2015). These techniques are increasingly being used in mental health to create treatments that can interact and adapt to individual people (Calvo, Milne, Hussain, & Christensen, 2017).

In conclusion, EMIs previously developed and evaluated have shown similar benefits for depression and anxiety to those found in other BITs such as websites and mobile apps. However, advances in EMIs are likely to take us one step closer to personal digital mental health assistants. These assistants will listen to people through sensed data, learn from people in the context of their daily lives, and guide people in directions that will support their mental health. Such personal digital mental health assistants will still be made up of combinations of interventions, decision points, tailoring rules, and decision rules but powered by advances in technologies and analytics that make each of these more personalized and more data-driven.

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