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Moving Toward Successful Implementation of Digital Mental Health Interventions: Improving User Attitudes and Evaluating User Behavior

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MOVING TOWARD SUCCESSFUL IMPLEMENTATION OF DIGITAL MENTAL HEALTH INTERVENTIONS: IMPROVING USER ATTITUDES AND EVALUATING USER BEHAVIOR

by

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ABSTRACT

This European-style dissertation examines strategies to improve user attitudes, encourage uptake, and evaluate user engagement for digital mental health interventions. This research is discussed in the context of efforts to successfully design, implement, and sustain digital mental health services in clinical settings. In the first chapter, I discuss the need for digital mental health interventions and strategies to implement them sustainably. This includes the burden of mental illness in the United States, poor access to traditional mental health treatment, the efficacy of digital mental health interventions, and challenges in implementation. In the second chapter, I present an experimental study that examined the effect of a treatment rationale and financial incentive on acceptability and uptake-related behavior for Internet-based cognitive behavioral therapy. This study found that a treatment rationale significantly improves acceptability for these programs, whereas a treatment rationale and small financial incentive did not significantly impact uptake-related behavior. This study addresses the need to improve participant attitudes toward Internet-based treatment, as studies have found low acceptability for these programs. In the third chapter, I present a follow-up study that examined the effect of a treatment rationale on attitudes toward Internet-based cognitive behavioral therapy in May through July 2020, during the COVID-19 pandemic. This study found that a treatment rationale improved acceptability, but not more so during the pandemic as compared to before the pandemic. This study addresses the need to examine the influence of individual context and experiences with the COVID-19 pandemic as they relate to perceptions of digital mental health programs. In the fourth chapter, I present a systematic review of the ways that user engagement is operationalized in clinical trials of mobile health interventions for depression. This review found that many clinical trials report engagement, but that there is a wide variety in engagement reporting and significant opportunities for improvement. This area of research is important because theoretical frameworks for implementation of digital mental health interventions call for ongoing evaluation of user engagement. In the final chapter, I discuss implications of this research, contextualize it in the literature on digital mental health, and make recommendations for future research.

INDEX WORDS: Digital mental health, mHealth, Acceptability, Engagement, Implementation, COVID-19

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DEDICATION

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1 INTRODUCTION

Mental illness is a leading global cause of disability (James et al., 2018; Prince et al., 2007). In the United States, approximately one in five adults meet diagnostic criteria for a mental disorder (Park-Lee et al., 2017) and suicide rates have sharply increased over the last 20 years (Steelesmith et al., 2019). The impact of mental illness has likely increased in 2020 due to the COVID-19 pandemic, which has caused increased rates of anxiety, depression, and substance use (Hochstatter et al., 2020; Huckins et al., 2020).

Despite the substantial burden of mental illness, fewer than half of U.S. adults with mental disorders receive treatment (Center for Behavioral Health Statistics and Quality, 2016; Park-Lee et al., 2017). Barriers to mental health treatment are common, such as lack of perceived need, mental health stigma, negative emotions about therapy, high cost, and lack of transportation (Andrade et al., 2014; Mohr, Ho, et al., 2010). Individuals who might seek mental health treatment commonly do not have access to a provider, as funding for mental health services and the number of mental healthcare providers in the U.S. are insufficient to meet the population’s needs (Weil, 2015). This is particularly true in rural communities, which have lower concentrations of mental healthcare providers and higher rates of mental illness and suicide (Steelesmith et al., 2019; Substance Abuse and Mental Health Services Administration, 2016). Additionally, community mental healthcare providers commonly do not use evidence-based treatments (Shiner et al., 2013; Wolitzky-Taylor et al., 2018) and most individuals are not sufficiently educated about evidence-based treatment to seek it out (Carman et al., 2010).

1.1 Digital Mental Health Interventions

Digital mental health interventions have been studied since the 1990's, when they were first administered over the Internet using personal computers (Andersson et al., 2019). Since the launch of the first smartphone "App Store" in 2008, many digital mental health interventions have also been developed for smartphones. Digital mental health interventions use strategies drawn from a range of psychotherapy paradigms to treat a variety of mental disorders. Common techniques include psychoeducation, behavioral activation, mindfulness techniques, and symptom tracking (Andersson et al., 2019). Programs can be unguided, i.e. designed to be completed without human support, or may incorporate guidance and support from a mental health professional or "coach" (Barak et al., 2009). Some interventions also utilize smartphone sensors for advanced capabilities like automated prediction of mood states using biological and behavioral data (Dogan et al., 2017).

Clinical trials and meta-analyses have demonstrated that digital mental health interventions are effective for a variety of mental disorders, particularly when they incorporate support from a therapist or coach. Computer-based mental health interventions have been found effective for depression and anxiety disorders (Andrews et al., 2018), posttraumatic stress disorder (Sijbrandij et al., 2016), eating disorders (Aardoom et al., 2013), and others (Hedman et al., 2012). Smartphone-based mental health interventions have also been found effective for depression, (Firth, Torous, Nicholas, Carney, Pratap, et al., 2017; Weisel et al., 2019), anxiety disorders (Firth, Torous, Nicholas, Carney, Rosenbaum, et al., 2017), and posttraumatic stress disorder (Possemato et al., 2016). Meta-analyses comparing unguided and therapist or coach-supported interventions have shown larger effect sizes when human support is provided (Andersson & Cuijpers, 2009; Richards & Richardson, 2012). Additionally, therapist or coach-supported digital mental health interventions have demonstrated comparable efficacy to face-to-face treatment (Andersson et al., 2014).

Internet and smartphone-based digital mental health interventions circumvent many barriers to face-to-face therapy, such as travel, time, and cost. Approximately 90% of U.S. adults use the Internet and an estimated 275 million use smartphones (Statista, 2019, 2020). This represents a significant opportunity to reach people who are unable to access face-to-face therapy and to provide mental healthcare with high fidelity to evidence-based practices. Programs that incorporate guidance from mental health professionals typically require a small fraction of the time commitment from providers as compared to face-to-face therapy, with some patients requiring less than 30 minutes total for an entire treatment (Ly et al., 2015). Mental health professionals who use these programs could therefore significantly increase their caseloads and provide care for a large number of people with unmet mental health needs. Additionally, studies that compare guidance from mental health professionals to trained volunteers have found equivalent effect sizes for both generalized anxiety disorder (Robinson et al., 2010) and major depressive disorder (Titov et al., 2010), representing an opportunity to significantly expand mental health service capacity using providers with relatively brief training.

1.2 Challenges in Implementation of Digital Mental Health

Although digital mental health interventions have been found effective in clinical trials, high rates of attrition are common in both clinical trials and real-world settings. This represents a major challenge for effective implementation, particularly for unguided interventions. In a review of 40 studies examining computer-based treatments for depression, Richards and Richardson (2012) found that over half of participants dropped out of treatment, with a 74% attrition rate for studies examining unguided programs. Gilbody et al. (2015) examined two widely used Internet-based treatments for depression using a large sample of primary care patients. They found that participants allocated to both programs completed one to two sessions on average and that there was no significant difference in symptom reduction from participants receiving standard care from a general practitioner. Whereas better adherence has been found for therapist and coach-supported interventions, these programs still demonstrate lower levels of treatment completion than face-to-face therapy (Van Ballegooijen et al., 2014). A recent meta-analysis of attrition in clinical trials of smartphone interventions for mental health problems found that a significant number of participants did not download the study app and fewer than half of participants completed treatment for most disorders (Linardon & Fuller-Tyszkiewicz, 2020). Additionally, large-scale deployment studies of open access mental health apps find that a majority of people stop using these apps before they could feasibly benefit from them, with many users opening the apps only once (Lattie et al., 2016). These findings are consistent with general user behavior across all smartphone apps, which typically lose about 70% of users within one week (Sigg et al., 2016).

High attrition from digital mental health interventions may be related to low acceptability and familiarity with these programs in the general population. A large survey study of U.S. adults in primary care found that 51.8% of respondents were "definitely not interested" in Internet-based treatment and that most preferred face-to-face therapy (Mohr, Siddique, et al., 2010). Another survey study of U.S. college students found that only 16% of students who were not currently seeking treatment rated guided Internet-based cognitive behavioral therapy as acceptable (Travers & Benton, 2014). This survey also found that negative perceptions of Internet-based treatment are common, such as the belief that Internet-based treatment is not helpful or that it is "pretend treatment." The disparity between high treatment satisfaction typically found in clinical trials of digital interventions (Andrews et al., 2018) and low acceptability in the general population may be due to the "denominator problem" (Mohr et al., 2017). When clinical researchers invite large numbers of people to participate in trials and a relatively small proportion of them volunteer, these participants may be unusually interested in digital mental health treatment as compared to the broader population. Widespread negative perceptions of digital mental health interventions may contribute to high attrition for individuals who start treatment, despite their established efficacy and ability to circumvent common barriers to care.

1.3 Strategies for Successful Implementation of Digital Mental Health

Gaps between efficacy studies and routine clinical practice are not unique to digital mental health. This problem has been widely documented across different areas of healthcare, including face-to-face psychotherapy (US Department of Health and Human Services, 2006). To address the "research-to-practice gap," researchers have developed theoretical models of translation and implementation of healthcare services (Proctor et al., 2009; Sussman et al., 2006). Typical translational models involve progression through a set of distinct stages. During early stages, researchers draw from theory and basic research to develop an intervention, then evaluate efficacy using tightly controlled trials that prioritize internal validity. During later stages, an intervention is deployed in clinical settings and evaluated using effectiveness trials that prioritize external validity. Researchers have commented that a disproportionate number of psychotherapy studies have focused on efficacy, which results in a high number of interventions that cannot be implemented in clinical settings (Heyman & Smith Slep, 2009). To address this problem, some researchers have recommended reducing emphasis on efficacy research and attending more to external validity when conducting clinical trials (Glasgow et al., 2003).

Several models of implementation for digital health interventions do not include efficacy trials at all (Mohr et al., 2017; Whittaker et al., 2012). Instead, these models recommend that interventions be completely designed and evaluated within settings where they will ultimately be used. For example, Mohr et al.'s (2017) “Accelerated Creation-to-Sustainment” model describes an iterative process for implementing digital mental health interventions using frequent input from stakeholders within the target healthcare setting. This includes initial interviews to inform intervention design and ongoing evaluation of user behavior with prototypes to identify effective components. It also involves planning for sustained implementation from the beginning, including engagement with support staff, administrators, and other relevant professionals who will ultimately administer the intervention. These models seem to hold promise for creating acceptable, engaging, and feasible interventions by prioritizing users’ goals for treatment and evaluating their actual behavior throughout the implementation process. They may also help researchers to overcome complex systemic barriers to digital mental health programs that have been documented within community healthcare settings (Anastasiadou et al., 2019).

Consistent with the models described above, researchers conducting treatment studies have increasingly made efforts to engage with end users during design and implementation of digital health interventions. For example, Schlosser et al. (2016) conducted in-depth individual interviews with young people with schizophrenia, their families, and other stakeholders in order to develop a guided mobile app for this population. During these interviews, participants generated a list of important priorities and tested paper prototypes of app features to determine usability and provide feedback. Schlosser et al. then progressed to a clinical trial phase, during which qualitative user feedback was elicited frequently from participants and a variety of user engagement metrics (e.g. log-ins, use of specific features) were recorded. Participant feedback prompted important changes during the trial, such as changes in the ways that coaches interacted with participants. Similarly, Caplan et al. (2018) specifically used Mohr et al.'s (2017) Accelerated Creation-to-Sustainment model to design a culturally adapted mobile app for primary care patients with depression in the Dominican Republic. The intervention was developed within primary care clinics with input from patients and clinic staff, then implemented with a small sample. In-depth, ongoing qualitative feedback was elicited from participants, who provided feedback every two days and completed an interview at the end of the study about usability, helpfulness, and cultural appropriateness. Changes to the app were made throughout the study, such as added animations that depicted common experiences of depression reported by participants. These trials are encouraging and demonstrate that the field is evolving toward more effective and user-centered implementation strategies.

1.4 Further Research to Inform Effective Implementation

This section will describe two areas of research that have the potential to inform user-centered implementation studies for digital mental health interventions. The three studies that are presented in subsequent chapters of this dissertation will be described in the context of this research.

1.4.1 Improving Attitudes and Treatment-Seeking

Strategies designed to improve attitudes and incentivize engagement with digital interventions may address low acceptability for people considering or starting treatment. Treatment rationales, which explain how a treatment works and describe its effectiveness, have been found to increase expectations that face-to-face psychotherapy will be effective (Ahmed & Westra, 2009). Several studies have examined video and text-based treatment rationales for digital mental health interventions and found that they significantly improve attitudes and intention to seek treatment in non-clinical samples (Casey et al., 2013; Mitchell & Gordon, 2007), primary care patients with depressive symptoms (Ebert et al., 2015), and individuals visiting a website for an online mental health intervention (Soucy et al., 2016). Treatment rationales may be a useful tool in the initial stages of implementation studies for digital mental health interventions, when researchers first engage with participants that are likely to have reservations or negative perceptions of digital treatment. Once participants start using the interventions, exposure to a treatment rationale may reduce attrition and promote effective engagement. To increase power and precision, studies that examine treatment rationales for digital mental health interventions should also control for variables that are known to be associated with acceptability for these interventions. These variables include age (Mohr, Siddique, et al., 2010) and psychopathology (Gun et al., 2011).

Small financial incentives are another common method of encouraging treatment-seeking and engagement with healthcare interventions. Although Mohr et al. (2011) caution that extrinsic incentives may be counterproductive because they undermine intrinsic motivation, financial incentives have been associated with high levels of enrollment and adherence to online interventions targeting health behaviors like exercise and smoking cessation (Crutzen et al., 2011; Sigmon & Patrick, 2012). They have also been effective in promoting adherence to face-to-face psychotherapy (Schacht et al., 2017). However, no study to the author's knowledge has experimentally examined the effect of a financial incentive on treatment-seeking or engagement with a digital mental health intervention. Small financial incentives may be a cost-effective way to encourage people with negative perceptions of digital interventions to start or complete treatment.

To add to these areas of research, the first study presented in this dissertation will examine the effect of a text-based treatment rationale on acceptability for Internet-based cognitive behavioral therapy in a non-clinical sample. Additionally, it will examine the effect of a treatment rationale and a small financial incentive on actual treatment-seeking behavior for digital mental health programs. The second study presented in this dissertation used follow-up data from the first study. Participants were re-contacted in May through July 2020, during the COVID-19 pandemic. This study will examine whether the same treatment rationale has a greater effect when administered in the context of COVID-19, which has caused increases in mental distress (Newby et al., 2020), use of telehealth (Perrin et al., 2020), and treatment-seeking for digital mental health interventions (Titov et al., 2020). Analyses in both studies will control for age and psychopathology.

1.4.2 Evaluating User Engagement Metrics

Studies that examine methods of evaluating user engagement are also important for implementation research. Systematic reviews have found substantial heterogeneity in the ways that user engagement is conceptualized and measured in clinical trials of digital interventions for chronic health conditions (Pham et al., 2019), behavior change (Perski et al., 2017) and mental health (Ng et al., 2019). These include metrics of objective engagement (e.g. log-ins, use of specific tools) and subjective engagement (e.g. attention, enjoyment), which are both commonly used in clinical research (Perski et al., 2017). Whereas some clinical trials of digital mental health interventions report a thorough range of engagement metrics (e.g. Schlosser et al., 2016), they are not consistently reported across studies. Iterative design based on careful evaluation of user engagement is an essential part of implementation for digital mental health interventions (Mohr et al., 2017). It is important that clinical researchers evaluating these interventions use a range of engagement metrics that are relevant to clinical outcomes. Systematic reviews of engagement measurement for digital interventions that target specific mental disorders may shed further light on the most useful ways to measure engagement for these disorders. Reviews of clinical trials that quantitatively assess relationships between specific engagement metrics and clinical outcomes may be particularly helpful in selecting appropriate metrics for feasibility research and larger clinical trials.

To address this need, the final study presented in this dissertation is a systematic review of engagement reporting in clinical trials of mobile interventions for depression. This review will separately examine reporting of objective and subjective engagement. It will also assess whether these studies assess the relationships between engagement metrics and other variables, such as participant characteristics and clinical outcomes.

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2 FIRST ARTICLE

Molloy, A., Ellis, D., Su, L., & Anderson, P. L. (2021). Improving acceptability and uptake behavior for Internet-based cognitive-behavioral therapy. *Frontiers in Digital Health, 3*, 653836. https://doi.org/10.3389/fdgth.2021.653686

2.1 Abstract

Internet-based cognitive behavioral therapy (iCBT) programs have the potential to improve access to mental healthcare, but they are not viewed as acceptable nor widely utilized by the general public. This study tested whether two acceptance-facilitating interventions improved acceptability and uptake-related behavior for therapist assisted and self-guided iCBT. Participants were randomly assigned to read a treatment rationale for iCBT (vs. a brief definition) and to receive a small financial incentive (or not) for seeking more information about evidence-based iCBT programs. Participants (N = 662) were a diverse group recruited from a university participant pool and the surrounding community. Participants completed standardized measures of attitudes towards and outcome expectancy for iCBT and a single question about willingness to use it and were given the opportunity to get information about accessing evidence-based iCBT programs. A series of MANCOVAs showed small, positive effects of the treatment rationale on attitudes and outcome expectancy for both self-guided and therapist-assisted iCBT, but not for willingness to use it. A hierarchical logistic regression model found no effect of the treatment rationale or financial incentive on whether participants sought additional information about how to access iCBT, although psychopathology symptoms and identifying as White or multiracial were positively associated with information-seeking. Inconsistent with past research, participants rated therapist-assisted and self-guided iCBT as equally acceptable. Participants recruited from the community reported greater willingness to use iCBT than university students.

These results underscore the urgent need for further research towards improving the acceptability and uptake of iCBT so that it may better fulfill its potential to fill the gap in unmet mental health need.

Index Words: acceptability, uptake, Internet-based cognitive behavioral therapy, mental health, treatment rationale, financial incentive, digital health, treatment access, mental health treatment inequities

2.2 Introduction

Internet-based cognitive behavioral therapy (iCBT) programs are cognitive behavioral interventions that treat psychological problems via digital platforms. iCBT programs have been shown to reduce symptoms across a range of mental disorders, including posttraumatic stress disorder (Hobfoll, Blais, Stevens, Walt, & Gengler, 2016), social anxiety disorder (Gershkovich, Herbert, Forman, & Glassman, 2016), and panic disorder (Fogliati et al., 2016), among others. iCBT creates an opportunity to disseminate treatment to people who cannot access face-to-face therapy, as over half of the global population has access to the Internet (International Telecommunication Union, 2019). Additionally, iCBT programs maintain fidelity with treatment protocols in a way that face-to-face treatment delivery in community settings may not (Wolitzky-Taylor et al., 2018). Given the insufficient number of licensed mental healthcare providers in the U.S., particularly in areas like rural communities (Substance Abuse and Mental Health Services Administration [SAMHSA], 2016), iCBT represents an opportunity to substantially increase access to evidence-based treatment delivered as intended.

iCBT can include support from a therapist or be delivered in a self-guided format. Therapist-assisted iCBT is thought to increase client adherence and reduce attrition (Mohr, Cuijpers, & Lehman, 2011). An obvious advantage of self-guided iCBT is that a person does not need to find a therapist to access mental healthcare, but a trade-off is that people using self-guided formats may not engage long enough to benefit as much (or at all). One meta-analysis of 12 randomized controlled trials for iCBT for depression and anxiety found that whereas therapist-assisted iCBT programs demonstrated large effect sizes for treatment outcomes, iCBT programs without therapist guidance or support showed small to moderate effects (Spek et al., 2007). Overall, people benefit from iCBT when paired with therapist assistance or used alone, although the magnitude of effect is likely higher for programs with therapist assistance (Johansson & Andersson, 2012).

Despite its efficacy, iCBT is widely underutilized by the general public (Carper, McHugh, & Barlow, 2013; Hennemann, Beutel, & Zwerenz, 2017; Waller & Gilbody, 2009), perhaps because they do not view it as an acceptable form of mental health treatment. Research in this area has defined and operationalized the concept of "acceptability" for digital mental health interventions in a variety of ways. Overlapping constructs like satisfaction, feasibility, and usability are used interchangeably with acceptability (Ng, Firth, Minen, & Torous, 2019). Operational definitions include single Likert scale items that assess participants' willingness to use iCBT (Handley, Perkins, Kay-Lambkin, Lewin, & Kelly, 2015; Wootton, Titov, Dear, Spence, Andrews, et al., 2011), longer questionnaires designed for individual studies (Travers & Benton, 2014), and one psychometrically validated questionnaire that assesses attitudes toward psychological interventions that are delivered online (Schröder et al., 2015). Studies have also operationalized acceptability using validated self-report measures for other constructs, like outcome expectancy - the expectation that one will benefit from treatment (Titov et al., 2010). The lack of precision in the conceptualization and measurement of the acceptability of iCBT may explain why estimates of the acceptability of iCBT vary widely across research studies.

People who use either self-guided or therapist-assisted iCBT report a high degree of user satisfaction (Andrews et al., 2018; Hedman, Ljótsson, & Lindefors, 2012; Van Ballegooijen et al., 2014). However, large survey studies have found that most people are unfamiliar with digital mental health interventions such as iCBT (Handley et al., 2015) and that people prefer other forms of treatment over Internet-based therapy (Mohr et al., 2010). Therapist-assisted iCBT programs are generally rated as more acceptable than self-guided programs (Casey, Joy, & Clough, 2013; Mitchell & Gordon, 2007), but one survey study found that only 16% of non-treatment-seeking adults would consider using therapist-assisted iCBT to address a mental health concern (Travers & Benton, 2014). The significant contrast between high user satisfaction in treatment studies and low acceptability in the general population may be due to the “denominator problem” (Mohr, Lyon, Lattie, Reddy, & Schueller, 2017). This refers to a bias that can result when a large number of people are invited to participate in a treatment study, but only the small proportion of those who are motivated and interested volunteer and enroll. However, even large survey studies that recruit potentially biased samples, such as people seeking treatment on mental health clinic websites, have found low acceptability for iCBT (Gun, Titov, & Andrews, 2011; Wootton, Titov, Dear, Spence, & Kemp, 2011). This points to a clear need for strategies to increase iCBT’s appeal to potential users.

Treatment rationales, which describe how specific therapy interventions work, have long been shown to improve outcome expectancy for face-to-face psychotherapy (Ahmed & Westra, 2009). A handful of studies have incorporated treatment rationales for digital mental health interventions into video or text-based materials designed to improve acceptability and related constructs. Studies generally find that these acceptability-facilitating interventions improve acceptability and intention to use digital mental health programs (Casey et al., 2013; D. D. Ebert et al., 2015; Mitchell & Gordon, 2007; Soucy, Owens, Hadjistavropoulos, Dirkse, & Dear, 2016) but not all (Baumeister, Reichler, Munzinger, & Lin, 2014). One limitation to this literature is that most studies used samples that were small or that may not be representative of the general population: Mitchell & Gordon (2007) studied a small (N=20) sample of undergraduate students, Ebert et al. (2015) studied primary care patients, and Soucy et al. (2016) recruited participants who had already demonstrated an interest in using iCBT. Only one study has examined the impact of an intervention to improve acceptability of both self-guided and therapist-assisted programs (Casey et al., 2013).

No study to date has examined the effect of treatment rationales and related strategies on behaviors related to the actual uptake of iCBT. A few studies have examined whether financial incentives (e.g. vouchers, nominal cash payments, or raffles) improve adherence to mental health treatment (Burton, Marougka, & Priebe, 2010; Post, Cruz, & Harman, 2006; Stanley, Chu, Brown, Sawyer, & Joiner, 2016), but none have examined their impact on behaviors signaling a willingness to try iCBT. This leaves a notable gap in the literature regarding the potential benefit of providing a small monetary incentive to increase behaviors related to the uptake of iCBT.

The current experimental study examined the effect of a treatment rationale on self-reported acceptability and uptake-related behavior for iCBT among a non-treatment-seeking sample. Acceptability was defined as a set of cognitively based, positive attitudes towards these interventions (Schröder et al., 2015). Given the wide variability in the ways that acceptability has previously been measured, three separate measures were drawn from the literature and analyzed together to measure this construct. The study also examined the effect of a financial incentive ($25 raffle) on seeking information about how to access iCBT programs. Given past research, the authors hypothesized the following: 1) a treatment rationale would increase acceptability for both therapist-assisted and self-guided iCBT, 2) participants would report higher acceptability for therapist-assisted iCBT as compared to self-guided iCBT, and 3) a treatment rationale and a financial incentive would increase behaviors related to the uptake of iCBT.

2.3 Materials and Methods

2.3.1 Participants

Participants were recruited from a large southeastern university in an urban setting and canvassed from public areas in the surrounding metropolitan area. University student participants (N = 403) were recruited online from a university-based research participant pool for psychology course credit. Community participants (N = 346) were recruited from public spaces and given the opportunity to enter a raffle with a 1 in 30 chance of winning a $25 gift card as compensation. To be included in the study, participants had to be aged 18 or over and literate in English.

Of the 749 individuals who expressed interest in the study, six respondents were excluded due to failure to meet inclusion criteria. Of the remaining participants (N = 743), 81 respondents were excluded from analyses because they took less than five minutes on the survey or failed the study's manipulation check (11%). In all, data from 662 participants (University N = 365; Community N = 297) were included for data analysis. Demographic data for these participants are presented in Table 2.1.

2.3.2 Procedure

All study procedures were completed using Qualtrics, a survey-creation platform and secure hosting server. University student participants completed the study on their own personal web-enabled devices. Community members completed the study on a tablet computer (i.e., iPad) provided by a research assistant or received an email with instructions to complete the study online.

All participants were assigned a study identification number and completed informed consent procedures prior to starting the study. Upon enrollment, participants were immediately randomized to receive a treatment rationale for iCBT (or a brief definition of iCBT) and a financial incentive to seek information about how to access evidence-based iCBT programs (or none) in a 2x2 experimental design. Experimenters were blinded to study condition. Participants first completed questionnaires assessing demographic information and symptoms of depression, anxiety, and stress. Next, depending on experimental condition, participants received a treatment rationale for iCBT or a brief definition of self-guided and therapist-assisted iCBT. Participants then answered questions about their history using and familiarity with online mental health interventions and completed measures of acceptability for self-guided and therapist-assisted iCBT. After completing these measures, participants were informed that they would receive an email within 24 hours with a link to access and download iCBT programs, if interested. This link connected participants to a brief online survey in which they could select iCBT programs with empirical support from randomized clinical trials and receive information about how to access them. Depending on experimental condition, participants were also told they would receive a small financial incentive for completing this survey, or not.

2.3.3 Experimental Conditions

2.3.3.1 Treatment Rationale

Participants assigned to the treatment rationale condition read an in-depth description of iCBT, including rates of usage, research basis, and accessibility. The rationale used persuasion techniques that have been proposed to increase outcome expectancy for psychotherapy, including an authoritative speaker (a university professor and licensed clinical psychologist) and emphasis on empirical support (Ametrano, Constantino, & Nalven, 2017). The rationale ended with a “frequently asked questions” section that specifically addressed the most commonly perceived advantages and disadvantages of therapist-assisted iCBT (Travers & Benton, 2014). The treatment rationale was approximately 800 words in length. As a manipulation check, participants who received the treatment rationale then answered three true or false questions about iCBT (see Appendix A.1 for full details).

Participants assigned to the brief definition condition did not receive the treatment rationale. Instead, these participants read a one-paragraph definition of iCBT, which described the difference between self-guided and therapist-assisted iCBT, so that they would have enough information to answer questions assessing their attitudes about these two modalities (see Appendix A.2). The brief definition of iCBT was 130 words in length.

2.3.3.2 Financial Incentive

Participants in the financial incentive condition were offered entry into a raffle with a 1 in 30 chance to a win a $25 e-gift card for completing a survey that included a list of iCBT programs with empirical support from randomized clinical trials about which they would receive information about how to access and download, if interested. Participants assigned to the no financial incentive condition were not offered a financial incentive to complete the survey.

2.3.4 Measures

2.3.4.1 Demographics & History of Psychotherapy

A 22-item demographics questionnaire was developed for the current study using items from the Standardized Data Set from the Center for Collegiate Mental Health at Penn State University (Center for Collegiate Mental Health, 2017). In addition, past and current experience using both face-to-face and internet-based mental health services was measured using a series of

Likert-type self-report items developed for the study (e.g., "Have you ever received face-to-face psychotherapy or counseling?", "If so, how helpful were these services").

2.3.4.2 Acceptability of iCBT

2.3.4.2.1 Attitudes Toward Psychological Online Interventions Scale (APOI)

The APOI is a 16-item validated measure of general attitudes toward online psychological interventions (Schröder et al., 2015). Although many questionnaires have been developed to evaluate acceptability toward Internet-based mental health programs, the APOI is the only psychometrically validated questionnaire to specifically examine this construct. Accordingly, it was selected for the current study over other non-validated questionnaires. Although not indicated in original paper (Schröder et al., 2015), positively valenced items were reverse-coded (J. Schröder, personal communication, February 12, 2020). Total scores range from 16-80 with higher scores indicating more positive attitudes towards iCBT. The APOI demonstrated strong overall internal consistency ($\alpha = .77$) in a sample of 1013 participants (Schröder et al., 2015) and demonstrated good internal consistency in the present sample for both self-guided iCBT ($\alpha = .83$) and therapist-assisted iCBT ($\alpha = .82$).

2.3.4.2.2 Credibility/Expectancy Questionnaire (CEQ)

The expectancy subscale of the CEQ (Devilly & Borkovec, 2000) consists of 3 items assessing expectations about efficacy for psychological treatments (0-100%), with higher scores indicating higher expectancy of efficacy. It was included in the current study because of its previous use as a measure of iCBT acceptability (Titov et al., 2010) and to evaluate the effect of outcome expectancy persuasion techniques that were included in the treatment rationale. The CEQ has demonstrated high internal consistency for the overall scale ($\alpha = .84$-$.85$), fair to excellent internal consistency for the expectancy subscale ($\alpha = .79$-$.9$), and good test-retest reliability (r = .83; Devilly & Borkovec, 2000). The internal consistency of the expectancy subscale in the present sample was excellent for both self-guided iCBT (α = .91) and therapist-assisted iCBT (α = .90).

2.3.4.2.3 Single Item

A single Likert scale item assessing willingness to use iCBT, “Would you use a [self-guided/therapist-assisted] iCBT program to improve your life (e.g., reduce stress, anxiety, depression)?” was used as a measure of acceptability based on use of similar items in past research (Handley et al., 2014). Response choices were scored on a 5-point Likert scale and comprised the following: “definitely would use,” “would likely use,” “unsure,” “unlikely to use,” and “definitely would not use,” with higher scores indicating greater willingness to use iCBT.

2.3.4.3 Psychopathology

2.3.4.3.1 Depression, Anxiety, and Stress Scale—21 Item (DASS-21)

The DASS-21 is a 21-item validated measure of mental illness symptoms that yields three subscales: depression, anxiety, and stress (Lovibond & Lovibond, 1993). Scores for the total DASS-21 scale range between 0 and 126, with higher scores indicating more distress or impairment. The DASS-21 demonstrates strong convergent validity with both the Beck Anxiety Inventory (BAI; r = .81) and Beck Depression Inventory (BDI; r = .74) indicating satisfactory ability to discriminate between both anxiety and depressive symptoms (Lovibond & Lovibond, 1995). The DASS-21 demonstrated excellent internal consistency in the present sample (α = .90).

2.3.5 Uptake Behavior for iCBT

Participants were classified as having engaged in behavior related to the uptake of ICBT (or not) if they completed the survey that included a list of iCBT programs about which they would receive information about how to access and download (or not).

2.3.6 Statistical Analyses

2.3.6.1 Acceptability of iCBT

Age and psychopathology were included as covariates in all models examining acceptability of iCBT, given their association with interest in Internet-based behavioral and psychological treatment (Gun et al., 2011; Mohr et al., 2010). A two-way MANCOVA was used to evaluate the effects of rationale condition and recruitment source (community, university) on acceptability of self-guided and therapist-assisted iCBT. A two-way mixed-design MANCOVA was used to evaluate differences in acceptability between self-guided and therapist-assisted iCBT. The three dependent variables within each MANCOVA model included general attitudes (as measured by the APOI), outcome expectancy (as measured by the expectancy subscale of the CEQ), and a single item assessing willingness to use iCBT. For each model, recruitment source was included as an independent variable to test for a two-way interaction. In the absence of an interaction, recruitment source was collapsed and main effects were interpreted across all participants. Listwise deletion was used for participants with missing data, which created variation in sample sizes across models.

2.3.6.2 iCBT Uptake Behavior

A two-step hierarchical logistic regression was performed to test the hypothesis that a treatment rationale (vs. brief definition of iCBT) and a financial incentive (vs. none) would improve participants' likelihood of seeking out information about how to access and download iCBT programs. Uptake behavior was classified as a binary dependent variable (yes vs. no). In step one, four variables were entered to control for participant characteristics that have previously been shown to relate to uptake of iCBT or use of other mental health services: age, psychopathology (DASS-21 total score), gender, and race/ethnicity. Age was included due to evidence that older age is negatively related to use of health-related technologies (Or & Karsh, 2009). Psychopathology was included to account for current need for mental health treatment. Race was included due to research showing that African Americans are less likely to initiate iCBT treatment than Whites (Jonassaint et al., 2017) and U.S. national data demonstrating that White and multiracial individuals seek mental health treatment at higher rates than other racial groups (SAMHSA, 2020). Accordingly, this variable was dummy coded to compare racial identities associated with higher and lower levels of mental health service utilization (White, multiracial vs. Black/African-American, Hispanic/Latinx, Asian). Gender was included due to U.S. national data demonstrating that women seek mental health treatment at higher rates than men (SAMHSA, 2020) and was dummy coded to compare men and women. In step two of the model, treatment rationale and financial incentive conditions were entered to assess the influence of these experimental manipulations while controlling for participant characteristics. All analyses were conducted using Statistical Package for the Social Sciences (SPSS) version 25.0.

2.4 Results

Table 2.2 shows descriptive statistics and intercorrelations for key variables. Whereas 37.5% of participants reported a history of face-to-face psychotherapy, only 2.1% of participants reported using an online mental health program. Responses to the *Depression, Anxiety, and Stress Scale – 21* indicated that, on average, participants did not endorse severe levels of psychopathology (M = 31.90, SD = 21.80) based on the suggested cutoff of 60 for severe mental illness (Lovibond & Lovibond, 1993). However, many participants met or exceeded clinical cutoffs suggested by Lovibond and Lovibond (1993) for mild depression (Cutoff: 10; N = 285, 43.1%), mild anxiety (Cutoff: 8; N = 335, 50.6%), or mild stress (Cutoff: 15; N = 220, 33.2%), with a total of 411 participants (60.2%) meeting the cutoff for mild symptoms on at least one of these three subscales.

2.4.1 Acceptability of iCBT

2.4.1.1 Assumptions

The three dependent variables within each MANCOVA model were moderately correlated and there was no multicollinearity. Normal distribution of dependent variables was assessed visually and using the Shapiro-Wilk test. Several dependent variables were significant ($p < .05$), however, visual inspection of Q-Q plots revealed that dependent variables were approximately normal. Given that MANCOVA is robust to minor violations of normality (Verma, 2016), the authors proceeded with analyses. Relationships between dependent variables and covariates were linear with homogeneous regression slopes, as determined by visual inspection of scatterplots. Residuals were normally distributed, as assessed by visual inspection of Q-Q plots. To determine the influence of outliers, each model was run with and without univariate and multivariate outliers. All results are reported with outliers included, as removal of outliers did not cause meaningful differences, with one exception (discussed below). Homogeneity of covariance matrices varied across models and is discussed below.

2.4.1.2 Rationale and Self-Guided iCBT

For the two-way MANCOVA (rationale * recruitment source with age and psychopathology as covariates) examining acceptability for self-guided iCBT, there was homogeneity of covariance matrices, as assessed by Box's M test ($p = .093$). The multivariate main effect of recruitment source on the combined dependent variables was significant with seven univariate outliers (standardized residual $\geq$ 3.0) included in the model (p = .048), but fell to non-significance when these outliers were removed (p = .051). Because the outliers appeared to be valid observations, results for this parameter with and without inclusion of outliers are reported.

See Table 2.3 for multivariate effects. There was no statistically significant interaction effect between rationale condition and recruitment source on the combined dependent variables, $F(3, 587) = 0.762$, $p = .516$, Wilks' $\Lambda = .996$, partial $\eta 2 = .004$. The main effect of rationale condition on the combined dependent variables was statistically significant, $F(3, 587) = 3.617$, $p = .013$, Wilks' $\Lambda = .982$, partial $\eta 2 = .018$. There was a statistically significant univariate effect of rationale condition for general attitudes, $F(1, 589) = 9.382$, $p = .002$, partial $\eta 2 = .016$, and for outcome expectancy, $F(1, 589) = 5.886$, $p = .016$, partial $\eta 2 = .010$, such that these two variables were higher for participants who received the treatment rationale. There was no statistically significant univariate effect of rationale condition for the single-item rating of willingness to use iCBT (p = .133). The main effect of recruitment source on the combined dependent variables was statistically significant with outliers included in the model, $F(3, 587) = 2.657$, $p = .048$, Wilks' $\Lambda = .987$, partial $\eta 2 = .013$. There was a statistically significant univariate effect of recruitment source on willingness to use iCBT, $F(1, 589) = 7.033$, $p = .008$, partial $\eta 2 = .012$, such that community participants reported greater willingness to use self-guided iCBT. When outliers were removed from this model, the multivariate effect of recruitment source on the combined dependent variables fell to non-significance (p = .051).

2.4.1.3 Rationale and Therapist-Assisted iCBT

For the two-way MANCOVA (rationale * recruitment source with age and psychopathology as covariates) examining acceptability for therapist-assisted iCBT, Box's M test was significant, indicating a violation of homogeneity of covariance matrices ($p < .001$). Accordingly, Pillai's Trace was used as a multivariate test statistic to control for inflation in Type I error rate (Olson, 1976).

See Table 2.3 for multivariate effects. There was no statistically significant interaction effect between rationale condition and recruitment source on the combined dependent variables, $F(3, 571) = 0.227$, $p = .878$, Pillai's Trace = .001, partial η2 = .001. The main effect of rationale condition on the combined dependent variables was statistically significant, $F(3, 571) = 7.421$, $p < .001$, Pillai's Trace = .038, partial η2 = .038. The main effect of recruitment source on the combined dependent variables was not statistically significant, $F(3, 571) = 1.829$, $p = .141$, Pillai's Trace = .010, partial η2 = .010. There was a statistically significant univariate effect of rationale condition for general attitudes, $F(1, 573) = 12.814$, $p < .001$, partial η2 = .022, and outcome expectancy, $F(1, 573) = 6.045$, $p = .014$, partial η2 = .010, such that these two variables were higher for participants who received the treatment rationale. There was no statistically significant univariate effect of rationale condition for willingness to use iCBT ($p = .578$).

2.4.1.4 Type of iCBT

For the mixed design two-way MANCOVA (type of iCBT * recruitment source with age and psychopathology as covariates) comparing acceptability for self-guided and therapist-assisted iCBT, there was homogeneity of covariance matrices, as assessed by Box's M test ($p = .053$).

See Table 2.4 for multivariate effects. There was no statistically significant interaction effect between type of iCBT and recruitment source on the combined dependent variables, $F(3, 558) = 0.527$, $p = .664$, Wilks' $\Lambda = .997$, partial $\eta 2 = .003$. The main effect of type of iCBT on the combined dependent variables was not statistically significant, $F(3, 558) = 2.293$, $p = .077$, Wilks' $\Lambda = .988$, partial $\eta 2 = .012$. The main effect of recruitment source on the combined dependent variables was statistically significant, $F(3, 558) = 2.650$, $p = .048$, Wilks' $\Lambda = .986$, partial $\eta 2 = .014$. There was a statistically significant univariate effect of recruitment source on willingness to use iCBT, $F(1, 560) = 7.582$, $p = .006$, partial $\eta 2 = .013$, such that community participants reported greater willingness to use iCBT.

2.4.2 iCBT Uptake Behavior

See Table 2.5 for results of regression analysis. Participants were excluded from the analysis if they did not fit into the coding scheme for gender (N = 13, 2.0%) or race/ethnicity (N = 14, 2.1%), did not receive a timely follow-up email with a list of iCBT programs due to experimenter error (N = 28, 4.2%), or did not have complete data for variables included in the analysis (N = 22, 3.3%). Of the 662 total eligible participants, 588 participants were eligible for regression analysis. Out of these participants, 47 (8.0%) sought out information about how to access and download iCBT programs and 541 (92.0%) did not. Step one of the model, which included participant characteristics, significantly predicted uptake behavior, $\chi 2(4) = 12.172$, $p = .016$. Step one explained 4.8% (Nagelkerke R2) of the variance in uptake behavior and correctly classified 92.0% of cases, although it should be noted that the model predicted that 100% of participants would not engage in uptake behavior. In this step, psychopathology was positively related to uptake behavior for iCBT (OR = 1.026, p = .046) and identifying as Black/African-American, Hispanic/Latinx, or Asian was negatively associated with uptake behavior compared to identifying as White or multiracial (OR = 0.509, $p = .029$). Step two of the model, which added the rationale and financial incentive conditions as regressors, did not explain significantly greater variability in uptake behavior than step one, $\Delta R2 = .003$, $p = .703$. Rationale condition (OR = 0.893, $p = .717$) and financial incentive condition (OR = 1.264, $p = .452$) did not significantly predict uptake behavior, although the full model remained significant, $\chi 2(6) = 12.876$, $p = .045$.

2.5 Discussion

Consistent with hypotheses, participants who read a treatment rationale reported significant increases in acceptability as measured by general attitudes and outcome expectancy for self-guided and therapist-assisted iCBT across a community and university student sample. Inconsistent with hypotheses, the treatment rationale had no influence on participants' willingness to use either self-guided or therapist-assisted iCBT. Surprisingly, participants' ratings of acceptability (across all three measures) did not significantly differ between self-guided and therapist-assisted iCBT; this finding is inconsistent with prior research, which has generally found that people prefer therapist-assisted over self-guided iCBT. This is the first study to examine the effect of an acceptability-facilitating intervention on behavior related to the uptake of iCBT. Neither the rationale nor the financial incentive influenced uptake behavior, which was very low.

Although the effects of the treatment rationale on acceptability were significant, they were small compared to similar controlled studies of acceptability-facilitating interventions for Internet-based mental health treatment. These interventions, which include treatment rationales, have produced medium-sized increases in acceptability (Casey et al., 2013; Ebert et al., 2015). Differences in the effects of acceptability-facilitating interventions between studies may be driven by variations in intervention content, overall length, and method of operationalizing acceptability. For example, past studies examining acceptability-facilitating interventions have used information about iCBT and techniques to increase outcome expectancy, much like in the current study. However, they have also used psychoeducation on specific mental disorders, personalized symptom assessments with feedback, patient testimonials, and appeals to participants’ self-efficacy to use a specific program (Baumeister et al., 2014; Ebert et al., 2015; Ebert et al., 2019).

The smaller effect of the rationale on acceptability of iCBT in the current study relative to past studies may also be related to length. The current study’s rationale was approximately 800 words in length. Previous research has found that treatment rationales of approximately 250 words may be the optimal length for enhancing outcome expectancy (Horvath, 1990). Additionally, Casey et al. (2013) found that an acceptability-facilitating intervention of approximately 400 words caused a medium-sized increase in acceptability for Internet-based mental health treatment. For the current treatment rationale, the authors prioritized describing iCBT in depth, incorporating outcome expectancy persuasion techniques, and addressing perceived advantages and disadvantages of iCBT that have been reported in previous research. The greater length may have caused fatigue or failed to hold participants’ attention, which could have prevented participants from fully processing all of the information, thereby reducing its effect. Researchers constructing treatment rationales and other interventions to improve acceptability for iCBT in the future should be aware that acceptability-facilitating interventions which require longer reading times may reduce their impact.

The current study is the first to examine the effects of a treatment rationale and financial incentive on behavior related to the uptake of iCBT. Contrary to hypotheses, neither intervention significantly affected uptake-related behavior. Psychopathology symptom severity and race/ethnicity were associated with uptake of iCBT, although it should be noted that total regression model accounted for a very small proportion of variance (approximately 5%). Participants who reported higher psychopathology were more likely to seek out information about how to access and download iCBT programs. Unlike some prior research on acceptability-facilitating interventions, participants from this study were not drawn from a treatment-seeking sample. It is possible that participants did not believe that they needed iCBT. Lack of a perceived need for mental health treatment is a widely documented barrier to seeking mental health services, particularly among people with mild to moderate symptoms (Andrade et al., 2014). Given that over half of the participants in this study reported at least mild mental health symptoms, interventions designed to increase uptake of iCBT in the general population might have greater success using materials that emphasize the benefit of iCBT as a low-intensity intervention for individuals with mild to moderate symptoms. Personalized feedback about mental health symptoms may be particularly helpful for individuals who are unaware that they may benefit from iCBT. Conversely, people experiencing mild mental health symptoms may believe that they could benefit from iCBT, but be uninterested in making efforts to improve their mental health because their distress is relatively low. Future research on iCBT uptake could evaluate participants' readiness for change and tailor acceptability-facilitating interventions to increase motivation for change if this is a common barrier.

Participants identifying as 'White' or 'multiracial' were more likely to engage in behavior related to the uptake of iCBT than participants who self-identified as 'Black/African-American', 'Hispanic/Latinx', or 'Asian.' Given that people who identify as racial/ethnic minorities are less likely to have access to and to use mental health services (Stockdale, Lagomasino, Siddique, McGuire, & Miranda, 2008), this is a sobering finding. Digital mental health interventions, like iCBT, have the potential to overcome practical barriers to mental health treatment that disproportionately affect minority groups, such as cost and transportation (Alegria et al., 2012; Snell-Johns, Mendez, & Smith, 2004). The results from this study suggest that these communities may not be inclined to seek out such treatments, simply because they circumvent such practical barriers. Although a small number of studies have examined perceptions and interest in iCBT within specific racial and cultural minority communities (Choi, Andrews, Sharpe, & Hunt, 2015; Jonassaint et al., 2017), many more are needed. It is also critical that future research identify the extent to which acceptability-facilitating interventions need to be culturally tailored to increase uptake in minority communities.

There are meaningful distinctions to be made between general appraisals toward an intervention, personal expectations of efficacy, and a willingness to engage with an intervention – the three dependent measures of acceptability in this study. Our results indicate that interventions which improve general attitudes and outcome expectancy for iCBT programs do not cause corresponding increases in willingness to use them. This may be due to method-variance, given that willingness to use iCBT was assessed using a single item. If, however, the finding is replicated and valid, it is concerning, because it suggests that attitudinal changes caused by treatment rationales and other interventions do not lead to greater self-reported willingness to use iCBT. This is reinforced by this study’s finding that the treatment rationale did not increase uptake-related behavior for iCBT. Interestingly, community adults reported slightly greater willingness to use iCBT than university students, an effect that was not attributable to differences in age or psychopathology between samples. This may be due to disparities in access to face-to-face mental health treatment – the university students recruited for this study have access to no-cost counseling services, whereas most community participants likely do not.

2.5.1 Strengths and Limitations

This is the first experimental study to measure the effects of a treatment rationale on acceptability and uptake-related behavior for iCBT. It is also the first to examine the effect of a financial incentive on uptake-related behavior for iCBT. To date, this is the largest study to examine an acceptability-facilitating intervention for Internet-based mental health treatment. Furthermore, this study operationalized acceptability in a robust way by using three widely used measures of this construct, including a psychometrically validated measure of acceptability towards online mental health interventions. This is important because much of the existing literature that has examined acceptability toward iCBT has used heterogeneous measures of this construct. The need to increase the diversity and inclusion of minority and underrepresented populations in the literature concerning attitudes and utilization of iCBT is paramount. The study used a robust sampling method, recruited a diverse sample of urban community adults and university students, and reported participant characteristics that are associated with underutilization of mental health services. This is a major contribution to the literature; the majority of studies (97%) in a widely cited meta-analysis of randomized controlled trials supporting the efficacy and acceptability of iCBT (Andrews et al., 2018) did not report the racial/ethnic make-up of their sample.

Despite the study's strengths, there are limitations that warrant attention. The small differences between the two rationale conditions in the current study may be due to the nature of the "brief definition" control condition. The authors determined that it was important to define self-guided and therapist-assisted iCBT for participants assigned to the control condition because iCBT is a relatively nascent technology and most people are unfamiliar with Internet-based mental health treatment (Handley, Perkins, Kay-Lambkin, Lewin, & Kelly, 2015). The brief definition, however, may have functioned like an active control and reduced the comparative effect of the treatment rationale. The use of a survey-based metric for examining uptake-related behavior may have limited our ability to detect true iCBT uptake, as it was insensitive to actual usage of programs. The results for uptake-related behavior cannot be generalized to gender nonconforming people and people outside of the specific racial identities that were predominant in our sample, as we did not have enough of these participants to examine them in our regression model. Additionally, although research has generally supported the use of raffles for incentivizing behavior change, it is possible that the ratio of financial incentive to odds of winning (1:30 chance for $25) was too weak to influence uptake-related behavior. Lastly, the majority of participants were college-educated, which may have implications for measuring attitudes toward Internet-based mental health treatments as educational attainment has been linked to mental health treatment-seeking (Steele, Dewa, Lin, & Lee, 2007).

2.5.2 Future Directions

More research is needed to systematically investigate differences in acceptability-facilitating interventions for iCBT that use different types of content. Studies should also examine whether interventions that cause significant improvements in acceptability also lead to measurable increases in uptake-related behavior. Studies examining financial incentives should evaluate the impact of different "doses" of incentive and their cost-effectiveness in healthcare delivery systems. Future research should investigate the relationship between acceptability for iCBT and access to other forms of care across different populations. Studies that recruit diverse samples across different demographic characteristics are vital for understanding the effect of individual characteristics on acceptability and uptake-related behavior for iCBT, as well as other relevant constructs. For example, certain minority racial identities are associated with lower levels of mental health service utilization (SAMHSA, 2020) and racial disparities in trust and experiences with healthcare institutions may play a role in acceptability of digital forms of treatment in comparison to face-to-face care (Boulware, Cooper, Ratner, Laveist, & Powe, 2003). It will be necessary to identify how iCBT appeals differently across racial groups and other demographics to maximize its delivery to those who can most benefit.

2.5.3 Conclusion

iCBT is well positioned to leverage its intrinsic benefits of standardization, cost-effectiveness, and ease of access to help fill the gap in unmet mental health need. However, iCBT will be unable to fulfill these goals if acceptability towards these interventions is not significantly improved for the average consumer. The authors hope that future research will build on the findings of the current study to develop effective methods of improving acceptability and uptake-related behavior for iCBT programs in order to fully realize their potential.

2.6 Author Contributions

AM and PA devised the project, the main conceptual ideas, and protocol outline. AM, DE, and LS coordinated data collection for the study and wrote the manuscript. AM conducted all statistical analyses. AM and DE designed the figures and tables. PA supervised the project. All authors contributed to the final version of the manuscript.

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Table 2.1 Participant Characteristics

Demographics		Rationale Condition N = 292 (%)	Definition Condition N = 369 (%)	Total N = 662 (%)
Age	Mean Age (*SD)*	25.46 (11.88)	25.96 (11.68)	25.76 (11.76)
	Range	18 - 85	18 - 73	18 - 85
Gender	Man	79 (27.1)	149 (40.4)	228 (34.4)
	Woman	208 (71.2)	211 (57.2)	420 (63.4)
	Transgender	1 (0.3)	1 (0.3)	2 (0.3)
	Self-Identify	2 (0.7)	8 (2.2)	10 (1.5)
	Did not disclose	2 (0.7)	0 (0)	2 (0.3)
Race/Ethnicity	African American / Black	111 (38.0)	148 (40.1)	260 (39.3)
	American Indian or Alaska Native	0 (0)	3 (0.8)	3 (.5)
	Asian American / Asian	37 (12.7)	55 (14.9)	92 (13.9)
	Hispanic / Latino/a	40 (13.7)	41 (11.1)	81 (12.2)
	Multi-racial	16 (5.5)	17 (4.6)	33 (5.0)
	White	82 (28.1)	97 (26.3)	179 (27.0)
	Self-Identify	3 (1.0)	8 (2.2)	11 (1.7)
	Did not disclose	3 (1.0)	0 (0)	3 (.5)
Sexual Identity	Heterosexual	231 (79.1)	296 (80.2)	528 (79.8)
	Lesbian	4 (1.4)	8 (2.2)	12 (1.8)
	Gay	8 (2.7)	12 (3.3)	20 (3.0)
	Bisexual	27 (9.2)	31 (8.4)	58 (8.8)
	Questioning	12 (4.1)	7 (1.9)	19 (2.9)
	Self-Identify	8 (2.7)	12 (3.3)	10 (3.0)

	Did not disclose	2 (0.7)	3 (0.8)	5 (0.8)
Current Financial Status	Always Stressful	21 (7.2)	42 (11.4)	64 (9.7)
	Often Stressful	67 (22.9)	75 (20.3)	142 (21.5)
	Sometimes Stressful	118 (40.4)	164 (44.4)	282 (42.6)
	Rarely Stressful	68 (23.3)	67 (18.2)	135 (20.4)
	Never Stressful	15 (5.1)	21 (5.7)	36 (5.4)
	Did not disclose	3 (1.0)	0 (0)	3 (0.5)
Treatment History	Received face-to-face psychotherapy	102 (34.9)	145 (39.3)	248 (37.5)
	Has not received face-to-face psychotherapy	185 (63.4)	218 (59.1)	403 (60.9)
	Unsure	0 (0)	1 (0.3)	1 (0.2)
	Did not disclose	5 (1.7)	5 (1.4)	11 (1.5)
	Used an online mental health program	7 (2.4)	7 (1.9)	14 (2.1)
	Did not use an online mental health program	274 (93.8)	354 (95.9)	629 (95.0)
	Unsure	3 (1.0)	1 (0.3)	4 (0.6)
	Did not disclose	8 (2.7)	7 (1.9)	15 (2.3)
Relationship Status	Single	171 (58.6)	211 (57.2)	383 (57.9)
	Serious dating or committed relationship	75 (25.7)	97 (26.3)	172 (26.0)
	Civil union, domestic partnership or equivalent	5 (1.7)	3 (0.8)	8 (1.2)
	Married	26 (8.9)	41 (11.1)	67 (10.1)
	Separated	2 (0.7)	5 (1.4)	7 (1.1)

	Divorced	8 (2.7)	10 (2.7)	18 (2.7)
	Widowed	2 (0.7)	0 (0)	2 (0.3)
	Did not disclose	3 (1.0)	0 (0)	5 (0.8)

Table 2.2 Means, Standard Deviations, and Correlations between Acceptability of iCBT and Indicators of Mental Health Symptomatology

Variable	1	2	3	4	5	6	7
1. APOI (SG)	1						
2. APOI (TA)	.72**	1					
3. CEQ (SG)	.46**	.46**	1				
4. CEQ (TA)	.38**	.49**	.86**	1			
5. Single Item (SG)	.45**	.43**	.58**	.49**	1		
6. Single Item (TA)	.31**	.40**	.51**	.54**	.73**	1	
7. DASS-21	-.16**	-.12**	.02	.03	.14**	.17**	1
M	49.37	50.54	12.63	13.57	3.15	3.28	31.90
SD	6.85	6.56	6.75	6.82	1.09	1.08	21.78
Range	16 - 74	16 - 80	0 - 30	0 - 30	1 - 5	1 - 5	0 - 114

Note. University Participants (N = 347 – 363) and Community participants (N = 254- 295) depending on the pattern of data missingness. APOI (SG) = Attitudes Towards Psychological Online Interventions (Self-guided); APOI (TA) = Attitudes Towards Psychological Online Interventions (Therapist-assisted); CEQ (SG) = Credibility/Expectancy Questionnaire (Self-guided); CEQ (TA) = Credibility/Expectancy Questionnaire (Therapist-assisted); Single Item (SG) = Single Item (Would you use Self-guided iCBT to improve your life?); Single Item (TA) = Single-Item Questionnaire (Would you use Therapist-assisted iCBT to improve your life?); DASS = Depression, Anxiety, & Stress Scale - 21 item
***significant at p < .01*

Table 2.3 Multivariate Effects for MANCOVA Models Examining the Impact of a Treatment Rationale on Attitudes towards iCBT

	Self-Guided iCBT				Therapist-Assisted iCBT			
	Wilks' Λ	F	*p*	Partial η2	Pillai's Trace	F	*p*	Partial η2
Age	.993	1.357	.255	.007	.003	.636	.592	.003
Psychopathology	.918*	17.578	<.001	.082	.068*	13.778	<.001	.068
Rationale	.982*	3.617	.013	.018	.038*	7.421	<.001	.038
Recruitment Source	.987*[†]	2.657	.048	.013	.010	1.829	.141	.010
Rationale x Recruitment Source	.996	.762	.516	.004	.001	.227	.878	.001

**significant at p < .05*

[†]This effect fell to non-significance (*p* = .051) when outliers were removed from the model.

Table 2.4 Multivariate Effects for MANCOVA Comparing Attitudes towards Self-guided and Therapist-assisted iCBT

	Wilks' Λ	F	*p*	Partial η2
Age	.992	1.465	.223	.008
Psychopathology	.900*	20.767	<.001	.100
Type of iCBT	.988	2.293	.077	.012
Recruitment Source	.986*	2.650	.048	.014
Rationale x Recruitment Source	.997	.527	.664	.003

**significant at p < .05*

Table 2.5 Hierarchical Logistic Regression Model Predicting Uptake-related Behavior

	Uptake-related Behavior			
	Step One		Step Two	
	B	Odds Ratio	B	Odds Ratio
Constant	-2.920*	0.054*	-2.952*	0.052*
Age	0.022	1.022	0.021	1.021
Psychopathology	0.026*	1.026*	0.025	1.026
Gender	-0.410	0.664	-0.446	0.640
Race/Ethnicity	-0.675*	0.509*	-0.680*	0.507*
Rationale	-	-	-0.114	0.893
Financial Incentive	-	-	0.234	1.264
R^2	0.048		0.051	
χ^2	12.172*		12.876*	
ΔR^2	0.048		0.003	
$\Delta\chi^2$	12.172*		0.703	

**significant at $p < .05$*

3 SECOND ARTICLE

Molloy, A. & Anderson, P. L. (2021). Increasing acceptability and outcome expectancy for Internet-based cognitive behavioral therapy during the COVID-19 pandemic. *Telemedicine and E-Health*. Advance online publication. https://doi.org/10.1089/tmj.2021.0393

3.1 Abstract

Background: E-health interventions for mental health have the potential to reduce burdens on healthcare systems, but large survey studies find low acceptability for these interventions. The COVID-19 pandemic may make attitudes towards e-health more malleable. The current study examined whether an intervention to improve attitudes towards Internet-based cognitive behavioral therapy (iCBT) has a greater impact during the COVID-19 pandemic than before the pandemic. Materials and Methods: Individuals (N=662) recruited from a large university and surrounding community who participated in a study about the acceptability of iCBT in 2018 and 2019 were asked to participate in a follow-up survey. In the original study, participants were randomized to receive or not receive a rationale designed to increase acceptability of iCBT, then completed measures of acceptability and outcome expectancy for iCBT. Fifty-one participants enrolled in the follow-up study from May to July, 2020. They received a treatment rationale for iCBT (or not) in keeping with randomization from the parent study and re-completed measures assessing acceptability and outcome expectancy for iCBT. Results: Contrary to hypotheses, two-way ANCOVA's demonstrated that there was no significant interaction between time point and rationale condition on acceptability or outcome expectancy for iCBT. There was a significant main effect of rationale condition on acceptability, such that participants who received a treatment rationale reported greater acceptability for iCBT. There were no significant main effects of time. Conclusions: A treatment rationale was effective

in improving acceptability for iCBT in a general population sample, but not more so during the COVID-19 pandemic.

Keywords: acceptability, internet-based cognitive behavioral therapy, iCBT, mental health, treatment rationale, COVID-19, digital health, treatment access

3.2 Introduction

Researchers from around the world have documented widespread increases in mental distress since the beginning of the COVID-19 pandemic[1,2]. During this time of increasing need for mental health services, the risk of COVID-19 infection has caused a rapid, large-scale disruption of face-to-face mental healthcare. Many providers have transitioned to videoconferencing-based telemedicine[3] and researchers have speculated that this transition may spur increased use of digital solutions to systemic healthcare problems[4,5]. This includes conventional psychotherapy delivered via videoconferencing and e-health mental health interventions that can be completed on one's own or with relatively brief human support.

Internet and mobile-based digital mental health interventions significantly reduce symptoms for many mental health problems, including depression, anxiety, stress, and substance abuse[6,7]. These programs can be completed independently, i.e. "self-guided," or incorporate support from a therapist or coach. Internet-based mental health programs are effective, but they are widely underutilized[8,9], and large survey studies conducted prior to the COVID-19 pandemic have found low levels of acceptability and confidence that these interventions will work[10,11,12]. However, this may have changed in the context of the COVID-19 pandemic, which dramatically expanded the role of technology in many people's lives. With millions of people in the U.S. working from home and switching to technology-mediated forms of communication, there has been a large-scale increase in the use of telemedicine[13,14], downloads for mental health apps[15,16], and treatment-seeking for Internet-based mental health programs[17].

Although people's openness to e-health for mental healthcare seems to have increased during COVID-19, many who could benefit from these programs may still need persuasion to use them. Video and text-based treatment rationales designed to improve attitudes toward digital mental health programs have shown promising results[18,19,20]. These rationales explain how a treatment works and describe the evidence that it is effective. They have been shown to increase acceptability, defined here as general attitudes and beliefs about programs, and outcome expectancy, the belief that a program will be effective. Treatment rationales for e-health mental health programs may be more effective in the context of the COVID-19 pandemic, due to increased distress, low availability of face-to-face treatment, and increased use of technology in day-to-day life. However, no study has examined this possibility by comparing the effects of a treatment rationale for digital mental health programs administered before and during the COVID-19 pandemic.

The current study focuses specifically on the effects of a treatment rationale for Internet-based cognitive behavioral therapy (iCBT), one of the most widely studied forms of e-health for mental health[21]. The authors re-contacted participants from a large experimental study that examined the effects of a treatment rationale for iCBT prior to the COVID-19 pandemic[20]. Respondents to the follow-up repeated study procedures from the parent study, including the original experimental manipulation of receiving a treatment rationale or not. The authors hypothesized that there would be significant interactions between rationale condition and time point, such that the rationale caused a larger increase in acceptability and outcome expectancy for iCBT when administered during the COVID-19 pandemic, as compared to before the pandemic.

3.3 Materials and Methods

3.3.1 Procedure

All procedures for this study were approved by the Institutional Review Board at Georgia State University (IRB00000716).

3.3.1.1 Parent Study

Individuals were recruited for a study examining the acceptability of iCBT from June 2018 to September 2019 (N=662)[20]. Participants in this parent study were students at a large university in the southeastern United States and adults from the surrounding urban community. Students participated online, whereas community participants were recruited in public places and completed the study on a tablet computer with a research assistant. Inclusion criteria included age 18 or older and ability to read in English. All participants completed a digital survey in which they were randomized to receive a rationale for iCBT or not. The treatment rationale was approximately 800 words in length and described iCBT in depth, using persuasion techniques to increase acceptability and outcome expectancy[22]. Participants assigned to the no-rationale condition read a definition of iCBT that was 130 words focusing on the difference between therapist-assisted and self-guided iCBT so that the participants could answer questions about both modalities. Participants then completed self-report measures of acceptability and outcome expectancy for self-guided and therapist-assisted iCBT. Participants also completed a measure of current psychopathology. For further details about the parent study, see Molloy et al.[20].

3.3.1.2 Follow-up Survey

Participants from the parent study were re-contacted by email in May 2020 and invited to participate in a follow-up survey. People who responded read a treatment rationale (or not) according to their original assignment in the parent study and completed the same self-report questionnaires as in the parent study, as well as a measure examining experiences with the COVID-19 pandemic. All participants were offered online gift cards as compensation for completing the follow-up survey.

3.3.2 *Participants*

Fifty-four participants (8.2% of the original sample) completed the study from May through July 2020. Differences in demographics and dependent variables between those who completed and did not complete the follow-up study were evaluated using *t* tests and chi-square analyses. People who completed the study were more likely to be women (chi-square = 6.377, $p = .012$) and rated therapist-assisted iCBT as significantly more acceptable than those who did not (Attitudes toward Psychological Online Interventions Scale; $t = 2.497$, $p = .013$). There were no significant differences on other demographic characteristics, psychopathology, familiarity with iCBT, acceptability for self-guided iCBT, or outcome expectancy for self-guided or therapist-assisted iCBT (all *p*'s > .05).

Three questions about the treatment rationale were administered as a manipulation check for participants in the rationale condition. Two participants who answered these questions incorrectly and one participant who completed the parent study in less than five minutes were excluded, resulting in 51 participants whose data were used. Demographics (collected in the parent study) are presented in Table 3.1. Twenty-one participants were originally randomized to the treatment rationale condition, whereas 30 were originally randomized to the brief definition condition.

3.3.3 Measures

3.3.3.1 Demographics and Use of E-Health

A 22-item demographics questionnaire was developed for the parent study using the Standardized Data Set from the Center for Collegiate Mental Health at Penn State University[23]. Participants also reported whether they were currently using an "online mental health or iCBT program" or had ever used one in the past.

3.3.3.2 Attitudes toward Psychological Online Interventions Scale (APOI)

The APOI[24] is a validated measure of attitudes toward digital mental health interventions, with greater scores reflecting more positive attitudes. The APOI has demonstrated strong internal consistency in previous research ($\alpha = 0.77$)[24]. It was used in the current study as a measure of acceptability for iCBT, defined as cognitive attitudes toward these interventions.

3.3.3.3 Credibility/Expectancy Questionnaire (CEQ), Expectancy Subscale

The expectancy subscale of the CEQ[25] is composed of three items that evaluate outcome expectancy for psychological interventions, with greater scores reflecting greater expectations of effectiveness. It is widely used in psychological research and has demonstrated high internal consistency ($\alpha = 0.79$-.90) and test-retest reliability ($r = 0.83$)[25].

3.3.3.4 Depression Anxiety Stress Scales 21 Item Version (DASS-21)

The DASS-21[26] is a commonly used measure of psychopathology, with individual subscales for depression, anxiety, and stress. It has strong convergent validity with the Beck

Anxiety Inventory (*r* = 0.81) and Beck Depression Inventory (*r* = 0.74)[26] and strong internal consistency for the overall scale ($\alpha = 0.93$)[27].

3.3.3.5 Pandemic Stress Index

A modified version of the PSI[28] evaluated participants' experiences with the pandemic. It included questions about common experiences related to the COVID-19 pandemic, e.g. social distancing, losing employment, or contracting COVID-19. It also assessed whether participants had used various forms of telemedicine or e-health to support their physical and mental health during COVID-19.

3.3.4 Statistical Analyses

3.3.4.1 Impact of COVID-19 and Use of Telemedicine

The frequency of common experiences with the pandemic and use of telemedicine were evaluated using the PSI. A matched-pairs *t* test was conducted to test for increases in psychopathology (DASS-21 total score) during the pandemic, as compared to before the pandemic.

3.3.4.2 Preliminary Analyses

A pair of two-way within-subjects ANOVA's were used to test for interactions between time point (pre-COVID-19 vs. during COVID-19 pandemic) and type of iCBT (self-guided vs. therapist-assisted iCBT) on acceptability of and expectations of effectiveness for iCBT. Because there was not a statistically significant two-way interaction for either acceptability or outcome expectancy of iCBT ($F(1, 50) = 1.060$, $p = .308$; $F(1, 50) = 0.516$, $p = .476$, respectively), type of iCBT was collapsed for the main analyses in order to increase power.

3.3.4.3 Main Analyses

Two two-way mixed ANCOVA's were used to test for interactions between time point (pre-COVID-19 vs. during COVID-19 pandemic) and treatment rationale condition (yes, no) to test the hypothesis that exposure to a treatment rationale would produce a greater increase in acceptability and outcome expectancy for iCBT during the pandemic as compared to before the pandemic. Consistent with the parent study, age and baseline psychopathology (DASS-21 score pre-pandemic) were used as covariates due to evidence that they are related to interest in Internet-based mental health treatment[11,29]. Type of iCBT was collapsed for main analyses by taking the sum of APOI and CEQ scores for self-guided and therapist-assisted iCBT, respectively. A Bonferroni correction of $\alpha = .025$ was used for all analyses to minimize Type 1 error for multiple comparisons, as each test was conducted with two dependent variables: acceptability and outcome expectancy for iCBT. All data were analyzed using SPSS version 25.0.

3.4 Results

3.4.1 Missing Data

Across all measures used for the current study's analyses, there were 11 missing values (0.002% of data). Data was missing completely at random (Little's MCAR Test, $p > .05$) and missing values were imputed using expectation maximization[30].

3.4.2 Impact of COVID-19 and Use of Telemedicine

See Table 3.2 for a summary of participants' experiences during COVID-19. A high proportion of participants reported that their lives had been impacted by the COVID-19 pandemic; the most common experiences included social distancing, following COVID-19-related media, and worrying about friends, family, and others. As shown in Table 3.3, a majority of participants had not used telemedicine or other electronic resources during COVID-19 to support their physical or mental health.

A matched-pairs *t* test was used to test for differences in psychopathology before and during the pandemic. DASS-21 total scores recorded before the pandemic (M = 37.99, SD = 25.76) and during the pandemic (M = 37.95, SD = 25.16) were highly correlated, $r = .593$, $p < .001$, and there was no significant difference between them, $t = .013$, $p = .989$.

3.4.3 Main Analyses

3.4.3.1 Effects of Time Point, Treatment Rationale, and their Interaction on Acceptability and Outcome Expectancy for iCBT

See Table 3.4 for results of main analyses. A pair of two-way ANCOVA's (rationale * time point with age and psychopathology as covariates) tested the hypothesis that receiving a treatment rationale for iCBT (versus no rationale) would cause a greater increase in acceptability and outcome expectancy for iCBT during the pandemic than before the pandemic. Statistical assumptions were met for two-way ANCOVA, including normality of residuals, homogeneity of variance and regression slopes, and homoscedasticity. For the ANCOVA examining acceptability, there was one residual outlier that significantly affected results (discussed below).

There was not a significant interaction or main effect of time point for either dependent variable (*p*'s > .033), nor a significant main effect of the experimental condition on outcome expectancy for iCBT (*p* =. 668). There was, however, a statistically significant main effect of the experimental condition on acceptability of iCBT, such that receiving a rationale for iCBT (versus no rationale) produced greater acceptability of iCBT ($p = .022$). The ANCOVA examining acceptability had one residual outlier (studentized residual = -3.12) and was re-run with this case removed. When the residual outlier case was removed, the main effect of rationale fell to non-significance ($p = .045$). This approach did not change any other aspects of the results.

3.5 Discussion

This is the first longitudinal study to compare the effects of a treatment rationale for e-health mental health interventions before and during the COVID-19 pandemic. Consistent with previous research, the treatment rationale used in the current study significantly increased acceptability for iCBT with a medium to large effect size. These findings replicate previous studies[18,31] and indicate that treatment rationales can increase acceptability of iCBT. However, the treatment rationale was not shown to be more effective in the context of COVID-19 and was not shown to affect participants' expectations that iCBT would be effective.

It is possible that the treatment rationale may have impacted aspects of acceptability that are distinct from participants' expectations that iCBT will be effective. There are several content areas within the measure of acceptability used in this study that could account for this, including perceptions that technology-based mental health interventions are risky (e.g. by increasing isolation), concerns about maintaining motivation or learning skills in the absence of a therapist, and potential benefits of greater confidentiality and reduced stigma that come with using an online mental health program. Theoretical models of technology adoption, such as the Unified Theory of Acceptance and Use of Technology[32], propose a range of constructs, including outcome expectancy, that impact decision-making about whether to use interventions like iCBT. Researchers should draw from these models and continue to examine the ways that acceptability-facilitating interventions like treatment rationales might improve specific dimensions of iCBT acceptability for individuals who have been impacted by COVID-19.

Healthcare providers may find treatment rationales for iCBT to be a useful decisional aid for patients that are considering a variety of mental healthcare options. Providing upfront education about iCBT for treatment-seeking individuals with mild to moderate symptoms may lead them to choose iCBT in lieu of face to face care. This is consistent with the goals of shared decision-making, a framework used in many healthcare settings to collaborate with patients and promote their autonomy when choosing their course of treatment[33]. If significant numbers of patients choose iCBT, this would conserve providers' time for patients with more severe symptoms, a critical goal given the long-standing problems with mental healthcare access in the United States that have been exacerbated by increased demand during COVID-19[34].

Surprisingly, although nearly all of the current study's participants reported that their lives were affected by the pandemic, there were no significant differences in psychopathology before and during the pandemic, which perhaps helps explain why a minority of participants had used any digital resources for mental healthcare (31.4%) or online programs like iCBT (15.7%). These results are inconsistent with studies showing that people have experienced increased anxiety and depression due to COVID-19[1] and sought telehealth services at increased rates, including iCBT specifically[17]. Future studies with participants who experienced a need for healthcare and significant disruption in access to face-to-face services during COVID-19 may find that these individuals have become more responsive to treatment rationales for e-health, even if this change is not evident in non-treatment seeking samples.

iCBT may particularly benefit communities that have been disproportionately impacted by COVID-19 and have lower access to healthcare, such as Black Americans[35], people in rural communities[36], and people experiencing homelessness[37]. Researching the types of experiences that may increase people's responsiveness to acceptability-facilitating interventions for iCBT, including experiences with COVID-19 and telemedicine, is an important way to promote health equity by increasing access to care. The current study found that a treatment rationale significantly improved acceptability for iCBT in a racially diverse sample of adults. However, the sample was also relatively young, predominantly female, and recruited from an urban area. Future researchers examining this topic should make efforts to recruit diverse samples, study specific vulnerable communities, and report the demographics of their samples.

3.5.1 Limitations

There are several important limitations to this study. It is possible that the effect of the treatment rationale was increased by the fact that participants read it twice – once during the parent study and again at follow-up. If the effect of the treatment rationale in the parent study was maintained until follow-up, then a greater difference between experimental groups during the pandemic as compared to pre-pandemic (the central hypothesis of this study) could be a cumulative effect of administering the rationale twice. Given the 1-2 year gap between time points, the authors feel it is unlikely that the rationale's effect from the parent study was maintained until follow-up. However, future studies examining the effects of acceptability-facilitating interventions for iCBT over time should control for this potential source of bias if possible.

Participants who completed this study reported more positive attitudes towards iCBT during the parent study than those who did not. This type of bias, which can result when large numbers of people are invited to participate in a study on e-health interventions and a small proportion of them volunteer, is unfortunately a common problem in this research area (for a discussion of this issue, see Mohr et al.[38]). Accordingly, inferences should be drawn cautiously from these results. For example, participants may have already been highly responsive to a treatment rationale for iCBT before the pandemic, which could limit changes in the effect of the rationale due to experiences with COVID-19. Whereas this study was sufficiently powered to detect large effects, the sample size also limited the ability to detect medium or small effects – even the fairly large effect of the treatment rationale on acceptability for iCBT fell below significance when an outlier was removed. In summary, given the characteristics of our sample and its relatively small size, these findings should be taken as preliminary and replication is needed.

3.6 Conclusion

The treatment rationale used in this study significantly increased acceptability for iCBT during the COVID-19 pandemic. However, it was not shown to be more effective during the pandemic as compared to before the pandemic. Continued research is needed to explore the effects of treatment rationales and other acceptability-facilitating interventions for individuals who have been affected by COVID-19. As healthcare systems expand their use of telemedicine and e-health programs for mental health, this line of research has significant potential to engage greater numbers of patients with these effective and accessible interventions.

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3.8 Author Contributions

AM and PLA devised the project, the main conceptual ideas, and protocol outline. AM coordinated data collection for the study, conducted all statistical analyses, and designed the tables. AM and PLA contributed to writing the manuscript. PLA supervised the project.

3.9 Author Disclosures

The authors have no competing financial interests to report.

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Table 3.1 Participant Characteristics

Demographics		Rationale Condition N = 21 (%)	No Rationale Condition N = 30 (%)	Total N = 51 (%)
Age	Mean Age (*SD)*	23.10 (8.98)	24.43 (12.20)	23.88 (10.91)
	Range	18-48	18-61	18-61
Gender	Man	4 (19.0)	5 (16.7)	9 (17.6)
	Woman	17 (81.0)	23 (76.7)	40 (78.4)
	Self-Identify	0 (0.0)	2 (6.7)	2 (3.9)
Race/Ethnicity	African American / Black	7 (33.3)	11 (36.7)	18 (35.3)
	Asian American / Asian	0 (0.0)	7 (23.3)	7 (13.7)
	Hispanic / Latino/a	2 (9.5)	4 (13.3)	6 (11.8)
	Multi-racial	1 (4.8)	2 (6.7)	3 (5.9)
	White	11 (52.4)	6 (20.0)	17 (33.3)
Sexual Identity	Heterosexual	14 (66.7)	23 (76.7)	37 (72.5)
	Lesbian	0 (0.0)	2 (6.7)	2 (3.9)
	Gay	0 (0.0)	1 (3.3)	1 (2.0)
	Bisexual	5 (23.8)	1 (3.3)	6 (11.8)
	Questioning	1 (4.8)	0 (0.0)	1 (2.0)
	Self-Identify	1 (4.8)	3 (10.0)	4 (7.8)
Current Financial Status	Always Stressful	5 (23.8)	2 (6.7)	7 (13.7)
	Often Stressful	7 (33.3)	7 (23.3)	14 (27.5)
	Sometimes Stressful	4 (19.0)	16 (53.3)	20 (39.2)
	Rarely Stressful	5 (23.8)	5 (16.7)	10 (19.6)

Treatment History	Received face-to-face psychotherapy	12 (57.1)	10 (33.3)	22 (43.1)
	Has not received face-to-face psychotherapy	9 (42.9)	20 (66.7)	29 (56.9)
	Used an online mental health program	2 (9.5)	0 (0.0)	2 (3.9)
	Did not use an online mental health program	19 (90.5)	29 (96.7)	48 (94.1)
	Unsure	0 (0.0)	1 (3.3)	1 (2.0)
Relationship Status	Single	12 (57.1)	16 (53.3)	28 (54.9)
	Serious dating or committed relationship	5 (23.8)	8 (26.7)	13 (25.5)
	Civil union, domestic partnership or equivalent	1 (4.8)	0 (0.0)	1 (2.0)
	Married	3 (14.3)	3 (10.0)	6 (11.8)
	Divorced	0 (0.0)	2 (6.7)	2 (3.9)
	Did not disclose	0 (0.0)	1 (3.3)	1 (2.0)

Note. All data in this table was collected during the parent study, from 2018-2019.

Table 3.2 Experiences with COVID-19 Pandemic

	N (%)
What are you doing/did you do during COVID-19 (coronavirus)?	
Practicing social distancing	50 (98.0)
Follow any media coverage related to COVID-19 pandemic	43 (84.3)
Isolating or quarantining yourself (i.e. while sick or if exposed)	20 (39.2)
Not working	20 (39.2)
Working from home	17 (33.3)
Change in routine face-to-face medical services	13 (25.5)
Caring for someone at home	7 (13.7)
No changes to my life or behavior	2 (3.9)
Which of the following are you experiencing (or did you experience) during COVID-19 (coronavirus)?	
Worrying about friends, family, partners, etc.	40 (78.4)
More sleep, less sleep, or other changes to your normal sleep pattern	37 (72.5)
Fear of getting COVID-19	34 (66.7)
Fear of giving COVID-19 to someone else	34 (66.7)
More anxiety	34 (66.7)
Loneliness	31 (60.8)
Personal financial loss	25 (49.0)
More depression	24 (47.1)
Feeling that I was contributing to the greater good by preventing myself or others from getting COVID-19	23 (45.1)
Getting emotional or social support	18 (35.3)
Getting financial support	16 (31.4)
Not having enough basic supplies (e.g. food, medication, shelter)	15 (29.4)
Increased alcohol/other substance use	14 (27.5)
Confusion about what COVID-19 is, how to prevent it, or why social distancing/isolation/quarantines are needed	11 (21.6)
Stigma/discrimination from others (e.g. for your identity or symptoms)	10 (19.6)
Diagnosed with COVID-19	1 (2.0)

Table 3.3 Telemedicine and E-Health Usage during the COVID-19 Pandemic

	N (%)
Did you use any of the following to support your physical health during the COVID-19 pandemic?	
Telehealth services	13 (25.5)
Online programs	0 (0.0)
Apps	3 (5.9)
Internet	9 (17.6)
Any of the above	23 (45.1)
Did you use any of the following to support your mental health during the COVID-19 pandemic?	
Telehealth services	6 (11.8)
Online programs	1 (2.0)
Apps	5 (9.8)
Internet	8 (15.7)
Any of the above	16 (31.4)
Are you currently using an online mental health or iCBT program?	
Yes	4 (7.8)
No	47 (92.2)
Have you ever used an online mental health or iCBT program?	
Yes	8 (15.7)
No	43 (84.3)

Note. All data in this table was collected at follow-up. iCBT = Internet-Based Cognitive Behavioral Therapy.

Table 3.4 Results for ANCOVA Models Examining the Impact of Treatment Rationale and Time Point on Acceptability and Outcome Expectancy for iCBT

	Acceptability (APOI)			Outcome Expectancy (CEQ)		
	F	*p*	Partial η2	F	*p*	Partial η2
Age	6.670[a]	.013	.124	10.865[a]	.002	.188
Psychopathology	2.319	.135	.047	0.024	.877	.001
Rationale x Time Point	1.494	.228	.031	0.013	.911	.000
Time Point	0.000	.985	.000	4.833	.033	.093
Rationale	5.607[a,b]	.022	.107	0.186	.668	.004

Note. APOI = Attitudes toward Psychological Online Interventions Scale. CEQ = Credibility/Expectancy Questionnaire.
[a]Significant at $p < .025$
[b]This effect fell to non-significance ($p = .045$) when an outlier was removed from the analysis.

4 THIRD ARTICLE

Molloy, A. & Anderson, P. L. (2021). Engagement with mobile health interventions for depression: a systematic review. *Internet Interventions, 26,* 100454. https://doi.org/10.1016/j.invent.2021.100454

4.1 Abstract

Background: Depressive disorders are a major public health problem, and many people face barriers to accessing evidence-based mental health treatment. Mobile health (mHealth) interventions may circumvent logistical barriers to in-person care (e.g., cost, transportation), however the symptoms of depression (low motivation, concentration difficulties) may make it difficult for people with the disorder to engage with mHealth. Objective: The aim of this systematic review is to examine assessment and reporting of engagement in clinical trials of mHealth interventions for depression, including objective engagement (e.g., number of times program is used), subjective engagement (e.g., qualitative data on users' experiences), and associations between engagement and other clinically important variables (e.g., symptom improvement, participant characteristics). Methods: Three electronic databases (PsycINFO, Web of Science, PubMed) were searched in February 2020 using search terms for mHealth and depression. Studies were included in the review if they tested a mHealth intervention designed for people with depressive disorders or elevated depression symptoms. Results: Thirty studies met inclusion criteria and were reviewed. Most studies reported objective engagement (N=23, 76.7%), approximately half reported subjective engagement (N=16, 53.3%), and relatively few examined associations between engagement and clinical improvement, participant characteristics, or other clinically relevant variables (N=13, 43.3%). Conclusions: Although most studies in this small but rapidly growing literature report at least one measure of engagement,

there is substantial heterogeneity. Intentional, theory-driven, and consistent measurement of engagement with mHealth interventions for depression may advance the field's understanding of effective engagement to facilitate clinical improvement, identify dose-response relationships, and maximize generalizability for underserved populations.

Keywords: Depression, Mood Disorders, mHealth, Smartphone, Engagement, Analytics

4.2 Introduction

Depressive disorders have an enormous impact on global health and quality of life, affecting over 250 million people worldwide, ranking as the third leading cause of global disability (James et al., 2018), and being associated with unemployment, poor physical health, poor social function, and suicide (Hawton et al., 2013; World Health Organization, 2017). There are effective medications and psychotherapies that improve depressive symptoms, but there are not enough trained mental health professionals to deliver them (Liu et al., 2017; World Health Organization, 2017).

Mobile health, or "mHealth," is viewed as a promising way to overcome well-documented barriers to in-person treatment and increase access to mental health services, particularly among underserved communities. mHealth refers to "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants and other wireless devices" (van Heerden, et al., 2012). Delivering treatment via smartphone creates a substantial opportunity to expand access to mental health treatment, as there are an estimated 3.5 billion smartphone users worldwide (Statista, 2019) and relatively low disparities in smartphone ownership along racial and socioeconomic lines in the U.S. (Pew Research Center, 2019).

Meta-analyses examining clinical trials of smartphone-based mHealth programs for depression have demonstrated that they significantly reduce depression symptoms (Firth et al., 2017; Weisel et al., 2019), but attrition and low engagement with these programs are a significant concern. Studies of publicly accessible mHealth programs for mental health find that many people stop using these programs shortly after downloading them, before they are likely to achieve any clinical benefit (Lattie et al., 2016). This is broadly true of commercially available smartphone apps, which typically lose about 70% of users within one week of download (Sigg, et al., 2016). A better understanding of factors that influence engagement in mHealth interventions for depression is needed to fully realize their potential.

Engagement with digital health interventions is a complex, multifaceted construct. Perski, et al. (2017) conducted a systematic review from an interdisciplinary perspective to create a conceptual framework explaining how engagement with digital interventions leads to behavior change. Drawing from the computer science and behavioral science literatures, they define engagement with digital interventions as "the extent (e.g. amount, frequency, duration, depth) of usage and (2) a subjective experience characterised by attention, interest and affect" (p. 261). They emphasized that engagement can be understood and measured objectively, by recording user behavior, and subjectively, by evaluating self-reported qualitative dimensions of users' experiences while engaging with an intervention. The model also purports that engagement is influenced by the intervention itself (e.g., content, delivery mechanism) and by context, which includes individual characteristics of the population using the intervention and their sociocultural environment.

Depression is characterized by behavioral avoidance, difficulty concentrating, anhedonia, and negative cognitions (Beck, 2008), all of which could impact engagement with a mHealth intervention. Additionally, depressed people experience greater levels of social impairment, relationship dysfunction, unemployment, and medical comorbidities (McKnight & Kashdan, 2009), contextual factors that should not be ignored in clinical research. In order to understand and specifically target types of engagement that have the greatest impact on clinical improvement for people with depression, clinical researchers should select engagement metrics that shed light on interactions between individual characteristics, context, different types of engagement, and clinical improvement.

Systematic reviews that examine engagement reporting in clinical trials of mHealth programs have found substantial variety in how it is measured, which limits generalizability across studies and progress in this area. For example, Pham et al. (2019) outlined 14 engagement-related constructs that have been used by mHealth researchers (e.g. “use,” “adherence,” “compliance,” “feasibility”) across studies of mHealth programs for chronic health conditions. Reviews of mHealth for mental health find that researchers report engagement quite differently across studies (Linardon & Fuller-Tyszkiewicz, 2020; Ng, et al., 2019). Additionally, it is uncommon for studies to evaluate relationships between engagement and clinical outcomes, participant characteristics, or other relevant variables, which limits researchers’ ability to develop contextualized models of engagement for specific populations.

Researchers that capture engagement using a variety of different metrics can examine relationships between engagement, clinical outcomes, and participant characteristics, such as baseline depression severity or cultural background. These findings could inform and test theoretical models of engagement with mHealth engagement or clinical decisions about the appropriateness of specific mHealth programs for different populations. Comparing engagement between different mHealth interventions, examining changes in engagement over time, and examining associations between different metrics of engagement could inform mHealth program design and the ways that patients are instructed to use programs. It is therefore important to know whether clinical researchers consistently report engagement, the most common ways that engagement is operationalized, and extent to which researchers examine associations between engagement and other variables in clinical trials.

4.2.1 The Current Study

Engagement may pose a particular problem for individuals experiencing depression, but no review to date has specifically examined engagement reporting in studies of mHealth interventions for depression. The current systematic review examined measurement and reporting of engagement in clinical trials of these programs. Studies that did not report engagement were included to evaluate the consistency of engagement reporting in the literature. Both objective and subjective metrics of engagement for mHealth interventions were reviewed. Additionally, the review examined which studies tested for associations between metrics of engagement and other variables, given the potential for these associations to inform future research and implementation of mHealth interventions for depression. Findings are discussed as they relate to theoretical models for, improvement of clinical research on, and optimization of mHealth interventions for depression.

4.3 Methods

4.3.1 Electronic Searches

A systematic review was conducted using the PsycINFO, PubMed, and Web of Science databases. After a review of the literature, search terms were developed for mobile devices, mHealth, and depression and entered on February 9th, 2020. See appendix for specific search terms. In keeping with previous systematic reviews of mobile interventions (Donker et al., 2013;

Dubad et al., 2018), only studies published 2008 and afterward were included because this is the year that the first mobile applications became publicly available for download. The first author completed the electronic searches, removed duplicates, then screened titles and abstracts for inclusion and exclusion criteria. Following title and abstract review, full texts of articles that seemed to meet criteria based on titles and abstracts were then reviewed by both authors to reach final decisions about inclusion. Disagreements were resolved through in-depth discussion.

4.3.2 Data Extraction

A data extraction form was developed by the first author based on recent systematic reviews of participant engagement in digital mental health interventions (Linardon & Fuller-Tyszkiewicz, 2020; Ng et al., 2019; Pham et al., 2019) and a preliminary review of articles that met inclusion criteria. For each study, the first author first extracted the methods of assessing depression (assessment for specific diagnosis or cutoff on a self-report measure) and the mobile device used for the study intervention (e.g., app). Interventions were then coded as “structured” if they used locked, sequential modules, “unstructured” if they used tools that can be accessed at any time, “hybrid” if they used structured and unstructured components, or “ecological momentary assessment” if they solely prompted users to complete brief assessments of mood or other constructs (EMA; see Shiffman, et al., 2008). Information about the demographic characteristics of the sample (e.g., age, race), major components of mHealth programs (e.g., behavioral activation, cognitive restructuring), and presence or absence of coaching were also recorded. Lastly, the first author coded studies for the types of information they reported about user engagement. These are presented in Figure 4.1 and fall into three broad categories: objective user engagement, subjective user engagement, and assessment of associations between engagement and other variables.

4.3.3 Study Selection Criteria

Studies were included if they met the following criteria: 1) original peer-reviewed articles, 2) published in English, 3) participants met criteria for a unipolar depressive disorder (e.g. major depressive disorder, persistent depressive disorder) as assessed by a structured interview or confirmed by medical records, or had elevated depression symptoms established by any cutoff on a validated self-report measure, and 4) examined a digital psychological intervention delivered via a mobile device (e.g. smartphone, tablet) that specifically targets depression and was intended to be used more than once. Studies were excluded for the following reasons: 1) did not report their assessment of depression or cite a resource with this information, such as a published study protocol, 2) included participants without depression (e.g. mixed samples with depression and/or anxiety), unless the non-depressed sample represented a separate study condition and was examined separately, 3) examined an intervention that functioned simply as a means of communication between user and therapist (e.g. videoconferencing, texting), 4) examined an intervention that did not target psychological symptoms (e.g. targeting only sleep or exercise), or 5) examined an intervention that requires no active input from the user, such as programs that exclusively use passive mobile sensors.

Studies examining EMA or mood tracking programs were included in the review when these were conceptualized as interventions, given the evidence that mood tracking alone has the potential to reduce depression symptoms (Dubad et al., 2018). Blended interventions containing a mobile component alongside other components (e.g. web-based intervention, face to face therapy) were included. Studies examining digital psychological intervention that could be completed without a mobile device (e.g., could be completed using a computer) were not included in the current review. These studies were excluded to focus on engagement metrics that are specifically relevant to mobile devices, which may differ from metrics used for interventions that are commonly accessed using desktop computers. Because metrics of engagement are informative in non-controlled studies, studies with and without a comparison group for the active treatment were included. Lastly, secondary analyses of primary studies were included given that these studies have the potential to report information about engagement that was not reported in the primary article.

4.4 Results

4.4.1 Study Selection

A total of 4473 references were identified through the database search. After duplicates were removed, 3613 articles were reviewed by title and abstracts. The authors reviewed 289 full text articles and 30 were ultimately included in the systematic review. A Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Moher, et al., 2009) flow chart of the study selection process is presented in Figure 4.2.

4.4.2 Study Characteristics

Table 4.1 shows the various types of depression assessment, mobile devices, structured interventions, and coach support used in the studies included in this review. Details about individual studies, including the specific mHealth intervention used, participant demographics, whether and how objective/subjective engagement was measured, and whether the study assessed associations between engagement and other variables are presented in Table 4.2. The majority of studies were published recently, with nine published in 2018 (30.0%) and 12 published in 2019 (40.0%).

4.4.2.1 Participants

Depression was most commonly assessed using a cutoff on a validated self-report measure, either alone (N=16, 53.3%) or in combination with a confirmed diagnosis of a unipolar depressive disorder (N=9, 30.0%). A smaller proportion of studies selected participants based on diagnosis of a depressive disorder without a self-report measure (N=5, 16.7%).

4.4.2.2 Interventions

Most studies examined smartphone interventions specific to iPhones (N=8, 26.7%) or compatible with multiple operating systems (N=7, 23.3%). A smaller proportion of studies used interventions specific to Android smartphones (N=3, 10.0%) or examined interventions that were delivered on multiple devices (e.g. smartphone with smart watch or tablet; N=4, 13.3%). A number of studies used smartphone interventions with unspecified operating systems (N=8, 26.7%). Studies most commonly examined unstructured interventions (N=15, 50.0%), followed by an equal number of studies that examined structured (N=5, 16.7%), hybrid (N=5, 16.7%), and EMA (N=5, 16.7%) interventions. About a third of interventions were self-guided (N=11, 36.7%) and the rest involved some level of support from a therapist or coach (N=19, 63.3%).

4.4.3 Metrics of Objective Engagement

There was a high level of heterogeneity in reporting of objective engagement. Twenty-three studies (76.7%) reported at least one objective metric of engagement. Frequencies of reporting for all metrics of user engagement are presented in Table 4.3.

4.4.3.1 Program Use by Day or Week

This was the most commonly reported metric of user engagement in the current review. Studies used different intervals for tracking; most studies tracked program use by the number of active days (i.e. number of days the program was used at least once; N=7), whereas others reported by active week (i.e. number of weeks the program was used at least once; N=6). One study of an unstructured intervention (Caplan, et al., 2018) reported the number of participants that used the intervention "several times per week" as their sole objective metric of engagement.

4.4.3.2 Use of Specific Program Features

Use of specific program features was also one of the most commonly reported objective engagement metrics in included studies. Generally, studies reported the number of times that participants used specific tools, such as setting goals for behavioral activation (Dahne, Collado, et al., 2019; Dahne, Lejuez, et al., 2019), completing cognitive restructuring exercises (Stiles-Shields, et al., 2019), or interacting with peers (Sawyer et al., 2019).

4.4.3.3 Total Number of Sessions

Five studies reported the average number of times that participants accessed the intervention. Burns et al. (2011) merged any "log-ins" to their intervention that occurred within one hour of each other to avoid counting brief sessions that occurred in quick succession.

4.4.3.4 Interaction with Coach or Therapist

Of the 19 studies that examined coach or therapist-supported interventions, five studies reported at least one objective metric of interaction with a coach or therapist. There was substantial variety in the ways that coaching was delivered in these interventions and in how it was reported. Economides et al. (2019) reported the number of days that participants were in contact with a therapist and did not specify whether this contact was via messaging or phone (participants had access to both). Other studies reported the number of messages sent to a coach (Ly et al., 2014; Schlosser et al., 2017) or the average amount of time that participants spoke with coaches via phone (Stiles-Shields et al., 2019). Schlosser et al. (2017) examined the construct of “social initiative” by reporting the proportion of interactions between participants and coaches that were initiated by the participant.

4.4.3.5 Completion of Structured Modules

Four studies reported completion of structured modules as a metric of engagement. Two of these were a primary study and secondary analysis that examined a structured intervention (Furukawa, Horikoshi et al., 2018; Mantani et al., 2017). One examined a hybrid intervention (Watts et al., 2013) and one examined an unstructured intervention (Menezes et al., 2019) that included regular behavioral activation sessions which were not in locked sequence.

4.4.3.6 Total Duration of Use

Four studies reported the total duration that participants used the study intervention. Duration was reported in average minutes or hours that the program was used per participant. Three studies reported total duration of use throughout the study, whereas one study reported total duration of use per week (Takahashi, et al., 2019).

4.4.3.7 Response to EMA Prompts

Of the five EMA studies included in this review, four reported the number of completed EMA prompts. One study reported this as its sole metric of objective engagement (Moukaddam et al., 2019), whereas three reported it in combination with other metrics (Cormack et al., 2019; Hung et al., 2016; Torous et al., 2015).

4.4.3.8 Average Duration between Sessions

Three studies reported the average duration between times that participants accessed an intervention (Furukawa, Horikoshi et al., 2018; Mantani et al., 2017; Menezes et al., 2019). All of these studies also reported completion of structured modules and average duration between participants’ completion of structured modules.

4.4.3.9 Average Duration of Sessions

Three studies examining unstructured and structured interventions reported the average duration of use whenever a participant opened the program (Dahne, Collado, et al., 2019; Dahne, Lejuez, et al., 2019; Furukawa, Horikoshi, et al., 2018). Two of these studies examined similar behavioral activation apps, one of which was adapted for delivery in Spanish.

4.4.3.10 Adherence to Usage Instructions

Two studies examining unstructured interventions reported the proportion of participants who adhered to specific recommendations for program usage (Arean et al., 2016; Takahashi et al., 2019). Arean et al. (2016) categorized participants into "none," "suboptimal," and "optimal" usage groups depending on the number of weeks that they used the intervention as instructed. Arean et al. (2016) also reported total number of sessions, whereas Takahashi et al. (2019) also reported average total duration of use per week.

4.4.3.11 Context of Use

Two EMA studies reported the context in which participants responded to EMA prompts (Cormack et al., 2019; Torous et al., 2015). Both studies examined the proportion of prompts to which participants responded across morning, afternoon, and night. Both of these studies also reported overall percentage of response to EMA prompts and the number of days the program was used.

4.4.3.12 Assessment of "Active Use"

Schlosser et al. (2017) was the only study in the current review that specifically quantified the extent of participant activity within their intervention as compared to overall duration of use. The authors calculated an "active use rate" by comparing participants' posts, comments, and interactions with coaches and peers within the intervention to the amount of time that participants used it.

4.4.4 Metrics of Subjective Engagement

The majority of studies reported at least one metric of subjective user engagement (N=16, 53.3%). Studies that reported subjective engagement used self-report measures (N=15, 50.0%) or qualitative interviews with participants (N=5, 16.7%).

4.4.4.1 Self-Report Measures

Fifteen studies used a self-report measure to examine some aspect of participants' subjective experience of an intervention. There was substantial heterogeneity in these measures. Some studies used validated questionnaires like the Credibility Expectancy Questionnaire (Devilly & Borkovec, 2000), User Engagement Scale (O'Brien & Toms, 2010), System Usability Scale (Brooke, 1996), and others. These measures assess a range of constructs including outcome expectancy, focused attention, perception of time during use, and satisfaction. Other studies used questions that were developed by the researchers. Most studies examined subjective engagement at the end of the study, but several assessed it at multiple time points. For example, Caplan et al. (2018) administered three questions about usefulness of their program every two days throughout their study.

4.4.4.2 Qualitative Interviews

Five studies used semi-structured, open-ended qualitative interviews to examine subjective engagement. All studies described highlights of user feedback, although interview content was reported in varying levels of detail. Several studies reported highly detailed interview content, organized content into themes, and included direct quotes from participants.

4.4.5 Assessment of Association between Engagement and Other Variables

Fewer than half of the reviewed studies assessed associations between engagement and other variables (N=13, 43.3%). These studies assessed associations between engagement and the following variables, in order of frequency: clinical improvement (N=9, 30.0%), baseline participant characteristics (N=6, 20.0%), comparison across multiple mobile interventions (N=4, 13.3%), changes in engagement over time (N=2, 6.7%), and association between multiple engagement metrics (N=1, 3.3%).

4.4.5.1 Clinical Improvement

Nine studies examined the association between engagement and participants' clinical outcomes in response to an intervention. Many of these studies used complex statistical models to assess for associations. For example, Economides et al. (2019) used multiple regression models to examine the impact of several objective engagement metrics on symptom reduction. Others categorized participants into responders and non-responders and compared engagement between these groups (Dahne, Lejuez, et al., 2019; Furukawa, Horikoshi et al., 2018). Overall, four studies found a statistically significant positive association between engagement and clinical improvement. Furukawa, Horikoshi et al. (2018) found that "beneficiaries" (i.e. participants with greater clinical improvement) logged more behavioral activation activities within the study app, completed specific behavioral activation activities at different rates, reported higher levels of mastery and pleasure during behavioral activation, and completed a higher number of cognitive restructuring exercises than "nonbeneficiaries." Using data from the same study, Furukawa, Imai et al. (2018) found that completed behavioral activation activities with greater mastery and pleasure ratings were associated with greater clinical improvement. Inkster et al. (2018) split participants into "high use" and "low use" based on the number of times participants accessed the study app and found that "high use" participants had greater clinical improvement. Schlosser et al. (2017) found positive relationships between clinical improvement and active use of the app as well as interaction with a coach.

4.4.5.2 Baseline Participant Characteristics

Six studies examined the association between engagement and participant characteristics at baseline. Studies typically assessed associations with either demographics or baseline psychopathology. Five of the six studies found at least one statistically significant association between an engagement metric and a baseline participant characteristic. Arean et al. (2016) found that participants with higher baseline depression and anxiety accessed their two study apps less frequently, whereas participants with higher baseline disability accessed the apps more frequently. They also found an interaction between app condition and marital status on engagement, such that married participants were less likely to open an app based on problem-solving therapy as compared to an app designed to improve cognitive control. Dahne, Collado, et al. (2019) recruited local participants from primary care clinics and remote participants using advertisements on social media. They found that remote participants demonstrated less engagement across multiple objective metrics as compared to participants who were recruited locally. Hung et al. (2016) found that participants with more restrictive smartphone data plans used the study app on more days than people with more generous or unlimited data plans. Inkster et al. (2018) conducted a thematic analysis of qualitative user feedback for their app and found more favorable feedback from participants who found it "hard to cope with daily tasks" and who reported recent relationship problems. Schlosser et al. (2017) found that female participants accessed their intervention significantly more often than men.

4.4.5.3 Comparison across Multiple Mobile Interventions

Four studies examined multiple mobile interventions and assessed for differences in engagement between intervention conditions. Three of the four studies found a statistically significant difference on at least one engagement metric between two interventions. Arean et al. (2016) tested for condition-by-baseline variable interactions and found that differences in usage between two smartphone apps were significantly associated with participant characteristics. Specifically, married participants were relatively less likely to use a problem-solving therapy app at least once, baseline depression was associated with relatively lower likelihood of using a cognitive control app at least once, and higher alcohol use was associated with relatively lower use of a cognitive control app. Dahne, Collado, et al. (2019) found that participants self-reported more frequent usage of a Spanish-language behavioral activation app as compared to a Spanish-language cognitive restructuring app. Stiles-Shields et al. (2019) found that a behavioral activation app was opened more often but rated as less usable than a cognitive restructuring app.

4.4.5.4 Changes in Engagement over Time

Two studies statistically tested for changes in engagement over time. Economides et al. (2019) found that participants used their hybrid intervention on fewer days and contacted their therapist less frequently as more time elapsed from baseline. Similarly, Cormack et al. (2019) found that participants responded to fewer EMA prompts as more time elapsed from baseline.

4.4.5.5 Association between Engagement Metrics

One study examined the association between engagement metrics. Stiles-Shields et al. (2019) tested for an association between the number and duration of coach calls and metrics of program usage. They found no significant associations.

4.5 Discussion

This systematic review of clinical trials of mHealth interventions for depression found that the majority of studies reported at least one objective (77%) or subjective (53%) measure of engagement, but that the specific metrics used varied widely across studies. These results are consistent with previous reviews of mHealth interventions for a variety of mental health concerns (Linardon & Fuller-Tyszkiewicz, 2020; Ng, et al., 2019). This variability may prove to be a significant barrier to understanding engagement with these programs for people with depression. Relatively few studies tested for associations between engagement and other clinically relevant variables, such as clinical improvement (N=9; 30%), participant characteristics (N=6; 20%) or differences in engagement between interventions (N=4, 17%), changes in engagement over time (N=2, 7%) or associations between engagement metrics (N=1, 3%). The literature on measuring and reporting engagement with mHealth for depression is still in its infancy. What follows is a series of tentative conclusions based on a synthesis of results from the review and suggestions to improve engagement reporting in clinical trials in order to make progress toward multi-dimensional, contextualized models of engagement with mHealth for people with depression. For a list of the specific recommendations discussed below, see Figure 4.3.

4.5.1 All Objective Measures of Engagement are not Created Equal

Objective engagement was most commonly measured by reporting program use by day or week and use of specific program features. Two studies reported program use by day or week as their sole metric of engagement (Caplan et al., 2018; Hantsoo et al., 2018), which is likely to be insensitive to a substantial amount of potential variability in user activity. Conversely, use of specific program features is an excellent metric of engagement because it provides both a sensitive assessment of usage and qualitative information about the most popular features of a program. Many mHealth interventions are complex and multifaceted, so understanding which aspects of a program participants use is crucial information for program development or detailed assessments of clinical efficacy.

An innovative objective measure of engagement quantified “active” and “passive” use by comparing the amount of activity within the intervention to overall duration of use and found that active use was related to clinical improvement, but passive use was not (Schlosser et al., 2017). This is crucial because it demonstrates that longer engagement with a program may be ineffective or inefficient if a large proportion of that use is passive. In the same study, the “social initiative” of users was operationalized by the proportion of peer interactions within the program that were initiated by each user. An objective metric of engagement of social initiative could test questions about achievement of behavior change via social learning and social modeling theories within mHealth programs. For example, users that observe others initiating social contact within mHealth programs and then subsequently initiate social contact themselves support a social-cognitive model of mHealth engagement for programs that use these features. It also reflects greater motivation and social functioning, which are common deficits in depression and important potential mechanisms of improvement.

Examining the time of day that people with depression use mHealth (Cormack et al., 2019; Torous et al., 2015) is another helpful objective engagement metric because sleep disruption is a core symptom of depressive disorders (Nutt et al., 2008). It is possible that as people improve, they will use mHealth more during the day than at night. Such a metric could also be used to test whether people use mHealth during times that traditional mental health providers are typically unavailable (i.e. outside business hours), suggesting that mHealth programs overcome logistical barriers to care for people with unmet mental health needs (Su & Anderson, under review).

4.5.2 Subjective Feedback Contextualizes Objective Measures of Engagement, but it is Less Widely Used

Approximately half of studies (53%) measured subjective engagement, which was less commonly measured than objective engagement. This disparity has been observed previously in digital mental health research, despite findings that subjective engagement with digital interventions can sometimes be more strongly associated with clinical improvement than objective metrics (Graham et al., 2021). A small number of studies (N=5; 17%) included open-ended qualitative feedback from participants. This represents a significant limitation of the literature, as qualitative feedback can explain and contextualize patterns of objective engagement. For example, participants completed fewer mood assessments to "train" an ecological momentary intervention app for depression over the course of a clinical trial (Burns et al., 2011). During semi-structured interviews, participants reported that they would have completed more ratings later in the trial if the mHealth intervention had provided more prompts. This feedback points to an actionable strategy to sustain engagement that could be tested in future research. A decline in participation may reflect well-documented deficits in memory and executive functioning among people with depression (Rock et al., 2014) and may function as a specific barrier to sustained engagement with mHealth for this population.

Subjective data is key for developing culturally responsive interventions for depression. Caplan et al. (2018) assessed the experiences of depressed low-SES adults in the Dominican Republic with a Spanish-language mHealth intervention, which informed cultural adaptations to their mHealth program. For example, the researchers learned that feelings of depression were frequently expressed as anger in their sample of Dominican adults. This information was used to develop animations that depicted the relationship between depression and anger, which were well-received by participants. These examples underscore the importance of measuring subjective engagement more consistently in research on mHealth for depression.

4.5.3 Engagement is not Consistently Associated with Clinical Improvement

A tentative, yet important take-away is that engagement with mHealth interventions is not consistently associated with clinical improvement among people with depression (at least as measured in the studies included in this review). Only four of the nine studies examining the relationship between some form of engagement and clinical improvement found that greater engagement was associated greater reduction in depressive symptoms. Although it is possible that there is no relation between how people with depressive symptoms engage with mHealth interventions and clinical improvement, it seems unlikely. Furthermore, it is not best practice to 'count studies' in systematic reviews in support of a conclusion. It is therefore imperative to develop and test models of engagement to maximize benefit from mHealth interventions for depression.

Furukawa, Horikoshi et al. (2018) measured engagement extensively and found a number of interesting differences between "responders" and "non-responders" to their behavioral activation intervention. For example, they found that responders logged a greater number of behavioral activation activities, reported greater levels of mastery and pleasure, and tended to select activities with longer durations. This information is highly valuable because it allows for inferences about "macro-engagement" (Yardley et al., 2016), i.e. broader behavior change associated with using a mHealth intervention. Macro-engagement is particularly important for behavioral activation, because success in this intervention is contingent on completing activities that provide positive reinforcement (Cuijpers et al., 2007). Many of the studies in this review targeted behavioral activation and reported the number of activities that participants logged during the study, but these studies typically did not examine the relationship between frequency or type of activities and clinical improvement. Future mHealth studies, particularly those examining behavioral activation apps, can be improved by consistently examining the effects of macro-engagement on clinical improvement and measuring macro-engagement directly, as opposed to relying on self-reported data. Additionally, researchers may improve their precision by analyzing engagement as a continuous variable, as opposed to arbitrary groupings of “high” and “low” users.

4.5.4 Engagement is Associated with Demographic Characteristics and other Individual Differences

In contrast to relatively small number of studies that found associations between engagement and clinical improvement, each study examining engagement and baseline participant characteristics (with one exception) found significant associations. Studies that examine these questions are valuable to inform selection and tailoring of mHealth interventions to account for personal characteristics and sociocultural context. For example, Schlosser et al.’s (2017) finding that women accessed their app more often than men could reflect masculine cultural norms in the U.S. that stigmatize help-seeking (Vogel et al., 2011), a barrier that could be addressed to improve initiation and engagement with mHealth among men with depression. Two studies in this review provided useful information about the interaction between participants’ social context and the types of mHealth they may find most engaging. Arean et al. (2016) found that married participants were less likely to open a problem-solving therapy app as compared to a cognitive training app. This could be because married participants receive more social support and assistance with problem-solving than single participants, making a problem-solving intervention less appealing. Inkster et al. (2018) found that participants who endorsed relationship problems provided more positive feedback for a conversation agent-based app, which could reflect that interventions which simulate social interactions are more engaging for individuals with social isolation and impairment, which are common in depression. These findings demonstrate the value of measuring and examining specific symptoms of depression, such as social impairment, and the ways that they are associated with engagement. As another example, Hung et al. (2016) found that participants with limited data cell phone plans used their app more frequently, which they attributed to the fact that their app could be used offline. This feature could be easily incorporated into mHealth apps to improve mental health equity and increase access across socioeconomic lines. Continued attention to these questions will be critical in future research, which should thoroughly evaluate the impact of individual differences on engagement across diverse participants. Researchers should also collect detailed qualitative data whenever possible to aid interpretation of engagement patterns and minimize the need for speculation. This will be particularly important for understanding the needs of marginalized minority groups, who are underrepresented in research and stand to benefit the most from mHealth because of lower access to mental health services.

4.5.5 Engagement can vary Across Types of mHealth Interventions

For example, Stiles-Shields et al.'s (2019) comparison between a behavioral activation and cognitive restructuring app is particularly interesting, because it demonstrates the potential for divergent, distinct profiles of engagement between different interventions. They found that participants launched a behavioral activation app more frequently, but rated a cognitive restructuring app as more usable at mid-treatment. Participants using the cognitive restructuring app also demonstrated clinically significant improvement as compared to a waitlist control, which was not observed for the behavioral activation app despite significantly greater use for this app. This profile of objective engagement, subjective engagement, and clinical improvement between multiple interventions provides many directions for future research, due to a study design that directly compared engagement across interventions. Stiles-Shields et al. also directly examined associations between several of their engagement metrics. This line of research could inform strategies to increase engagement, because a strategy that targets one specific type of engagement may lead to greater clinical benefits if it also affects other types of engagement that are interrelated.

4.5.6 Developing a Model of 'Effective Engagement' for mHealth Interventions among People who are Depressed

"Effective engagement" refers to the functional importance of various types of engagement with digital health interventions among specific populations to achieve specific outcomes (Yardley et al., 2016). To develop models of "effective engagement" for digital health interventions for specific populations, researchers should measure both objective and subjective engagement within these populations and examine relationships between engagement and users' personal characteristics and sociocultural context to deepen understanding of engagement over the course of treatment. This can inform strategies to increase the most effective forms of engagement with specific interventions, while ensuring that these programs are effective and engaging for the population of interest and for minority groups that face well-documented barriers to healthcare and perhaps stand to benefit the most from mHealth. Using the construct of 'effective engagement' could help researchers of mHealth for depression choose objective and subjective measures of engagement for specific populations, examine associations with specific outcomes (e.g., clinical improvement), test theoretical models of engagement, and personalize mHealth for depression. Researchers have begun to develop theoretical models that include engagement as a mechanism of improvement for mental health interventions, which is a promising step toward developing interventions that effectively engage users to maximize symptom reduction (Graham et al., 2019).

4.5.7 Identifying Minimal and Optimal Doses of mHealth Interventions for People who are Depressed

The dose-response relationship is a widespread concept in medical research, including mHealth (Perski et al., 2017). Understanding the association between the "dose," or level of engagement, and reduction of symptoms should be a major goal of mHealth research. Many of the studies in this review have demonstrated that mHealth programs can effectively treat depression using a range of different strategies, including behavioral activation, cognitive techniques, mindfulness, and facilitating social engagement. However, little is known about which specific types of engagement have the strongest relationships with clinical success. The relationship between engagement (i.e. dose) and clinical response may also vary between interventions and populations. Measuring and reporting how engagement interacts with personal characteristics and context across various populations will be important for defining 'effective engagement', allowing for personalized evidence-based recommendations for users and mental health professionals.

4.5.8 Strengths and Limitations

This is the first systematic review of engagement with mHealth for depression, which advances the literature because it focuses on a specific population that, by nature of the disorder, would be expected to have difficulty engaging with these interventions. The review is a step towards understanding ‘effective engagement’ with mHealth interventions, which will help these interventions fulfill their promise of improving access to, utilization of, and benefit from science-based interventions, as well as their potential to improve mental health equity. Strengths of this review include a systematic approach and comprehensive set of search terms. The review also included a range of different types of mHealth programs, including EMA programs, which capture a broad picture of the mHealth literature.

This review also has several limitations. Although both authors participated in full-text review and selection of included articles, the first author independently conducted title and abstract review as well as data extraction. Because there was substantial heterogeneity in engagement reporting across included studies, the categories used for data extraction did not capture some important distinctions, e.g. the specific constructs assessed by self-report measures of subjective engagement. Internet-delivered programs were excluded from the review, but may be accessed via mobile devices and thus have similar patterns of engagement. Further research should address the potential similarities between engagement for Internet-based treatments and mHealth-only interventions. Most studies in this review reported data from samples that were disproportionately female, and a number of studies did not report the race or ethnicity of their samples. This raises questions about the generalizability of these studies to men who experience depression and racial and ethnic minorities. Additionally, the authors did not conduct a meta-analysis of the associations between engagement metrics and other variables due to an insufficient number of studies that examined these associations and high heterogeneity of reported engagement metrics. Accordingly, firm conclusions should not be drawn about statistically significant associations in individual studies.

Importantly, all of the studies that examined relationships between engagement and other factors in the current review did so observationally, which does not allow for inferences about causal relationships. Finding ways to experimentally manipulate engagement with mHealth for individuals with depression will be a valuable next step for clinical trials. Researchers and clinicians could draw from theories of learning and persuasion to experimentally test strategies that improve engagement with programs (Molloy et al., 2021), then examine whether these types of engagement significantly mediate clinical outcomes. For example, interventions could be designed to encourage adherence to recommendations using prompts, "gameification," and other persuasive design features (Kelders, et al., 2012). This is critical not only for testing strategies that promote engagement, but also to address probable confounding variables in correlations between engagement and clinical outcomes, such as motivation and executive functioning.

4.5.9 Conclusion

The potential for mHealth interventions to reduce depression is limited by the fact that people who could benefit from them often do not engage with them. Research on engagement with mHealth interventions for depression is beginning; the majority of studies included in this review were published within the last two to three years. The review shows there is high heterogeneity among studies in reporting engagement, which represents an opportunity for researchers to carefully consider and use the types of engagement metrics that will lead to a better understanding of effective engagement with mHealth interventions for people who are depressed. The authors recommend that future researchers measure and report a combination of objective and subjective engagement metrics and test for associations between these metrics and variables that are functionally important, such as clinical improvement and participant characteristics, which will assist in testing models of effective engagement in developing mHealth interventions for depression for diverse populations.

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4.7 Author Contributions

AM and PLA devised the project and the main conceptual ideas. AM conducted searches, title and abstract review, and data extraction. AM designed the tables. AM and PLA contributed to final article selection and writing the manuscript. PLA supervised the project.

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Table 4.1 Proportion of studies using various types of depression assessment, mobile device, structured interventions, and coach support

Characteristic	*N*	%
Depression Assessment		
Cutoff on self-report measure only	16	53.3
Depressive disorder diagnosis only	5	16.7
Depressive disorder diagnosis and cutoff on self-report measure	9	30.0
Mobile Device		
iPhone	8	26.7
Android	3	10.0
Smartphone: Multiple OS	7	23.3
Smartphone: Unspecified OS	8	26.7
Other device or multiple devices	4	13.3
Structure of Intervention		
Structured	5	16.7
Unstructured	15	50.0
Hybrid	5	16.7
Ecological Momentary Assessment (EMA)	5	16.7
Coaching Support		
Coached	19	63.3%
Self-guided	11	36.7%

Table 4.2 Characteristics of Individual Studies

First Author, Year	mHealth Programs	Key Components and Treatment Target	Sample Size	Sample Demographics	Objective Engagement	Subjective Engagement	Assessed Association between Engagement and Other Variables
Arean (2016)	Project: EVO iPST	Uses video games designed to increase cognitive control Uses principles of problem-solving therapy to assist with goal-setting and action plans	626	Mean age = 33.95 (SD 11.84); 79.0% Female; 13.7% African-American, 1.0% American Indian, 8.6% Asian, 65.5% White, 10.5% > 1 race, 0.6% Native Hawaiian/Pacific Islander, 12.6% Hispanic	Adherence to instructions; Total number of sessions	None	Compared interventions; Participant characteristics
Burns (2011)	Mobilyze!	Uses behavioral activation strategies, EMA, ecological momentary intervention cued by passive mobile phone sensors, behavioral skills training, didactic content	8	Mean age = 37.4 (SD 12.2); 87.5% female; 13% Hispanic Caucasian, 88% Non-Hispanic Caucasian	Total number of sessions	Self-report measure; Qualitative Interview	None
Caplan (2018)	El Buen Consejo Movil	Provides self-help audio messages based on cognitive-behavioral therapy, encourages social engagement using group forum with messaging and user mood ratings	36	Sample 1: Mean age = 36; 83% Female; 78% from Dominican Republic, 16% from Venezuela, 6% from United States; Sample 2: Mean age = 42; 86% Female; 100% from Dominican Republic	Use by day or week	Self-report measure; Qualitative Interview	None
Cormack (2019)	Cognition Kit	Uses EMA for regular assessment of mood and cognitive function	30	Mean age = 37.2 (SD 10.4); 63.3% Female; Race/Ethnicity not reported	Use by day or week; EMA Prompts; Context of use	Qualitative Interview	Engagement over time; Participant characteristics

Dahne (2018)	Behavioral Apptivation	Uses behavioral activation strategies in conjunction with face-to-face therapy	11	Mean age = 24.91 (SD 11.73); 90.9% Female; 45.50% White, 18.20% Black, 27.30% Asian, 9.10% Other	None	Self-report measure	None
Dahne, Collado (2019)	¡Aptívate!;	Uses behavioral activation strategies, mood monitoring, and provides social support	42	Mean age = 36.05 (SD 11.44); 66.7% Female; 23.8% White, 2.4% Black, 2.4% Native Hawaiian/Pacific Islander, 7.1% Native American, 11.9% Multiracial, 52.4% Other, 100% Hispanic ethnicity	Total number of sessions; Average session duration; Total duration of use; Use of specific features; Use by day or week	None	Compared interventions; Participant characteristics
	iCouch CBT	Uses cognitive restructuring techniques to cope with stressful situations					
Dahne, Lejuez (2019)	Moodivate	Uses behavioral activation strategies, mood monitoring, and provides social support	52	Mean age = 43.79 (SD 13.27); 84.6% Female; 40.4% White, 55.8% Black, 3.8% Other, 3.8% Hispanic ethnicity	Total number of sessions; Average session duration; Total duration of use; Use of specific features; Use by day or week	None	Clinical Improvement
	Moodkit	Uses cognitive restructuring techniques to cope with stressful situations					
Economides (2019)	Ascend	Sequential modules teach skills drawn from mindfulness-based stress reduction, mindfulness-based cognitive therapy, and cognitive-behavioral therapy	197	Mean age = 32.9 (SD 10.3); 77.5% Female; 78.4% from Finland, 21.6% from United States	Use by day or week; Total duration of use; Interaction with coach	None	Clinical Improvement; Engagement over time
Fuller-Tyszkiewicz (2018)	BlueWatch	Sequential modules teach skills drawn from cognitive-behavioral therapy including behavioral activation, cognitive restructuring, and problem-solving	5	Mean age = 22.4 (SD 2.71); 80% Female; Race/Ethnicity not reported	None	Self-report measure; Qualitative Interview	None

Furukawa, Horikoshi (2018)	Kokoro app	Sequential modules teach skills drawn from cognitive-behavioral therapy including thought recording, behavioral activation, and cognitive restructuring	164	Mean age = 40.2 (SD 8.8); 57% Female; Race/Ethnicity not reported	Complete structured modules; Duration between sessions; Use of specific features; Average session duration	None	Clinical Improvement
Furukawa, Imai (2018)	Kokoro app	Sequential modules teach skills drawn from cognitive-behavioral therapy including thought recording, behavioral activation, and cognitive restructuring	78	Mean age = 40.4 (SD 8.8); 56.4% Female; Race/Ethnicity not reported	Use of specific features	None	Clinical Improvement
Hantsoo (2018)	Mood Tracking and Alert app (MTA)	Uses EMA for regular assessment of activity and mood, prompts mental healthcare provider to contact participant if symptoms worsen	72	Sample 1: Mean age = 26.3 (SD 4.9); 100% Female; 96% African-American, 11% Hispanic ethnicity; Sample 2: Mean age = 26.5 (SD 6.2); 100% Female; 95% African-American, 10% Hispanic ethnicity	Use by day or week	Self-report measure	None
Hung (2016)	iHOPE	Uses EMA for regular assessment of depression, anxiety, sleep quality, and cognitive functioning	54	Mean age = 37.9 (SD 13.9); 63% Female; Race/Ethnicity not reported	Use by day or week; EMA Prompts	None	Participant characteristics
Hur (2018)	Todac Todac	Uses brief vignettes and quizzes to teaches cognitive behavioral strategies, promotes social engagement with other users with a "timeline" feature	34	Mean age = 23.71 (SD 3.26); 88.2% Female; Race/Ethnicity not reported	None	None	None
Inkster (2018)	Wysa	Uses an AI-driven chatbot to teach strategies based on positive psychology	129	No demographics reported	Use by day or week; Use of specific features	Self-report measure	Participant characteristics; Clinical Improvement

Li (2019)	Run4Love	Sequential modules teach techniques from cognitive behavioral stress management, target behavioral activation by promoting exercise	300	Mean age = 27.5; 7.7% Female; Race/Ethnicity not reported	None	None	None
Ly (2014)	"BA treatment"	Uses selection and tracking of pleasurable activities to promote behavioral activation	81	Mean age = 36.1 (SD 10.8); 70% Female; Race/Ethnicity not reported	Use by day or week; Interaction with coach	Self-report measure	Compared interventions; Clinical Improvement
	"Mindfulness treatment"	Uses audio tracks to teach mindfulness skills					
Ly (2015)	"Blended BA treatment"	Uses selection and tracking of pleasurable activities to promote behavioral activation, blended with in-person behavioral activation-based therapy	93	Mean age = 30.6 (SD 11.4); 69.9% Female; Race/Ethnicity not reported	None	Self-report measure	None
Mantani (2017)	Kokoro app	Sequential modules teach skills drawn from cognitive-behavioral therapy including thought recording, behavioral activation, and cognitive restructuring	164	Sample 1: Mean age = 40.2 (SD 8.8); 57% Female; Race/Ethnicity not reported; Sample 2: Mean age = 41.6 (SD 8.9); 50% Female; Race/Ethnicity not reported	Complete structured modules; Duration between sessions; Use of specific features	None	None
Menezes (2019)	CONEMO	Uses sequential sessions to increase pleasurable and healthy activities to promote behavioral activation	66	Age: 6% 21-40, 53% 41-60, 41% $\geq$ 61; 71% Female; Race/Ethnicity not reported	Complete structured modules; Duration between sessions	Self-report measure	None
Moukaddam (2019)	SOLVD	Uses EMA for regular assessment of mood and anxiety, passively collects smartphone data	25	Mean age = 50.28 (SD 10.07); 76% Female; 40.9% White, 36.4% African American, 18.2% Hispanic, 4.5% Asian	EMA Prompts	None	None

Pratap (2018)	Project: EVO	Uses video games designed to increase cognitive control	1040	Mean age = 34.9 (SD 10.92); 77.19% Female; 53.3% Non-Hispanic White, 30.7% Hispanic/Latino, 7.2% African-American/Black, 0.9% American Indian/Alaskan Native, 7.0% Asian, 0.9% Other	None	None	None
	iPST	Uses principles of problem-solving therapy to assist with goal-setting and action plans					
Sawyer (2019)	eMums Plus	Uses sequential modules to teach strategies drawn from cognitive behavioral therapy, provides education on child development and parenting, uses social media feature to promote social engagement with nurses and other mothers of young children	133	Mean age = 31.1 (SD 5.0); 100% Female; Race/Ethnicity not reported	Use by day or week; Use of specific features	Self-report measure	None
Schlosser (2017)	PRIME-D	Uses social platform to track and share goals related to health, relationships, creativity, and productivity, promotes social engagement with other users	36	Mean age = 31.33 (SD 12.4); 77.8% Female; 61.1% Caucasian, 19.5% African American, 8.3% Asian American, 11.1% Other, 83.3% Non-Hispanic ethnicity, 16.7% Hispanic ethnicity	Use by day or week; Use of specific features; Interaction with coach; Assessed active use	Self-report measure; Qualitative Interview	Participant characteristics; Clinical Improvement
Schuster (2019)	MindDistrict	Uses activity scheduling to promote behavioral activation, blended with in-person ACT-based therapy	27	Mean age = 37.70 (SD 13.66); 51.9% Female; Race/Ethnicity not reported	Use of specific features	Self-report measure	None
Stiles-Shields (2019)	Boost Me	Uses activity scheduling mood monitoring to promote behavioral activation	30	No demographics reported	Total number of sessions; Use of specific features; Interaction with coach	Self-report measure	Compared interventions; Clinical Improvement; Other engagement metrics
	Thought Challenger	Uses cognitive restructuring techniques					

Takahaski (2019)	SPSRS	Uses videos and positive words to promote behavioral activation	22	Mean age = 20 (SD 0.62); 27.3% Female; Race/Ethnicity not reported	Total duration of use; Adherence to instructions	Self-report measure	None
Torous (2015)	Mindful Moods	Uses EMA for regular assessment of mood	13	Female mean age = 35 (SD 13); Male mean age = 48 (SD 16); 77% Female; Race/Ethnicity not reported	Use by day or week; Context of use; EMA Prompts	None	None
Watts (2013)	Get Happy	Uses sequential modules containing stories and homework assignments to teach cognitive behavioral strategies, interpersonal skills, and sleep hygiene	35	Mean age = 41 (SD 12.38); 80% Female; Race/Ethnicity not reported	Complete structured modules; Interaction with coach	Self-report measure	Clinical Improvement
Zhu (2019)	Run4Love	Sequential modules teach techniques from cognitive behavioral stress management, target behavioral activation by promoting exercise	300	Median age = 27.5; 7.7% Female; Race/Ethnicity not reported	None	None	None

Note. EMA = Ecological Momentary Assessment

Table 4.3 Engagement Reporting

Characteristic	*N*	%
Objective Engagement		
None	7	23.3
Program use by day or week	12	40.0
Use of specific program features	10	33.3
Total number of sessions	5	16.7
Interaction with coach or therapist	5	16.7
Completion of structured modules	4	13.3
Total duration of use	4	13.3
Response to EMA prompts	4	13.3
Average duration between sessions	3	10.0
Average duration of sessions	3	10.0
Adherence to usage instructions	2	6.7
Context of use	2	6.7
Assessment of “active use”	1	3.3
Subjective Engagement		
None	14	46.7
Self-report measure	15	50.0
Qualitative interview	5	16.7
Assessed Association between Engagement and other Variables		
None	17	56.7
Clinical improvement	9	30.0
Baseline participant characteristics	6	20.0
Compared between multiple interventions	4	13.3
Engagement over time	2	6.7
Multiple engagement metrics	1	3.3

Note. Categories are not mutually exclusive except for “None.”

Objective Engagement Metrics:

- Total duration of use (e.g. used app for XX minutes total or XX minutes per week)
- Program use by day or week (e.g. used app at least once on XX days or XX weeks)
- Total number of sessions (i.e. “log-ins”)
- Average duration between sessions
- Average duration of sessions
- Use of specific program features (e.g. used a specific tool XX times or for XX minutes)
- Context of use (e.g. times app was accessed at a specific location, time of day, etc.)
- Interaction with coach or therapist (e.g. number of calls, number of messages)
- Assessment of “active use” (number of features used compared to overall duration of app use)
- Completion of structured modules
- Adherence to usage instructions (e.g. XX% of participants used app as instructed)
- Response to EMA prompts

Subjective Engagement Metrics:

- Self-report measure
- Qualitative interview

Assessed relationship between engagement metrics and other variables:

- Comparison between multiple interventions
- Comparison across baseline participant characteristics (e.g. demographics, baseline psychopathology)
- Relationship with clinical improvement in response to intervention
- Relationship between multiple engagement metrics
- Statistical testing of changes in engagement over time

Figure 4.1 Metrics of Engagement Examined in the Current Study

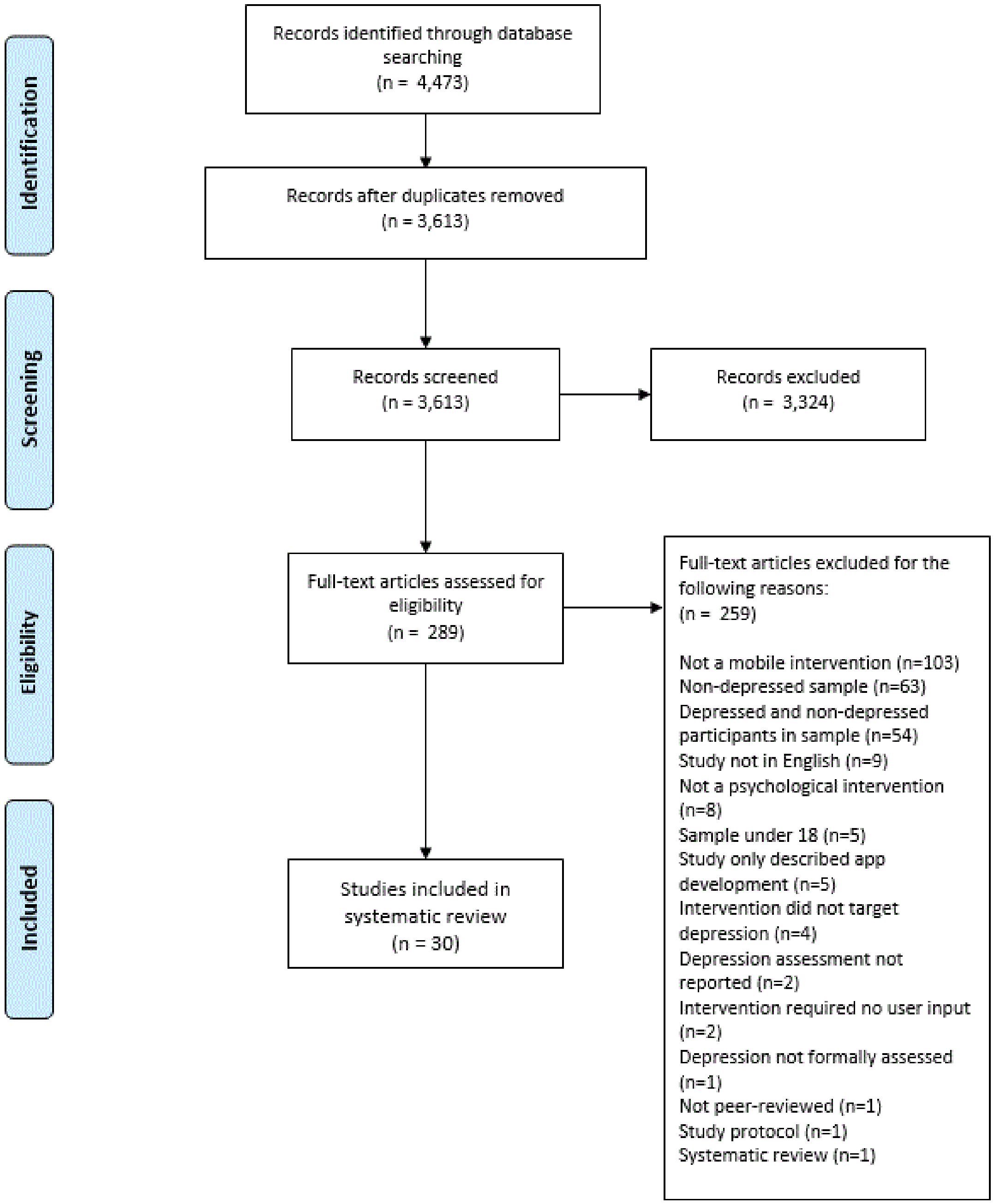

Figure 4.2 Preferred Reporting Items for Systematic Reviews and Meta-Analyses Flow Diagram

- Report varied metrics of objective and subjective engagement
- Collect open-ended feedback to contextualize and better understand patterns of engagement
- Engagement metrics should capture as much detailed information as possible
- Examine associations between engagement and clinical improvement
- Examine associations between engagement and participant characteristics, including specific depression symptoms, demographics, and cultural factors
- Evaluate macro-engagement, i.e. broader behavior change associated with mHealth
- Compare engagement across different types of mHealth interventions
- Develop models of "effective engagement" for specific populations and interventions
- Examine dose-response relationships for engagement with mHealth
- Experimentally manipulate engagement to examine causal relationships

Figure 4.3 Recommendations for Future Research on Engagement with mHealth Interventions

5 CONCLUSION

To successfully implement digital mental health interventions, researchers and clinicians need strategies to increase acceptability, encourage uptake, and carefully measure engagement. Taken together, the three studies presented in this dissertation offer opportunities to refine these key aspects of implementation efforts. Studies 1 and 2 replicated previous research (Casey et al., 2013; Mitchell & Gordon, 2007) and demonstrated that it is possible to increase acceptability for iCBT using a text-based treatment rationale. Study 2 found that a treatment rationale for iCBT was effective during the COVID-19 pandemic, but not more so as compared to before the pandemic. This research demonstrates that treatment rationales, which are relatively simple to implement in healthcare settings, can be an effective acceptance-facilitating intervention for digital mental health programs. Study 1 did not find that a treatment rationale influenced uptake-related behavior for iCBT. Although small financial incentives have been demonstrated to increase adherence to psychotherapy (Burton et al., 2010; Post et al., 2006) and online programs targeting health behavior (Crutzen et al., 2011), the financial incentive used in Study 1 also did not affect iCBT uptake behavior in this population. Further research is needed to explore interventions that may increase uptake for digital mental health interventions in individuals with mild symptoms who are not currently seeking treatment. Study 3 reviewed the clinical literature on mHealth interventions for depression and examined the extent to which these studies report user engagement. Many studies report engagement in useful and innovative ways, but the review found significant limitations and high heterogeneity between studies. This demonstrates an opportunity to more thoroughly examine engagement, better understand the ways that people with depression use mHealth interventions, and use this information to improve implementation. The sections below will explore several areas of ongoing development in the field of digital mental health, what the three studies presented in this dissertation contribute to these areas, and directions for future research.

5.1 Defining and Measuring Constructs

The literature on acceptability and engagement with digital mental health interventions defines these constructs in a wide variety of ways. For the purposes of Study 1, we used a broad definition of acceptability taken from Schröder et al., (2015, p. 137): "cognitively based, positive attitudes towards such interventions." This definition encompassed all of the ways that acceptability was operationalized in Study 1 – a broad measure of attitudes toward iCBT, a measure of outcome expectancy, and a measure of willingness to use iCBT. Each of these were drawn from the clinical research on iCBT and analyzed together using multivariate analyses to create a robust measure of acceptability that represents of prior research. However, there are meaningful distinctions between these measures. For this reason, they were also examined individually using univariate analyses.

Findings in Studies 1 and 2 underscore the importance of specificity in measuring acceptability and attitudes toward digital mental health interventions. In Study 1, the treatment rationale caused improvements in general attitudes and outcome expectancy for iCBT, but not willingness to use iCBT. In Study 2, the treatment rationale improved general attitudes toward iCBT, but not outcome expectancy. In each study, the treatment rationale seems to have affected specific perceptions or attitudes about iCBT, but not others. Examining the impact of acceptance-facilitating interventions on a range of precisely measured constructs will likely benefit the field, as previous studies have used overlapping and often broad definitions of acceptability for digital interventions. Many theoretical models are available for guidance – for example, the Technology Acceptance Model (Davis, 1989) includes perceived usefulness and perceived ease of use as predictors of technology uptake. The Internet Interventions model (Ritterband et al., 2009) includes expectations for treatment, motivation, readiness for change, self-efficacy, and perceived benefits of treatment as predictors of website use and symptom improvement. The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) includes expected effort required to use technology and social influences on technology use. Examining attitudes toward digital mental health interventions using a range of precisely measured and narrowly focused constructs may provide critical information for increasing uptake among individuals who could benefit from them.

The construct of engagement is also conceptualized and measured in a wide variety of ways. In a review of clinical trials of mHealth programs, Pham et al. (2019) found that many different terms are used interchangeably with engagement, including “acceptability,” “feasibility,” and “adherence,” among others. Similarly, Study 3 found that researchers examining mHealth interventions for depression do not consistently report engagement. It also found that engagement is measured and reported using a wide variety of methods. Thoughtful reviews and theoretical papers have synthesized the literature on engagement with digital health interventions to develop integrative models of engagement (Graham et al., 2019; Perski et al., 2017). These models are built on detailed definitions of engagement, which include constructs such as usefulness, usability, attention, and affect. They also include specific ways to operationalize objective and subjective engagement with digital mental health interventions. Drawing from these theories to thoroughly measure engagement using multiple methods has the potential to enhance clinical research and inform further development of engagement models.

5.2 What Influences Acceptability, Uptake, and Engagement?

Digital mental health researchers should carefully examine the ways that personal characteristics, experiences, and context influence use of these programs. For example, access to face-to-face treatment may significantly determine individuals' interest in digital interventions. In Study 1, community participants reported greater willingness to use iCBT programs as compared to university student participants. This could be due to the fact that university students have access to free counseling services, whereas community participants may face greater obstacles to face-to-face therapy such as time, cost, and availability of services. Study 2 was designed to examine the influence of the COVID-19 pandemic on attitudes and outcome expectancy for iCBT. Contrary to hypotheses, participants did not report more positive attitudes or higher outcome expectancy for iCBT during the pandemic. Additionally, the treatment rationale was not more effective during the pandemic, as compared to before the pandemic. There have been dramatic reductions in access to face-to-face mental health treatment due to COVID-19 and a corresponding expansion in telehealth (Perrin et al., 2020). However, this may not have substantially affected our sample, as they did not report increased psychopathology during the pandemic. People who used telehealth services for the first time during COVID-19 may be more open to digital mental health programs like iCBT. Future research should investigate the influence of past experiences with telehealth on acceptability and uptake for digital mental health interventions, particularly in the context of the COVID-19 pandemic.

With respect to engagement, many of the clinical trials of mHealth programs for depression reviewed in Study 3 examined relationships between engagement and other clinically relevant variables. For example, these studies found significant relationships between different forms of engagement and gender (Schlosser et al., 2017), marital status (Arean et al., 2016), and social impairment (Inkster et al., 2018). However, fewer than half of the studies in the review (N = 13, 43%) examined relationships between engagement and other variables. Understanding who engages with mHealth programs the most will help to identify groups that are best served by these programs. It will also help to identify groups for whom mHealth is not helpful or needs significant modification. This is an important line of research for better understanding individual factors that influence engagement.

5.3 Facilitating Acceptability, Uptake, and Engagement

In Studies 1 and 2, we experimentally tested the effect of a treatment rationale designed to improve acceptability for iCBT, operationalized using measures of general attitudes, outcome expectancy, and willingness to use iCBT. This rationale included techniques drawn primarily from the scientific literature on improving outcome expectancy for face to face psychotherapy. These techniques included an authoritative speaker, describing the treatment in detail, and emphasizing empirical support (Ametrano et al., 2017). The rationale was also designed to improve acceptability by directly addressing positive and negative perceptions of iCBT that have been found in previous research (Travers & Benton, 2014). Our acceptance-facilitating intervention did not include a variety of other techniques that have been used to improve attitudes toward mental health treatment and digital mental health interventions, such as personalized symptom feedback, education about psychopathology, or addressing attitudes toward help-seeking (Ebert et al., 2019). These strategies may have increased the effect of the treatment rationale, and future research should continue to examine which acceptance-facilitating interventions are most effective with specific populations.

One strength of Study 1 is that it directly measured uptake-related behavior for iCBT, which is an improvement on studies that test acceptance-facilitating interventions using only self-report measures. This study was limited, however, in that we used information-seeking about iCBT to gain insight into likelihood of iCBT uptake. Recording the effects of acceptance-facilitating interventions on uptake, engagement, and completion of digital mental health interventions is a valuable direction for future research. As pointed out in Study 3, few studies attempt to experimentally manipulate engagement with digital mental health interventions. Using strategies such as treatment rationales to improve engagement could potentially lead to significant clinical benefits for those who use digital mental health interventions.

Although none of the clinical trials reviewed in Study 3 experimentally tested strategies to increase engagement, many reported information that may help to promote engagement with mHealth. For example, Fuller-Tyszkiewicz et al. (2018) conducted a small usability study for individuals with depression, mental health professionals, and researchers with expertise on e-Health. The study reported in-depth subjective data from each of these groups to inform development of the mHealth app. This study revealed that clinicians and researchers rated the app as less usable than individuals with depression, who reported that it was easy to use. This underscores the importance of including end users in the process of app development. Participants gave suggestions to improve the app and make it more engaging, such as adding a glossary of terms and more graphics. Incorporating user feedback and measurement of app engagement, as well as consulting healthcare providers who may be involved in the delivery of a mHealth intervention, are excellent ways to enhance engagement. This is consistent with the goals of the Accelerated Creation to Sustainment model of digital mental health implementation (Mohr et al., 2017), which outlines a user-centered process of creating digital mental health interventions using feedback from the target population and healthcare professionals who will administer programs.

5.4 Translating from research to practice

Studies 1 and 2 examined the effects of acceptance-facilitating interventions for digital mental health in a sample of non-clinical, non-treatment-seeking adults. The majority of participants in Study 1 (60.2%) reported at least mild levels of depression, anxiety, or stress, suggesting that they could potentially benefit from using an iCBT program. However, it is likely that many participants chose not to seek information about iCBT because did not perceive a current need for treatment. Lack of perceived need for treatment has been documented as the number one global barrier to engaging in mental health treatment (Andrade et al., 2014). This represents an opportunity to increase engagement with iCBT by specifically educating individuals with mild symptoms that they stand to benefit from these programs. Reaching and educating non-treatment-seeking individuals about the benefits of digital mental health programs should be a major goal for the field. Studies 1 and 2 demonstrate that acceptance-facilitating interventions such as a treatment rationale can modify this population's attitudes, but that more may be required to influence actual uptake.

There are many large organizations that could benefit from addressing mental health needs of employees, students, and others with digital interventions. For example, colleges and universities serve large numbers of young adults who suffer from increasing rates of mental health problems (Xiao et al., 2017). In an international survey of 572 college and university counseling centers, 87.9% of directors reported an increasing demand for services and 37.5% reported using stepped care models that involve less intensive forms of treatment for individuals with milder symptoms (LeViness et al., 2019). This represents a significant opportunity to utilize digital mental health interventions, which have demonstrated effectiveness for college students in a large number of studies (Lattie et al., 2019). Educational institutions also have the ability and resources to use acceptance-facilitating interventions such as treatment rationales and financial incentives (e.g. credits for bookstores, fee reductions), which could increase utilization of digital mental health programs once they are made available. This may be particularly important for college students, given Study 1's finding that college students were less willing to use iCBT than members of the surrounding community.

Digital mental health interventions stand to play a critical role in healthcare systems because they can treat people with mild to moderate symptoms with substantially reduced time commitment from providers. This is important because the U.S. does not currently have adequate mental health services in place to meet the population's needs (Weil, 2015). Whereas Studies 1 and 2 focused on a non-treatment-seeking population, Study 3 reviewed clinical trials of people who were engaging in treatment for depression. The participants in these studies have more in common with treatment-seeking individuals seen in major healthcare systems. For individuals with clinically significant symptoms who have elected to use a digital mental health intervention, engagement with these interventions should be a major focus of research. This is consistent with Mohr et al.'s (2017) Accelerated Creation to Sustainment model, which recommends collecting data about program usage to inform optimization and measure sustainment once an intervention is in place. As Study 3 demonstrates, many clinical trials do not measure engagement thoroughly and this is a major limitation of the existing clinical research on digital mental health programs. Greater attention to this topic stands to inform efforts to utilize digital interventions within healthcare systems, expand access to care, and reduce provider burden.

5.5 Promoting mental health equity

As discussed in all three of the studies in this dissertation, digital mental health interventions stand to improve mental health equity by improving access to treatment for marginalized groups with lower healthcare access. In Study 1, White and multiracial participants were more likely to seek out information about iCBT programs as compared to Black/African-American, Hispanic/Latinx, and Asian participants. This reflects patterns of mental health service utilization observed in the broader U.S. population (SAMHSA, 2020) and evidence that racial minority individuals have lower rates of iCBT uptake and completion (Jonassaint et al., 2017). Unfortunately, Study 3 demonstrated that many studies of digital mental health interventions do not use diverse samples or report sample demographics. This limits generalizability of these studies to populations who may benefit the most from increased access to treatment. Diverse samples and thoroughly reported demographics are strengths of Studies 1 and 2, which both found that acceptability for iCBT can be increased in a diverse sample using a text-based treatment rationale. However, these studies also have limitations for certain groups. For example, people who identify as transgender or other minority gender identities face significant barriers to mental healthcare (Puckett et al., 2018), but could not be included Study 1's analysis of uptake behavior due to insufficient numbers in our sample. Research that specifically focuses on this population and others may help to increase their adoption and ability to benefit from digital mental health programs.

Researchers should also examine whether specific attitudes toward digital mental health interventions are culturally influenced, like other health-related behavior that has been examined in past research. For example, Lee et al. (2006) examined independent vs. interdependent self-construal and intentions to quit smoking in a sample of Asian/Pacific islander college students. Using the Theory of Planned Behavior (Ajzen, 1991), they found independent self-construal predicts perceived behavioral control over smoking cessation, whereas interdependent self-construal predicts the importance of subjective norms about smoking cessation. Perceptions and use of digital mental health interventions are likely related to cultural factors, which should be addressed during intervention development. Burns et al. (2013) created a useful framework to develop culturally tailored digital mental health interventions for understudied minority populations. They applied this framework to young sexual minority men and described ways in which a mHealth program can be well-suited to meet this population's needs, such as addressing loss of family support and emphasizing empowerment. This type of research is still needed for many specific marginalized groups that stand to benefit from digital mental health interventions.

Several of the clinical trials reviewed in Study 3 stood out for their attention to addressing cultural factors and diversity. For example, Hantsoo et al. (2018) provided an EMA intervention to low-income pregnant African-American women with depressive symptoms. Their "Mood Tracking and Alert" app administered regular assessments of mood and was programmed to alert healthcare providers to check in with participants if mood symptoms worsened. This addressed a specific need of these participants, as African-American women receive disproportionately low rates of treatment for post-partum depression (Kozhimannil et al., 2011). Although many mHealth studies included in this review addressed specific needs of various cultural groups, few of these studies directly examined the relationships between engagement and participant characteristics. This is an important area of growth for the field, as it would help build insight into increasing engagement among marginalized minority groups.

5.6 Conclusion

Digital mental health interventions are a convenient, effective, and evidence-based form of mental healthcare. People who use digital mental health interventions are generally satisfied and experience symptom reduction with far less time investment from providers than traditional face-to-face therapy. If they are used in a way that maximizes their potential, these programs stand to substantially expand access to effective mental health treatment. Popular attitudes about these programs are an important determinant of who uses them, and the research presented in this dissertation demonstrates that attitudes can be improved with relatively simple strategies. Once individuals elect to use digital programs, it is important to track engagement and carefully measure a range of specific attitudes that may affect clinical improvement. As a field, psychologists and other mental healthcare providers are making greater use of these tools, particularly in the context of the continuing COVID-19 pandemic (Perrin et al., 2020; Titov et al., 2020). In many ways, this topic of research is still in its early stages. The author hopes that the studies presented in this dissertation represent progress in implementation efforts and are useful to future researchers in this important area.

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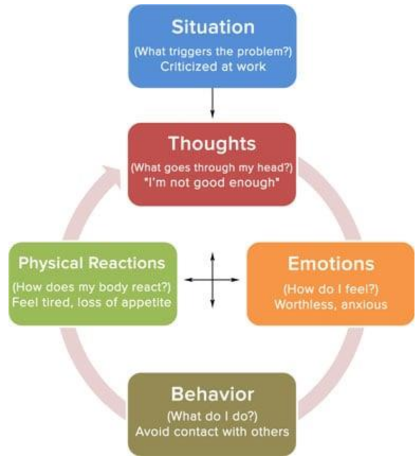
APPENDICES

Appendix A First Article

Appendix A.1 iCBT Treatment Rationale

Hi, I'm Dr. Anderson!
I'm a professor in the psychology department at Georgia State University.
As a licensed therapist, I've also spent a long time helping people work through common mental health problems like stress, anxiety, and depression.

One of my areas of research is online psychotherapy programs, or **iCBT**. The "CBT" stands for cognitive behavioral therapy, which research shows helps people reduce stress, anxiety, and depression. Here's how it works: You work with your therapist to set goals for therapy. CBT works by helping you understand and change thoughts, emotions, and behaviors that are keeping you from reaching your goals for therapy. There is a plan each week for what to work on. CBT works best when you practice the things you learn between therapy sessions, and you and your therapist will decide at the end of each session what you should practice before your next session. CBT is time-limited (typically once a week for about 8 weeks). Traditionally, CBT is done face-to-face, but it can also be done via the internet (iCBT)



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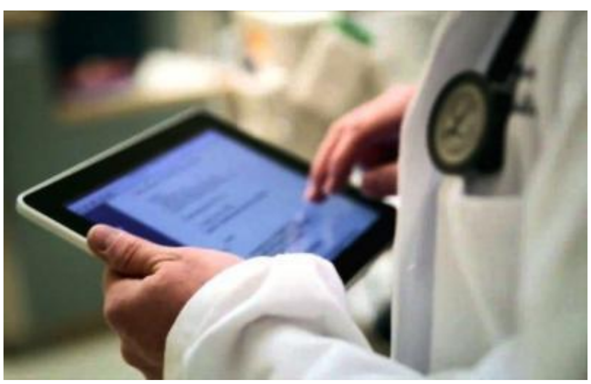
iCBT programs are widely used. Millions of people in the U.S. have used online programs and smartphone apps to improve their mental health. These programs are becoming an increasingly integrated part of major healthcare systems.



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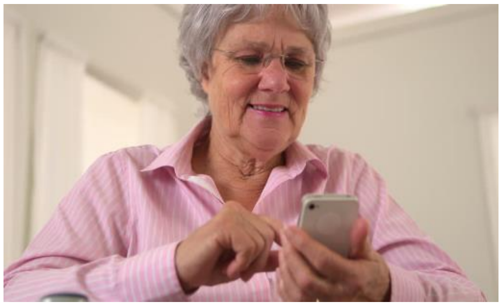
It can be intimidating for anyone to find mental health treatment, and especially hard to find the time to meet with someone face to face. That's one of the major reasons more and more people are deciding to try iCBT programs—you can do them on your own time on your computer or smartphone, so they work on any schedule. In addition to that, the format of CBT is typically easy to deliver online.



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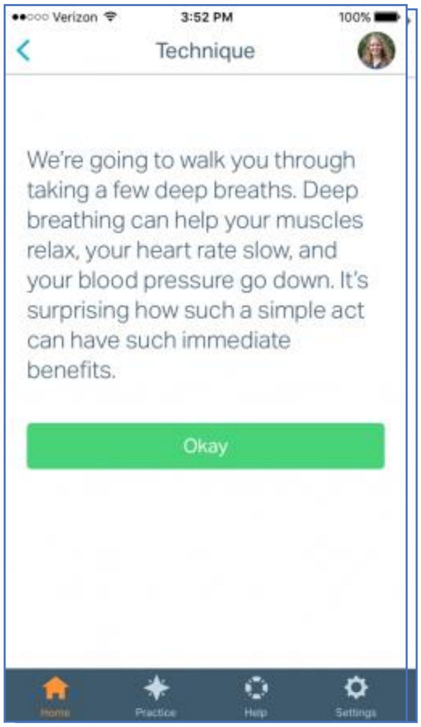

So how does iCBT work?

- Treatment typically involves completing a structured set of lessons online or on a smartphone. These are often done week by week.
- Programs are tailored to specific issues like stress, depression, or anxiety. Some have stories about people overcoming these problems as you gain the tools to do it.
- Lessons usually end with a set of goals to complete before starting the next session. These goals help you put the tools you learn about into action, and might involve something like exercising,

introducing yourself to someone new, or keeping a journal of thoughts that cause you distress.

- **Self-guided iCBT** programs are completed on your own at your own pace.
- **Therapist-assisted iCBT** programs involve completing lessons online and working with a therapist via instant messaging, email, phone, or video chat.

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Frequently Asked Questions

How much time does it take? Can I fit it in my schedule?

Lessons typically take 30 minutes to an hour to complete, and can be completed whenever you have the time. This is one of the major advantages of iCBT. Programs that offer real time interaction with a therapist may involve some scheduling.

How much does it cost?

While cost depends on the program, many of them are free. Some college counseling centers also offer free access to programs.

Is there a waiting period?

You can start most programs right away. Again though, this will depend on the program.

Does it really work?

Over a hundred published studies have shown that iCBT improves stress, anxiety, and depression, among other mental health problems. Most people get relief from symptoms and are highly satisfied with these programs after using them.

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Frequently Asked Questions

What if I try it and decide I want face to face therapy?

You can always switch. Nothing about starting an iCBT program stops you from seeking in-person therapy. Plus, if your program involves contact with a therapist they might be able to help you find someone.

Will I be able to talk to a therapist?

Some programs are self-guided, while others involve interaction with a therapist via instant messaging, email, phone, or video chat.

What if it's hard for me to write out my problems?

One common worry people have about iCBT is that they're afraid they won't be able to express their thoughts in writing. Most of the self-guided programs don't require writing. Therapist-assisted iCBT may offer communication through instant messaging, email, phone or video chat. This might be important to consider when looking for a program that works for you.

Is iCBT right for everyone?

iCBT isn't recommended for problems that pose serious risks to your safety. If you've been having thoughts of suicide or feel unsafe in any other way, you should seek in-person help as soon as possible (we'll give you some resources at the end of this survey). Also, some people just prefer talking to a therapist face to face, which is perfectly fine. However, iCBT is a treatment that works well for many people.

Page Break

Thanks for taking the time to learn about iCBT.
I hope the information was useful for you.
When you're ready, click the next button to complete the rest of the survey.

1.) Recap: True or False?

iCBT programs often use lessons, or modules, that can be completed on your own time using a computer or smartphone.

o True

o False

2.) Recap: True or False?

iCBT programs require meeting face to face with a therapist.

o True

o False

3.) Recap: True or False?

Some iCBT programs are completely self-guided, while others involve communication with a therapist via instant messaging, email, phone, or video chat.

o True

o False

Appendix A.2 Brief Definition of iCBT

Online mental health programs directly provide treatment for anxiety, depression, and other mental health problems.

Online cognitive behavioral therapy, or **iCBT** programs, are a common tool for addressing mental health problems. The "CBT" stands for cognitive behavioral therapy, which is a form of psychotherapy that works by helping you understand and change thoughts, emotions, and behaviors. iCBT programs might involve completing a structured set of lessons online. At the end of each lesson, programs often give you goals to practice the things you learn between therapy lessons and based on your feedback will decide which lessons will be completed next, or which may need additional practice for full benefit to you.

Self-guided iCBT programs are done independently.

Therapist-assisted iCBT programs involve support from a therapist via text, email, or videoconferencing.

Appendix B Third Article

Search Terms

PsycINFO

(smartphone OR "smart phone" OR "cell phone" OR "cellular phone" OR "mobile device" OR "mobile phone" OR "personal digital assistant" OR "iPhone" OR "mobile app*" OR "phone app*" OR mHealth OR "m-health" OR "mobile health" OR eHealth OR "e-health" OR "eMental health" OR "eTherap*" OR "digital behavior change intervention" OR "Information and communications technology" OR "Behavioral intervention technology" OR "Digital intervention" OR "Digital health intervention")

AND

(Depress* OR "affective disorder" OR "mood disorder" or MDD OR "affective symptoms")

Web of Science

TS=(smartphone OR “smart phone” OR "cell phone" OR “cellular phone” OR "mobile device" OR "mobile phone" OR “personal digital assistant” OR “iPhone” OR “mobile app*” OR “phone app*” OR mHealth OR “m-health” OR “mobile health” OR eHealth OR “e-health” OR “eMental health” OR “eTherap*” OR “digital behavior change intervention” OR “Information and communications technology” OR “Behavioral intervention technology” OR “Digital intervention” OR “Digital health intervention”)

AND

TS=(Depress* OR “affective disorder” OR “mood disorder” or MDD OR “affective symptoms”)

PubMed

("Cell Phone"[Mesh] OR “Cell Phone”[Text Word] OR “Cellular Phone”[Text Word] OR “Cell Phone Use”[Mesh] OR “Computers, Handheld”[Mesh] OR “Smartphone”[Text Word] OR “Smart Phone”[Text Word] OR “iPhone”[Text Word] OR “Mobile App*”[Text Word] OR “Phone App*”[Text Word] OR “Telemedicine”[Mesh] OR “Information Technology”[Mesh] OR “mHealth”[Text Word] OR “mobile health”[Text Word] OR “eHealth”[Text Word] OR “e-Health”[Text Word] OR “eMental health”[Text Word] OR “eTherap*”[Text Word] OR “digital behavior change intervention”[Text Word] OR “Behavioral intervention technology”[Text Word] OR “Digital intervention”[Text Word] OR “Digital health intervention”[Text Word])

AND

(“Depression”[Mesh] OR “Depress*”[Text Word] OR “Depressive Disorder”[Mesh] OR “Affective Symptoms”[Mesh] OR “affective symptoms”[Text Word])