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Adherence to a Mindfulness App for College Students with Depression: Patterns, Predictors, and Outcomes

Brynn Marie Huguenel

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LOYOLA UNIVERSITY CHICAGO

ADHERENCE TO A MINDFULNESS APP FOR
COLLEGE STUDENTS WITH DEPRESSION:
PATTERNS, PREDICTORS, AND OUTCOMES

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE GRADUATE SCHOOL
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

PROGRAM IN CLINICAL PSYCHOLOGY

BY

BRYNN M. HUGUENEL

CHICAGO IL

AUGUST 2021

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ABSTRACT

National trends indicate that mental health concerns, particularly rates of depression, continue to rise on college campuses; however, treatment utilization remains low. Technology-based mental health interventions, such as mental health apps (MHapps), are a promising means of overcoming treatment barriers. MHapps are effective in improving psychological outcomes, but low rates of adherence are a noted limitation. The current study explored patterns of adherence to a MHapp, investigated the bidirectional relation between adherence and depression, and identified motivational predictors of adherence rates. Undergraduate students ($N= 66$) reporting clinically-elevated depressive symptoms completed a three-month trial using Headspace, a mindfulness MHapp. Patterns of Headspace use revealed subsets of students who never initiated Headspace use or discontinued within the first month, and adherence declined markedly by the end of the second month. Further, depressive symptoms at the end of the first month predicted fewer minutes of Headspace completed during the second month. Connections were not found between depression and adherence for metrics of module completion, mental health practice, or depression practice. Finally, motivational factors of perceived and expected benefit, self-regulation, and behavioral intention predicted increases in the completion of depression content. The implications of these results for clinicians, college administrations, and users of MHapps are discussed, as well as directions for future research.

CHAPTER ONE

INTRODUCTION

Depression is a leading cause of disability both nationally and globally (Murray & Lopez, 2013; Whiteford et al., 2013) and prevalence rates have been rising over the past decade (Substance Abuse and Mental Health Services Administration, 2018). However, a large proportion of people experiencing depression do not receive mental health services due to various perceived barriers (Kazdin & Blase, 2011; Mohr et al., 2014). The disconnect between mental illness and treatment-seeking is particularly evident on college campuses, with some describing it as a campus crisis (Kadison & DiGeronimo, 2004).

Targeting mental health during college is critical since poor psychological health during the collegiate years has been linked to both short-term (e.g., lower GPA; Lipson et al., 2015) and long-term consequences (e.g., shorter life span; National Institute of Mental Health, 2018). Further, the college years typically coincide with the developmental period of emerging adulthood, which is a time when many mental illnesses, including depression, first emerge (McGorry et al., 2011; Schulenberg et al., 2004). Since both the college context and period of emerging adulthood confer risk for the development and exacerbation of mental illness, college students would uniquely benefit from expanded treatment options.

Technology-based mental health interventions, particularly smartphone mental health apps (MHapps), are a promising option that may overcome the barriers faced when seeking traditional face-to-face (FTF) services. FTF mindfulness interventions effectively reduce

depression symptoms and have been translated to MHapp platforms (Heeren & Philippot, 2011; Keng et al., 2011; Remmers et al., 2013). MHapps also are in a unique position to address prior methodological limitations in FTF mindfulness research since objective adherence data can be captured within each program. However, despite their potential, there is limited information about their implementation, and more research is needed to establish their effectiveness.

Similar to the FTF mindfulness literature, mindfulness-based MHapps lead to a variety of mental health benefits, including reduced depressive symptoms (Boettcher et al., 2014; Cavanagh et al., 2013). Headspace is a well-known mindfulness MHapp that research has supported in terms of its usability and effectiveness in reducing depressive symptoms, negative affect, and distress in samples of college students (Economides et al., 2018; Flett et al., 2019; Mani et al., 2015). However, a major concern of MHapps is adherence and continued engagement since these programs rely on user initiation and sustained motivation (Economides et al., 2018; Mohr et al., 2013b). Preliminary trends show low initiation rates and early discontinuation of use, particularly when participants engage in self-guided as opposed to prescriptive use (Christensen et al., 2009; Donkin et al., 2011; Kaltenthaler et al., 2008; Waller & Gilbody, 2009). Overall, more descriptive research is needed to better understand how users engage with MHapps due to the dearth of studies reporting adherence metrics.

To inform guidelines about best practices of MHapps, it is important to understand the relation between adherence and depression across time. Generally, research on FTF mindfulness interventions suggests that increased adherence is associated with improved outcomes, including reductions in depression (Carmody & Baer, 2008; Shapiro et al., 2008). In the MHapp literature, there is some evidence that greater exposure to content, more regular use, and longer continued engagement relate to improvements in mental health (Donkin et al., 2011; Flett et al., 2019;

Manwaring et al., 2008). It is noted that depression, in turn, may negatively affect adherence since symptoms can interfere with the ability to engage with an intervention over time (Van Ballegooijen et al., 2014); however, this link has not yet been explored in the MHapp literature. Additional research is needed to better understand the dynamic interplay between adherence and depression longitudinally, and to explore the directionality of this relationship.

Finally, given the challenges of low adherence, it is important to identify motivational characteristics that could be harnessed to enhance engagement. Based on the self-determination theory of motivation, a number of potential intrinsic and extrinsic factors have been hypothesized to influence intervention engagement (Michalak et al., 2004). Although self-regulation, behavioral self-efficacy, behavioral intent, routine, and expected and perceived benefit have been connected to medical and psychotherapy treatment adherence, the examination of these predictors in the context of MHapps is scant (Kalichman et al., 2011; Laurie & Blandford, 2016; Melville et al., 2010; Ribeiro et al., 2018).

The current study aims to address these limitations by exploring (1) adherence patterns, (2) the relation between adherence and depression over time, and (3) potential predictors of adherence in a college student sample. More specifically, descriptive analyses and data visualization will be used to describe adherence patterns over time. Using structural equation and multi-level modeling, the longitudinal relation between change in adherence and depression will be investigated, and motivational factors predicting adherence will be identified as well.

CHAPTER TWO

REVIEW OF THE RELEVANT LITERATURE

Prevalence and Burden of Mental Illness

In the United States, mental illness affects a significant number of adults and can have negative consequences at both individual and societal levels. A recent national survey estimated that 46.6 million American adults (19%) experienced mental illness in the last year, and approximately half of the population meets criteria for at least one psychiatric diagnosis during their lifetime (Kessler & Wang, 2008; Substance Abuse and Mental Health Services Administration [SAMHSA], 2018). Major depression is a common mental illness characterized by symptoms of low mood, anhedonia, changes in appetite and sleep, difficulty concentrating or making decisions, feelings of worthlessness or guilt, and suicidal ideation (American Psychiatric Association [APA], 2013). In 2017, approximately one in ten adults experienced a major depressive episode in the last year (SAMHSA, 2018). Of concern, both rates of depression and suicide have risen across the previous decade (SAMHSA, 2018; Stone et al., 2018). Given these trends, major depression represents a public health concern that warrants attention.

Depression is a leading cause of disease-related burden both nationally and globally (Murray & Lopez, 2013; Whiteford et al., 2013), and levels of disability due to mental illness have increased over time as well (Mojtabai, 2011; Murray & Lopez, 2013). Of those who experienced a major depressive episode in the past year, two-thirds indicated that their mood severely impaired their ability to function at home, work, or interpersonally (Kazdin & Blase,

2011; SAMHSA, 2018). Additionally, mental illness is associated with a higher risk of developing both chronic and treatable medical conditions (Colton & Manderscheid, 2006), as well as a lower likelihood of utilizing or adhering to medical care due to symptoms such as low energy and motivation (Broadbent et al., 2008; Shen et al., 2008). These individual-level effects can cascade into a societal impact. For example, depressive symptoms lead to absences at work, which has a yearly societal cost of over \$193 billion in lost earnings (Insel, 2008). Further, depression is the third most common reason for hospitalization among American adults, which contributes to higher healthcare and disability costs (Insel, 2008; Kazdin & Blase, 2011; Mark et al., 2007). Thus, if left unaddressed, depression will continue to serve as a burden to both individuals and society-at-large.

Treatment Considerations: Needs, Gaps, and Barriers

Despite the increased prevalence of mental health concerns, utilization of mental health treatment services has not exhibited a similar pattern. In 2017, approximately 13.5 million adults reported a need for mental health treatment in the past year, but did not receive it (SAMHSA, 2018). Of those experiencing depressive episodes, one-third perceives having an unmet need for mental health services (SAMHSA, 2018). Researchers and clinicians alike recognize that there is a critical gap in care, and because of this, reducing the burden of mental illness is cited as a priority in the field (Kazdin & Blase, 2011; Kessler et al., 2005; Mojtabai & Jorm, 2015).

However, perceiving a need for mental health services does not always translate into seeking services. The most common barrier to utilizing services is cost, and individuals are oftentimes limited in the services they can receive based on insurance reimbursement and out-of-pocket expenses (Mohr et al., 2014; SAMHSA, 2018). Additionally, some may not know where they can access services, or they may feel intimidated by the process of finding and initiating

care. Other barriers include limited time for appointments, lack of transportation, medical disabilities that may impede attendance, and concerns about confidentiality and stigma (Kazdin & Blase, 2011; Mohr et al., 2014; SAMHSA, 2018). Regional differences in rates of mental illness reflect disparities in treatment access, and more outreach is needed to connect new, interested clients (Barksdale et al., 2010; Mojtabai & Jorm, 2015). Due to the dearth of available services and the roadblocks to treatment utilization, it is necessary to harness new intervention models that can reach broader populations and overcome some of the identified barriers.

Implications of Emerging Adulthood and the College Environment

Similar trends in mental health rates and treatment gaps are highlighted in the emerging adult population—those aged 18 to 29, who identify neither as adolescents nor adults (Arnett et al., 2014). Emerging adulthood is characterized by change and instability in many life domains, such as living contexts, relationships, and identity, and thus can be a time of increased mental health problems (Arnett et al., 2014; Aseltine & Gore, 1993; Schulenberg et al., 2004). During this developmental time period, incidence rates increase for major depression (McGorry et al., 2011; Rohde et al., 2012), bipolar disorders (Lewinsohn et al., 2000; McGorry et al., 2011), schizophrenia (McGorry, 2011; McGorry et al., 2011), and borderline personality disorder (Grant et al., 2008). Estimates indicate that mental health concerns in this group are becoming both more prevalent and severe. Results from a national survey that began in 2005 found that rates of emerging adults who had a major depressive episode, as well as those who had suicidal thoughts, peaked in 2017 (SAMHSA, 2018). Additionally, emerging adults have reported increasing levels of impairment over the past decade due to their depressive symptoms (Mojtabai et al., 2016). Thus, this age group would particularly benefit from expanded treatment opportunities to lessen long-term impairment and burden.

This developmental period typically coincides with college attendance, as approximately 70% of high school graduates in the United States enroll in higher education the following year (U.S. Department of Labor, 2018). Emerging adults attending college are faced with a number of transitions simultaneously, including social, academic, developmental, and financial changes, which may prompt or worsen underlying mental health vulnerabilities (Aseltine & Gore, 1993; Harvey et al., 2006; Kennedy & Upcraft, 2010; Schulenberg et al., 2004). The transition to college is taxing on psychological well-being (Besser & Zeigler-Hill, 2014; Conley et al., 2014; Cooke et al., 2006), and declines evidenced in the first year extend into the latter years of college as well (Bewick et al., 2010; Conley et al., 2020; Edwards et al., 2010). As compared to individuals of similar age who are not attending college, a greater proportion of college students report feeling distressed (Adlaf et al., 2001), as well as having worse psychological health (Roberts & Zelenyanski, 2002; Stallman, 2010), social functioning (Roberts & Zelenyanski, 2002), and quality of life (Vaez et al., 2004). Therefore, while emerging adulthood is a developmental period of increased mental health risk, the stress and change of college appears to confer unique risk as well.

The College Mental Health Crisis

It is increasingly acknowledged that a “mental health crisis” is occurring on many campuses nationwide (Kadison & DiGeronimo, 2004, p. 156; also see Cook, 2007; Lipson et al., 2018a; Lipson et al., 2018b; Xiao et al., 2017). With more students seeking services than ever before, university presidents and mental health service directors cite student mental health as a top concern (Center for Collegiate Mental Health [CCMH], 2018; Kadison & DiGeronimo, 2004; Rubley, 2017). Within the past decade, the percentage of college students with mental health diagnoses increased from 22% to 36%, with depression as one of the most common

disorders (CCMH, 2018; Hunt & Eisenberg, 2010; Lipson et al., 2015; Lipson et al., 2018b).

Furthermore, the majority of college mental health service directors agree that more students are presenting with severe mental health concerns (Gallagher, 2014). For example, more than one-third of students feel so depressed that they are unable to function and 10% report having suicidal thoughts (Hunt & Eisenberg, 2010).

As compared to the general adult population, seven times as many college students perceive a need for mental health treatment (6% vs. 42% respectively; Healthy Minds Study [HMS], 2018; SAMHSA, 2018). Despite this, only about one-third of students with elevated mental health symptoms actually receive services (Lipson et al., 2018b; Lipson et al., 2015), and approximately half of students who screen positively for depression seek services annually (HMS, 2018). Of concern, students who are typically considered to be at-risk for poor psychological or academic adjustment (e.g., first generation, ethnic minority, or low socioeconomic students) are especially unlikely to seek mental health services in times of need (Lipson et al., 2018a). Help-seeking behavior has been consistently low across recent years, suggesting that service utilization is an ongoing problem (SAMHSA, 2018).

College students face a range of barriers that impede their utilization of mental health services. First, many students simply do not perceive a need for treatment because they view college as a time of struggle, and therefore misconstrue clinical symptoms as typical collegiate experiences (Eisenberg et al., 2007; HMS, 2018). However, even if a student recognizes a need for help, they may not seek it due to challenges in finding care, perceiving the resources as inconvenient (e.g., location on campus, hours of operation), or uncertainty about the effectiveness of available services (Eisenberg et al., 2011; HMS, 2018; Mowbray et al., 2006). Barriers continue to emerge even once a student presents to clinic. Many counseling centers

struggle to meet demands due to staff or budget limitations, which leads to session limits and lengthy waitlists (Association for University and College Counseling Center Directors [AUCCCD], 2016; Kadison & DiGeronimo, 2004; Kern et al., 2018; Xiao et al., 2017). To highlight the staff shortage, the average ratio is one university clinician for every 1,737 students (AUCCCD, 2016). Although college can serve as an ideal context to identify, prevent, and treat mental health concerns due to student's proximity to potential resources (Cavanagh et al., 2013; Kern et al., 2018; Lipson et al., 2015), it is clear that the traditional service options are not meeting the needs of the evolving college student.

Addressing mental health during college is imperative since poor psychological well-being can negatively impact students during their time on campus and beyond. Academically, depression is associated with lower grade point average (Eisenberg et al., 2009; Lipson et al., 2015) and an increased likelihood of dropping out of college, after accounting for prior academic performance (Eisenberg et al., 2009; HMS, 2018; Lipson et al., 2015). In fact, mental illness is associated with the highest college drop-out rates of any disability group (U.S. Department of Education, 2014). Further, depression can also contribute to a shortened life span given that suicide is the second leading cause of death for those aged 10 to 34 (National Institute of Mental Health, 2018). In regard to long-term effects, psychopathology during the first year of college predicts future psychological symptoms as well as future dysfunction in relationships, development, and thinking styles (Salmela-Aro et al., 2014). Thus, it is necessary to investigate alternative mental health practices on campuses to expand student resources, address disparities, and reduce the negative impact of mental illness on student functioning (Lipson et al., 2015).

Addressing Treatment Gaps: Mental Health Technologies

One seemingly simple solution to meet the increasing demand for mental health treatment is to expand college counseling services via additional staff. However, the student-to-counselor ratio is so large that even doubling the number of licensed clinicians would fail to adequately address the shortage (Kadison & DiGeronimo, 2004; Kazdin & Blase, 2011). Additionally, most universities do not have the budget or physical space for additional providers (Kazdin & Blase, 2011). Importantly, increasing the number of providers also does not affect the other barriers inherent of traditional face-to-face (FTF) services, such as confidentiality or transportation concerns. Notably, a quarter of college students report preferring to handle mental health concerns on their own, without the aid of a professional (HMS, 2018).

Instead, a promising avenue is to harness the benefits of technology, with some positing that technology may have the most significant impact on the future of psychological treatment (Kazdin & Blase, 2011; Lattie et al., 2019b; Patrick et al., 2016; Schueller et al., 2013). Behavioral intervention technologies (BITs) are Internet-based computer and mobile programs that deliver behavioral or psychological interventions that promote physical and mental health (Mohr et al., 2013a). The platform of BITs has evolved over time alongside technological advancements, shifting from telephones and CD-ROMs to videoconferencing and websites (Mohr et al., 2013b). While many BITs are still available in their older platforms, they are now more commonly delivered through mobile device applications (Mohr et al., 2013b). Similar to traditional FTF therapy, BITs teach users information and skills that can be practiced in their daily life, but they do so through program features such as videos, discussion boards, and messaging systems (Mohr et al., 2013b). Such technologies, including mental health applications (MHapps), are commercially available through online or mobile stores.

Mental health technologies are in a unique position to address many of the noted shortcomings of traditional in-person services. Primarily, given the ubiquity of smartphone ownership, MHapps have the potential to reach a wide range of individuals and reduce disparities in treatment access (Kazdin & Blase, 2011; Mohr et al., 2014; Schueller et al., 2013). Notably, 91% of college-aged Americans own a smartphone and students look at or use their phone almost 100 times per day (Bratu, 2018; Hitlin, 2018). Further, college students' comfort with smartphones and apps may foster greater interest in, and engagement with, MHapps since individuals typically prefer mental health content when it is delivered in a familiar format (Bakker et al., 2016; Lattie et al., 2019b). Having greater control over the accessibility of MHapps may particularly appeal to college students' developmental desire for autonomy (Arnett et al., 2014; Bakker et al., 2016). Being able to access MHapps anywhere and at any time also addresses barriers related to transportation, time constraints, and concerns about stigma and privacy (Bakker et al., 2016; Mohr et al., 2014). Additionally, MHapps are oftentimes free or have nominal yearly or one-time purchasing costs, which can be an appeal for those concerned about treatment cost (Mohr et al., 2014). Finally, advancements in technologies afford the ability to capture a wide variety of information (e.g., assessments, sensor-based activity, GPS location), deliver needed skills in real-time, administer individually tailored interventions and feedback, and incorporate features to encourage engagement, such as reminders (Bakker et al., 2016; Kazdin & Blase, 2011; Kern et al., 2018; Mohr et al., 2013b).

Kern and colleagues (2018) conducted a survey with college students to better understand their perceptions of MHapps as potential treatment options. More than a quarter of students are open to using MHapps, and one in ten students would prefer using a MHapp to engaging with FTF services. Students are particularly interested in MHapps' convenience, confidentiality, and

the immediate availability of resources (Kern et al., 2018). The preference for MHapps over FTF treatment is significantly more common for non-White, than White, students, which is important given disparities in access (Kern et al., 2018). Thus, the college environment provides fertile ground for the dissemination of MHapps given student interest (Kern et al., 2018; Lattie et al., 2019b; Mohr et al., 2013b).

Mindfulness-Based Therapy and Interventions

Mindfulness is the practice of paying attention purposefully in the present moment and without judgment (Kabat-Zinn, 1994). The practice of mindfulness is proposed to lead to positive changes in mental health and well-being through its cultivation of intention, present-moment awareness, and attitudes of openness and curiosity (Shapiro et al., 2006). Mindfulness is an evidence-based practice that has been increasingly incorporated into therapy, both as its own treatment and as a skill integrated into other models (e.g., acceptance and commitment therapy, dialectical behavioral therapy; Creswell, 2017). While the practice is referred to by various names and definitions in the literature (Creswell, 2017; Keng et al., 2011; Van Dam et al., 2018), the current study uses the term mindfulness to describe the aforementioned practice defined by Jon Kabat-Zinn.

Given its transdiagnostic nature, mindfulness can be used to target a number of mental health outcomes; in fact, it has even been proposed to function as a common factor in therapy (Martin, 1997). While its roots are in ancient Buddhist principles, mindfulness was adapted to Western medicine in the 1970s as a behavioral intervention to target pain (Keng et al., 2011). Since then, it has expanded to address a wide range of physical and psychological factors. The two most common mindfulness interventions are mindfulness-based stress reduction (MBSR) and mindfulness-based cognitive therapy (MBCT), both of which are manualized, group-based

programs lasting approximately 8 weeks. MBSR is broader in nature as individuals learn to relate to psychological and physical conditions in more positive ways, whereas MBCT is used to prevent relapse for individuals with remitted depression (Creswell, 2017; Keng et al., 2011). Although other mindfulness-based interventions beyond MBSR and MBCT have emerged in the field, the gold standard of an 8-week trial has continued since research consistently finds benefits in emotion regulation and cognitive processing from that length of practice (Creswell, 2017; Williams, 2010). Meta-analytic work suggests that mindfulness is particularly potent as a treatment for individuals who are already experiencing distress, as compared to the effects seen for mindfulness used as a prevention technique (Hoffman et al., 2010; see also: Keng et al., 2011; Schreiner & Malcolm, 2008).

Mindfulness, both as a practice and a trait, has been linked to a number of positive outcomes. Benefits include, but are not limited to, improved emotion regulation (Davis & Hayes, 2011; Remmers et al., 2016), cognitive functioning (e.g., attention, executive functioning; Gallant, 2016; Hoffman et al., 2010; Teper et al., 2013; Zeidan et al., 2010), interpersonal functioning (Simpson & Mapel, 2011), professional functioning (e.g., emotional exhaustion, job satisfaction; Hülshager et al., 2013), neurological activity and neuroplasticity (Way et al., 2010), and physical health (e.g., increased immune functioning, reduced pain; Simpson & Mapel, 2011). In terms of outcomes related to mental health, mindfulness is associated with *reductions* in depression (Pradhan et al., 2007; Schreiner & Malcolm, 2008), anxiety or worry (Schreiner & Malcolm, 2008; Verplanken & Fisher, 2014), general distress (Simpson & Mapel, 2011), and perceived stress (Charoensukmongkol, 2014; Ramler et al., 2016), as well as *increases* in positive affect (Remmers et al., 2016), self-compassion (Birnie et al., 2011), self-efficacy

(Donald et al., 2016), and quality of life (Carlson et al., 2003; Ribeiro et al., 2018; for reviews see also: Creswell, 2017; Davis & Hayes, 2011; Grossman et al., 2004; Keng et al., 2011).

In the FTF therapy literature, mindfulness is particularly effective in reducing symptoms of depression and subsequent relapse. Through mindfulness, individuals learn to shift their attention away from ruminative thoughts—a critical factor of depression—and toward the present moment. Further, mindfulness helps people to adopt an attitude of acceptance, curiosity, and openness toward feelings of sadness, which can lessen dysfunctional negative thoughts that may contribute to and maintain depressive symptoms (Baer, 2003; Hayes & Kelly, 2003; Heeren & Philippot, 2011; Keng et al., 2011). The process of focusing on one's present-moment internal experiences also helps to promote better emotional awareness, which can allow for the identification and acceptance of sadness, instead of repression or denial (Baer, 2003; Remmers et al., 2016; Schreiner & Malcolm, 2008).

The first wave of mindfulness research primarily examined the effects of the practice in clinic settings and with adult samples. More recently, the focus has shifted to conducting randomized controlled trials (RCTs) in different settings and with various populations to extend preliminary clinic-based findings (Creswell, 2017). Research has replicated many of the positive psychological findings in college samples (Donald et al., 2016; Ford, 2017; Remmers et al., 2016; Shapiro et al., 2008; Zeidan et al., 2010), and there is also evidence of benefits in other areas specific to students, such as college adjustment (Ramler et al., 2016). These encouraging results suggest that mindfulness programs may be able to help students cope with the challenges and pressures common in the collegiate environment (Bajaj & Pande, 2016; Ramler et al., 2016; Rasmussen & Pidgeon, 2011).

A primary challenge in the area of FTF mindfulness research is that the construct is typically assessed through self-report measures, which vary widely in their operationalization of mindfulness as well as their measurement format. The majority of studies examining FTF mindfulness use self-report measures of trait mindfulness as proxies of mindfulness practice or intervention dose, which has been criticized (Creswell, 2017; Davis & Hayes, 2011; Van Dam et al., 2018). Meanwhile, other studies capture mindfulness practice through participants' retrospective report of completed practices (e.g., Cavanagh et al., 2013). This is also problematic because retrospective report of one's own behavior is typically unreliable, overestimated, and subject to bias (Davis & Hayes, 2011; Rosenzweig et al., 2010). In fact, a study conducted by Wahbeh and colleagues (2011) identified differences in participants' report of their mindfulness practice when it was measured subjectively versus objectively, with the former reported as higher. Given that trait-based and self-report measures of mindfulness do not appear to accurately represent mindfulness meditation practice (Creswell, 2017; Davis & Hayes, 2011; Ribeiro et al., 2018; Van Dam et al., 2018), performance-based measures of mindfulness are needed (Davis & Hayes, 2011).

Mindfulness-Based Technologies

Technology-based mindfulness interventions are in a unique position to address the methodological issues in the FTF literature since practice can be recorded through the app in real-time, thereby circumventing researchers' reliance on self-report or trait-based measures (Cavanagh et al., 2013; Emmerik et al., 2017). Mindfulness-based MHapps, such as Headspace, Smiling Mind, Calm, and Mindfulness Coach, have been described by users as aesthetically pleasant and easy to navigate (Chittaro & Vianello, 2016a; Chittaro & Vianello, 2016b; Kern et al., 2018). Beyond usability, RCT studies have begun to establish the effectiveness of

mindfulness-based technologies by asking participants to use the platform for a discrete amount of time (typically 2 to 10 weeks) and examining outcomes. Trials differ in the content that participants are expected to cover, with some researchers setting clear expectations of the type, number, and/or frequency of exercises to be completed (e.g., Bennike et al., 2017; Emmerik et al., 2017), whereas others take a naturalistic approach by observing how participants use the MHapp without direction (e.g., Economides et al., 2018; Laurie & Blandford, 2016).

Across study designs, research has replicated the far-reaching benefits of FTF mindfulness interventions in those based online. For example, research supports that technology-based mindfulness programs *increase* resiliency (Aikens et al., 2014), quality of life (Emmerik et al., 2017), and professional functioning (e.g., work engagement, employee well-being; Aikens et al., 2014), as well as *decrease* depression (Boettcher et al., 2014; Cavanagh et al., 2013), perceived stress (Aikens et al., 2014; Cavanagh et al., 2013), and anxiety (Boettcher et al., 2014; Cavanagh et al., 2013). Consistent with findings from individual studies, a review of mindfulness-based online interventions found significant benefits for depression, anxiety, well-being, and stress with small to medium effect sizes (Spijkerman et al., 2016). Importantly, Cuijpers and colleagues (2010) conducted a meta-analysis directly comparing the effectiveness of Internet-based interventions with their FTF counterparts and did not find significant differences in outcomes.

Although MHapps and technologies have been developed for a range of specific disorders, depression is one of the most common targets and investigated outcomes (Donkin et al., 2011). Meta-analyses and reviews examining the effect of Internet-based treatments on depressive symptoms find medium to large effect sizes overall, which is similar to that of FTF therapy (Andersson & Cuijpers, 2009; Andrews et al., 2010; Johansson & Andersson, 2012). In

samples of college students, technology-based interventions lead to a number of improvements in emotion as compared to waitlist control groups, including increases in emotional well-being as well as reductions in depression, anxiety, and stress (Davies et al., 2014; Ellis et al., 2011; Harrer et al., 2018; Lee & Jung, 2018; Richards et al., 2013). Some of these studies specifically recruited samples of students reporting elevated levels of distress or depressive symptoms, indicating that such students may particularly benefit from technology-based interventions (Lee & Jung, 2018; Lintvedt et al., 2013).

While there is clear evidence that mindfulness-based technologies have the potential to benefit individuals in terms of their psychological health, potential users are faced with the challenge of determining *which* of thousands of apps are evidence-based and worth their investment (Patrick et al., 2016; Torous & Roberts, 2017; Van Amerigen et al., 2017). From an ethical perspective, it is important to identify the MHapps that are supported by research in order to protect consumers from potentially harmful or ineffective programs (Mohr et al., 2013a). In 2010, the National Institute of Mental Health held an expert panel to review the state of research on mental health technologies and determine future research priorities (Mohr et al., 2013a). The panel concluded that technologies have been developed for a variety of mental health problems and diagnoses, but more research is needed to establish their effectiveness and utility (Mohr et al., 2013b). Although preliminary research suggests that technologies are as effective as FTF treatments (Cuijpers et al., 2010), it cannot be assumed that all MHapps incorporating evidence-based techniques from the FTF literature are automatically evidence-based as well.

Finding a Needle in the Haystack: Support for Headspace

Headspace is a well-known mindfulness-based MHapp, with over one million active users worldwide as of 2018 (Headspace Inc., 2018). The MHapp is marketed as a “personal

meditation guide” wherein users are able to listen to guided, audio-recorded mindfulness exercises on their computer or smartphone. Out of 23 commonly used mindfulness-based MHapps, researchers awarded Headspace with the highest rating on the Mobile Application Rating Scale, which assesses app engagement, functionality, aesthetics, information quality, and subjective satisfaction (Mani et al., 2015; Stoyanov et al., 2015). Users also have noted that Headspace is easy to navigate, engaging, and accessible, and that they would recommend the app to others (Kubo et al., 2018; Mistler et al., 2017; Taylor et al., 2016). These are important qualities since they generate more positive user experiences and appeal, and thereby may enhance engagement (Cyr et al., 2006).

Importantly, research also has examined the effectiveness of Headspace in a range of samples, including general adults (Economides et al., 2018; Howells et al., 2014), medical residents (Taylor et al., 2016; Wylde et al., 2017), physicians (Wen et al., 2017), specific illness groups (e.g., cancer patients; Kubo et al., 2018; Rosen et al., 2018), psychiatric groups (e.g., inpatients diagnosed with schizophrenia; Mistler, et al., 2017), and college students (Noone & Hogan, 2018). On a foundational level, findings support that Headspace successfully increases levels of mindfulness in a dose-related manner (Bennike et al., 2017; Flett et al., 2019; Noone & Hogan, 2018; Wen et al., 2017). Interestingly, a study comparing Headspace to another reputable mindfulness-based MHapp, Smiling Mind, found that only those who used Headspace exhibited a significant increase in mindfulness after the 40 day trial (Flett et al., 2019). Although this may seem like a basic expectation of a mindfulness MHapp, the saturation of the market necessitates research showing that MHapps actually cultivate the skills to which they claim.

Standard 8-week RCTs comparing participants using Headspace to those in a waitlist control group find that Headspace leads to improvements in well-being (Bostock et al., 2018),

quality of life (Kubo et al., 2018; Rosen et al., 2018), compassionate behavior (Lim et al., 2015), and professional functioning (Bostock et al., 2018). Even more rigorous support for Headspace stems from studies finding significant improvements following its use as compared to active control treatment groups (DeSteno et al., 2017; Economides et al., 2018; Wylde et al., 2017). Further, Headspace may yield positive changes even after a short duration of use (typically 10 days), including *reduced* aggression and irritability (DeSteno et al., 2017; Economides et al., 2018), stress (Economides et al., 2018; Flett et al., 2019; Yang et al., 2014), and anxiety (Flett et al., 2019), as well as *increased* positive affect (Economides et al., 2018; Howells et al., 2014), resilience (Flett et al., 2019), and college adjustment (Flett et al., 2019).

Of particular interest, Headspace engagement is connected to reductions in distress, negative affect, and depressive levels, even after 10 days of use (Bostock et al., 2018; Economides et al., 2018; Flett et al., 2019; Howells et al., 2014; Kubo et al., 2018). Notably, this research includes both Headspace researchers (Economides et al., 2018) and independent scholars (Bostock et al., 2018; Flett et al., 2019; Howells et al., 2014; Kubo et al., 2018). In a sample of college students, Flett and colleagues (2019) found that open access to Headspace for 40 days resulted in clinically meaningful improvements, with depression levels significantly reduced below the clinical cut-off score by the end of the trial. Together, these findings serve as a testament to the quality of Headspace's content and platform, with specific promise for college students experiencing clinically elevated depressive symptoms.

Challenges and Limitations of MHapps

While MHapps are touted as a promising solution to the treatment gap, they do not come without challenges and limitations. Despite the efforts of researchers and developers to elucidate their utility and scientific basis, there appears to be a disconnect between research and practice as

MHapps remain under-utilized by clinicians, institutions, and students. In general, providers lack the knowledge and education about how to use such tools, and more critically, how to recommend that *others* use such tools. At this time, there are no guidelines specifying the ways in which these technologies can be used as stand-alone interventions or as tools incorporated into other FTF treatment modalities (Lattie et al., 2019b; Mohr et al., 2013b). To develop formal recommendations for MHapp use, research must first focus on better understanding the implementation of mental health technologies in different settings. Yet, few studies have examined such questions (Levin et al., 2015; Santucci et al., 2014). Similarly, it is necessary for research to progress from an efficacy focus, wherein individuals use the MHapp in the context of a controlled research design with prescriptive use or content, to an effectiveness focus, wherein individuals use the MHapp in a more realistic, self-guided manner (Flett et al., 2019).

Adherence to psychological services is identified as a primary challenge in the FTF therapy literature (Swift & Greenberg, 2012; Wierzbicki & Pekarik, 1993); however, this is an even larger concern for MHapps and technologies (Lattie et al., 2019b). In the medical field, the term adherence captures the extent to which an individual's behavior matches the recommendations from a health care provider (World Health Organization, 2003). Since this definition does not translate well to technology-based interventions, adherence in this realm captures the extent to which an individual experiences, or is exposed to, the content of the program (Christensen et al., 2009; Van Ballegooijen et al., 2014). As compared to traditional FTF services, the lack of person-to-person contact of MHapps weakens accountability, and thereby adherence, over time (Van Ballegooijen et al., 2014). Technology-based platforms are unique in that they are *pull* interventions, meaning that they require users to initiate contact and then engage in continued, independent practice (Mohr et al., 2013b). Due to their reliance on the

individual's own initiation, motivation, and continued engagement, technology-based interventions experience high rates of attrition and non-adherence (Economides et al., 2018; Mohr et al., 2013b), even more so than FTF services (Christensen et al., 2009).

To address concerns related to adherence, many technology-based interventions have incorporated supportive accountability features. The model of supportive accountability asserts that adding an interpersonal element to technology interventions supports adherence, even when compared to other methods to support adherence that are not socially-based, such as email reminders or app notifications (Mohr et al., 2011). Supportive accountability features may include supplementing technology with in-person participant meetings or adding a supportive coach, clinician, or research staff member who may regularly contact participants to discuss progress, success, and barriers (Mohr et al., 2013b). In particular, adding elements of staff or peer support can lead to improvements in emotional functioning since both giving and receiving support is psychologically beneficial (Chambers et al., 2012; Inagaki & Orehek, 2017; Naslund et al., 2016; Park & Conway, 2017; Pfeiffer et al., 2011). However, when such features have been added to technology-based interventions, they do not consistently improve adherence, and in fact, reductions in technology adherence may negatively affect participants' desire to support each other (Duffecy et al., 2013; Duffecy et al., 2019; Hu et al., 2019). Thus, despite the addition of supportive accountability features, adherence rates still vary widely and are oftentimes cited as a problem (Lattie et al., 2019b; Mohr et al., 2011; Mohr et al., 2013b).

Beyond the lack of external accountability, technology itself may contribute to low adherence rates. Many people report feelings of exhaustion, burn-out, and other negative emotions (e.g., depression, anxiety) due to their constant connection to smartphones and technology (Alabi, 2013; Derks & Bakker, 2014). This can be a particularly strong sentiment for

college students, whose academic and social lives exist largely online (Chak & Leung, 2004). As such, students may have conflicting feelings about MHapps wherein they value their ease of use, accessibility, and confidentiality, but also view their smartphone as a source of stress that they may be trying to limit. Further, smartphone and Internet engagement is quite frequent, but brief—70% of smartphone sessions last less than one minute (Andrews et al., 2015). This poses a challenge for MHapps like Headspace, wherein exercises typically last for 10 minutes or longer and thus require sustained engagement.

In addition to the risk for nonadherence due to the technology platforms themselves, the skill of mindfulness may also contribute to engagement challenges. While mindfulness may seem simple at face value, it actually requires significant effort. Given the distractions that individuals face on a minute-by-minute basis, bringing and maintaining focus to the present moment can be quite emotionally and cognitively effortful, especially for those new to the practice (Creswell, 2017; Donkin et al., 2011; Ribeiro et al., 2018; Rizer et al., 2016). Individuals may download mindfulness-based MHapps with high levels of motivation and intent to practice, but then demands of effort and time, as well as feelings of frustration, may erode motivation and lead to disengagement (Cheung et al., 2018). Further, technologies targeting depression have some of the highest rates of nonadherence (Mohr et al., 2013b). Depressive symptoms such as low energy, concentration difficulties, anhedonia, and rumination may interfere with one's ability to engage with both the MHapp and the practice of mindfulness (Van Ballegooijen et al., 2014). A similar challenge is found in the medical literature wherein those diagnosed with depression have lower rates of adherence to medical treatments as compared to non-depressed patients (Broadbent et al., 2008; Shen et al., 2008).

Given that there cannot be an opportunity for change if individuals do not initiate use of a MHapp, understanding adherence and identifying variables that may enhance adherence are top priorities (Keng et al., 2011; Mohr et al., 2011). Technology platforms, like MHapps, provide an excellent opportunity to examine questions related to adherence since the programs record detailed, objective data on usage patterns (Christensen et al., 2009).

A Closer Look at Adherence Metrics for MHapps

For Internet-based interventions, adherence has been measured in a variety of ways (Mohr et al., 2011). Early technology-based mindfulness research tracked intervention adherence through self-report, which is similar to FTF mindfulness therapy research. Some studies utilized retrospective self-report measures wherein participants estimated how frequently they completed mindfulness exercises within a particular time frame (e.g., the past week; Cavanagh et al., 2013; Donkin et al., 2011). Others used even cruder measurements of adherence, such as single items asking participants to rate on a Likert-style scale how consistently they completed practices (e.g., not at all, a little, somewhat, very much; Shapiro et al., 2008). Even more detailed records such as daily diary methods were problematic since they relied on participants to accurately complete logs, when in reality they may forget or falsify practice records due to the influence of socially desirable responding (Hülshager et al., 2013; Paulhus, 2001). Although MHapp have the ability to capture session completion in real-time, these data are not always accessible or used by researchers, causing them to rely on self-report measures of adherence despite their limitations (Donkin et al., 2011; Flett et al., 2019).

Even when the capabilities of technology-based interventions are harnessed to capture detailed objective adherence data, studies vary widely in the adherence metrics that are reported and included in analyses. A systematic review of 69 studies examining adherence to technology-

based mental health interventions identified total number of completed modules or exercises as the most commonly reported adherence metric (Donkin et al., 2011). Other metrics have been described as well, including average session length (Mohr et al., 2017), total sessions or minutes completed (Christensen et al., 2009; Mohr et al., 2017), number of logins (Christensen et al., 2009; Donkin et al., 2011), and number of webpages visited (Donkin et al., 2011; Manwaring et al., 2008). Programs involving a social component have captured data related to discussion boards as well (e.g., postings and read messages; Christensen et al., 2009; Donkin et al., 2011; Manwaring et al., 2008). Some have looked more closely at the specific content completed, such as examining the proportion of time spent on different exercises (Ribeiro et al., 2018). To simplify the abundance of adherence data that can be yielded from technology-based programs, others have reduced data into categorical variables, such as by characterizing participants as active or passive users (Lattie et al., 2016).

Applying web analytic principles to mental health technologies, Cheung and colleagues (2018) outlined three primary metrics of adherence: loyalty, regularity, and continued engagement. App loyalty captures the average number of sessions completed in a week, regularity is the average number of days in a week where at least one session was completed, and continued engagement is the duration of time between the first and last completed session (Cheung et al., 2018). Other studies have used similar measures of loyalty (Lattie et al., 2016; Mohr et al., 2017; Ribeiro et al., 2018), regularity (Ribeiro et al., 2018), and continued engagement (Lattie et al., 2016; Manwaring et al., 2008; Mohr et al., 2017). Lack of measurement consistency has likely contributed to mixed findings in the literature and makes it challenging to synthesize patterns (Mohr et al., 2013b). Future research should consider a broader range of adherence metrics to gain a clearer understanding of engagement over time.

Patterns, Consequences, and Determinants of Adherence

Adherence is an important consideration in technology-based mental health intervention research for several reasons, reviewed below. First, adherence patterns can be an indicator of intervention acceptability and utility, and at this time there is not a clear understanding of how students may engage with MHapps in a self-directed manner. Second, the bidirectional relation between adherence and depression is critical to examine to better understand the directionality of this link and whether the strength of these connections differ across adherence metrics (Cheung et al., 2018; Donkin et al., 2011; Mohr et al., 2013b; Van Ballegooijen et al., 2014). Third, challenges related to low adherence to MHapps necessitate the identification of potential motivational factors that may enhance adherence over time.

Adherence Patterns.

Despite the ease of collecting adherence data through MHapps and other technologies, few studies report such data and differing metrics makes it difficult to synthesize findings across studies (Donkin et al., 2011; Mistler et al., 2017). Early systematic reviews of general technology-based mental health interventions identified average drop-out rates ranging between 23-44% as well as some problems with low initiation rates (Donkin et al., 2011; Kaltenthaler et al., 2008; Waller & Gilbody, 2009). Additionally, adherence appears to decline when users are given less structure and prescriptive guidance (e.g., specific content or number of sessions to complete), such as in self-guided studies or during follow-up study periods (Christensen et al., 2009; Ribeiro et al., 2018).

Generally, objective engagement data reported by studies examining mindfulness-based MHapps and technologies highlight the challenge of continued engagement. Initially, adherence rates start high but then gradually reduce over time, with drop-offs occurring as soon as three

days after initiation (Chittaro & Vianello, 2016b). Concerningly, few participants show any engagement through self-guided follow-up periods (Cheung et al., 2018; Economides et al., 2018; Emmerik et al., 2017; Flett et al., 2019). Illustrating this issue further, Flett and colleagues (2019) found that college students, on average, used Headspace 8 times during the first 10 days of the study, but less than half engaged with Headspace *at all* in the subsequent 30 days. In a separate study, despite almost three-fourths of college students reporting some benefit from MHapps, the same proportion of students engaged with MHapps weekly or *less* (Kern et al., 2018). This highlights the gap between student interest in, and actual use of, MHapps.

It is important to note that there is some evidence that contradicts the picture of low adherence. Two groups of researchers found consistently high adherence rates across 8-week trials with non-clinical adult samples, with 57 - 71% of participants using the MHapp more than half of the days (Bostock et al., 2018; Kubo et al., 2018). Ultimately, more information is needed to obtain a clearer picture of MHapp adherence over time, though there appears to be preliminary evidence of a mismatch between perceived usefulness, and actual use of, MHapps for college students specifically.

Connecting Adherence to Intervention Outcomes.

In the FTF mindfulness therapy literature, the connection between adherence and psychological outcomes is mixed. Some studies find that greater adherence to mindfulness practice is associated with improved outcomes, including reductions in depressive symptoms (Carmody & Baer, 2008; Pradhan et al., 2007; Shapiro et al., 2008). Meanwhile, other FTF studies find no correlation between mindfulness practice—including metrics of time, type of exercises, and frequency—and outcomes (Ribeiro et al., 2018). However, as aforementioned, it is difficult to draw firm conclusions given the measurement limitations in this area of research.

Mixed findings are prevalent in the technology-based mental health literature as well, with the link between adherence and mental health outcomes differing depending on the metric of engagement. For MHapps more broadly, adherence metrics of content exposure, continued engagement, and completed modules are associated with improvements in psychological outcomes, whereas total time, logins, and individual exercises completed are not (Donkin et al., 2011; Manwaring et al., 2008). Research focusing on Headspace specifically shows that adherence in the long-term, but not short-term, affects outcomes, with more regular use predicting improvements in a variety of domains including depression (Flett et al., 2019).

It is also likely that the relation between adherence and depression is bidirectional. Research thus far with mental health technologies has typically examined adherence predicting depression, but it is also recognized that depressive symptoms can influence adherence as well. Symptoms of fatigue, difficulty focusing, anhedonia, and rumination that are common to depression can make engaging in both mindfulness practice and a longitudinal intervention challenging (Van Ballegooijen et al., 2014). A review of medical data spanning 30 years found a significant relation between depression and noncompliance, wherein an elevated screening for depression conferred three times greater likelihood of treatment nonadherence as compared to those who did not have elevated depressive symptoms (DiMatteo et al., 2000). Further, the effect of mental health on adherence appeared to be unique to depression, since a similar association was not found for other mental illnesses (e.g., anxiety; DiMatteo et al., 2000). Both in the medical and psychological literature, depression is linked to lower rates of treatment adherence, so it is important to account for and explore this path, and to better understand the relative strength of adherence affecting depression and vice versa (Broadbent et al., 2008; Gonzalez et al., 2011; Mohr et al., 2013b; Shen et al., 2008).

Research thus far has focused exclusively on the effect of MHapp adherence on depression, despite evidence showing that depressive symptoms can impact engagement as well. At this time, there is too little data to understand this complex question (Bennike et al., 2017; Ribeiro et al., 2018), and existing research is limited by inconsistent adherence metrics and simplistic analytic techniques (Ribeiro et al., 2018). Examining the interplay between adherence and depression over time will allow researchers to better understand the directionality of this relationship, which can be used to inform future MHapp guidelines and recommendations.

Motivational Predictors of Adherence.

Given that adherence is a primary issue for MHapps, it is equally important to identify factors, particularly motivation-related characteristics, that may enhance engagement (Donkin et al., 2011; Van Ballegooijen et al., 2014; Waller & Gilbody, 2009). Research investigating medical and mental health treatment adherence is commonly rooted in self-determination theory (Bakker et al., 2016; Michalak et al., 2004; Mohr et al., 2011). This theory posits that humans have a natural propensity for growth and development, and motivational factors exist on a continuum between intrinsic and extrinsic (Deci & Ryan, 1985; Deci & Ryan, 2008). Intrinsic determinants of motivation appeal to one's innate desire for independent, self-initiated actions wherein one seeks out challenges and goals for personal fulfillment. Meanwhile, extrinsic determinants are external factors that may exert influence on one's behavior and progress toward a goal. Generally, intrinsic motivational factors lead to more potent and lasting behavioral change than extrinsic factors (Deci & Ryan, 2008). A number of variables have been hypothesized as potential determinants of MHapp initiation and maintenance of use, largely based on theories of motivation and the health-behavior literature.

Self-regulation. Self-regulation is one's ability to intentionally exercise control over one's emotions, thoughts, motivations, or actions (Bandura, 1991). This is commonly referred to as self-management or self-monitoring in the medical field, and is recognized as a primary factor influencing treatment engagement (Bandura, 2005; Leventhal et al., 2016; Maes & Karoly, 2005; Modi et al., 2012). When preparing to develop a new behavioral pattern, such as practicing mindfulness through MHapp use, self-regulation is necessary to avoid succumbing to barriers and is critical in translating initial action into a maintained practice (Lally et al., 2011; Schwarzer, 2008). Studies examining the use of technologies in promoting health behaviors such as weight management, healthy eating, and physical exercise consistently find that self-regulation positively predicts improvements in health-related outcomes (Cadmus-Bertram et al., 2015; Helander et al., 2014; Krukowski et al., 2013). Similarly, developing participants' self-regulation skills is often recommended as a means of increasing treatment engagement in the medical literature. For example, Kalichman and colleagues (2011) found that interventions that build participants' self-regulation skills lead to improved adherence to a medical app. Despite its emphasis in the medical literature, the role of self-regulation in adherence has received little attention for technology-based therapeutic interventions.

Behavioral self-efficacy. While self-regulation is the perceived ability to control one's own internal experiences, self-efficacy captures one's perceived capability to learn and perform certain behaviors (Bandura, 1997). When considering healthy behavior change, many models consider perceived self-efficacy to be an important variable at all stages of change (e.g., Health Action Process Approach; Schwarzer, 2008). Self-efficacy is important both for the execution of the behavior change, as well as for the management of obstacles that may arise (Schwarzer, 2008). From the perspective of self-determination theory, feelings of self-efficacy and

competency foster a sense of mastery over time, which is a powerful intrinsic motivational factor that can enhance adherence (Bakker et al., 2016). The positive association between self-efficacy and adherence has been demonstrated for medical regimens (Barclay et al., 2007; Dunbar-Jacob & Mortimer-Stephens, 2001; Nokes et al., 2012) and FTF psychological treatments (Bouchard et al., 2003). Limited quantitative and qualitative research of mental health technologies has identified associations between greater self-efficacy and continued engagement with interventions, including Headspace (Laurie & Blandford, 2016; Melville et al., 2010).

Behavioral intent. Stage theories of health-related behavior change assert that, in addition to motivation, behavioral intent is essential for change to actually occur (Cohn et al., 2012; Prochaska & DiClemente, 1983; Schwarzer, 2008). Developing the intent to engage in a new behavior like mindfulness, such as through goal-setting, generates intrinsic motivation and in turn supports adherence (Mohr et al. 2011). Additionally, intention is a critical prerequisite for developing routines and habits that can sustain adherence to mindfulness and other behaviors over time (Chatzisarantis & Hagger, 2007; Gipson & King, 2012). For FTF therapies, having the intent to engage with an intervention is linked to better treatment adherence (Tsang et al., 2010). In fact, motivational interviewing techniques, which include building intention, have been developed to foster motivation and readiness for change, as well as to improve treatment adherence (Rollnick & Miller, 1995).

Routine. However, it is also important to recognize that intentions do not always translate into action since other factors can interfere, such as social and cognitive influences (e.g., forgetting; Wood & Neal, 2007). To support initiation and maintenance of a behavioral practice, such as using Headspace, intention must be coupled with routine. Although routines and habits both involve repetitive and regular behaviors, routines require attention and effort whereas

habits develop later once the behavior becomes automatic (Charmaz, 2002). Routine is cited as a critical factor for adherence (Leventhal et al., 2016), and incorporating mindfulness and other behavioral changes into one's daily routine is recommended for adherence (Murray et al., 2011). Behavioral routine predicts adherence to various health-related interventions, including medication use (Bolman et al., 2011; Tanenbaum et al., 2015). In fact, those who create a routine for their medication use are approximately 4 times more likely to be adherent over time than those who do not have a routine (Brooks et al., 2015). In terms of Headspace specifically, routine variability is associated with worse adherence as well (Laurie & Blandford, 2016).

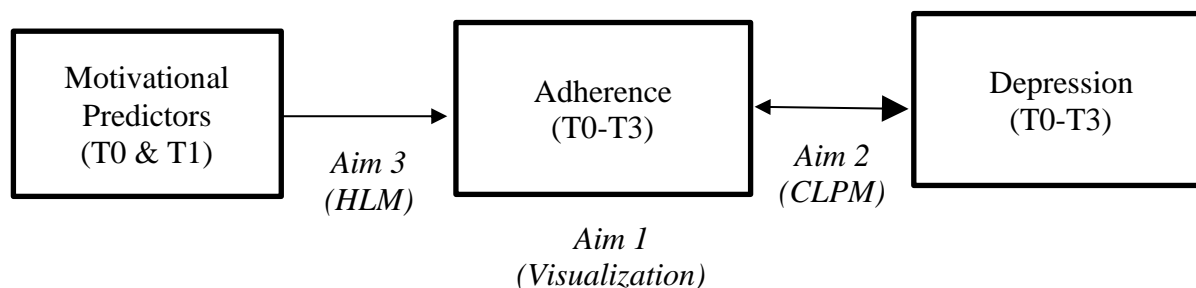
Expected and perceived benefit. Finally, both expecting positive outcomes from a treatment and perceiving positive changes once the treatment has begun are linked to greater adherence (Donkin et al., 2011). From the perspective of Becker and Maiman's Health Belief Model (1975), both expected and perceived benefits are essential for continued adherence as individuals weigh the benefits and costs of engaging in a new behavioral practice or intervention. As demonstrated in the medical field, having positive expectations for treatment can increase motivation and thus adherence to a range of medical treatments (Geers et al., 2005; Murphy et al., 2002; Reisi et al., 2016; Rubin, 2005). Similarly, the FTF therapy literature shows that positive expectations for treatment, as well as perceived benefit during treatment, are linked to better adherence (Adams & Scott, 2000). In a study of participants using Headspace, increased engagement was predicted by both positive expectations at the beginning of the study as well as perceiving more benefits from the MHapp once use began (Laurie & Blandford, 2016). However, other research fails to find a predictive relation between positive expectations for change and adherence, as measured by total time spent practicing mindfulness (Ribeiro et al., 2018).

Despite the extensive investigation of adherence predictors in the medical field, fewer studies have focused on these questions in the psychology literature, and even less so for mental health technologies. Considering the challenges to adherence for MHapps, more research is needed to elucidate potentially modifiable characteristics that could be bolstered to maximize engagement and thus intervention effects (Cavanagh et al., 2013; Mohr et al., 2013a).

Current Study

Prior research suggests that rates of depression have risen across the past decade, yet treatment utilization has not shown commensurate change over time. MHapps and technologies are touted as a potentially powerful means of addressing the treatment gap, and mindfulness-based interventions may be particularly effective in targeting depressive symptoms. While adherence has been identified as a primary challenge in this area, few studies report usage data and preliminary findings are difficult to synthesize due to varied adherence metrics. Further, more nuanced research is needed to better understand the relation between adherence and changes in mental health outcomes. Finally, little is known about potentially modifiable motivational characteristics that may predict and promote adherence. Given their high rates of distress, low treatment-seeking behavior, ubiquity of technology use, and reported interest in MHapps, college students represent an ideal population with whom to further explore such questions. Given the limitations in the prior literature, the proposed study addresses three primary aims (see Figure 1 for theoretical model).

Figure 1. Proposed Theoretical Model of Research Aims 1 to 3



Aim 1: Adherence Patterns.

The current study will explore patterns of adherence to the MHapp Headspace over a three-month trial among college students with elevated depressive symptoms. To extend prior research, a comprehensive picture of adherence will be provided by examining a range of adherence metrics (see Table 1). Metrics will include cumulative minutes spent on the MHapp, cumulative number of sessions completed, cumulative number of modules completed, loyalty (i.e., number of sessions completed each week), regularity (i.e., number of days in a week with at least one session completed), continued engagement (i.e., duration of time between the first and last completed session), depression practice (i.e., proportion of minutes and sessions completed each week from the depression module), and mental health practice (i.e., proportion of minutes and sessions completed each week that had a mental health focus). Adherence metrics will be presented using descriptive statistics (e.g., mean, standard deviation; generally captured weekly), and through data visualization techniques (e.g., line graphs, histograms; generally depicted monthly).

Table 1. Metrics of Adherence, Predictors of Adherence Trajectories, and Outcome

Adherence Metric	Description	Measurement Intervals (for Aim 1)	Expected Range
Cumulative minutes	Sum of total minutes completed	Daily	--
Cumulative sessions	Sum of total sessions completed	Daily	--
Cumulative modules	Sum of total modules completed	Daily	31-85
Loyalty	Average number of sessions completed	Weekly	0-7
Regularity	Average number of days with at least one session completed	Weekly	0-7
Continued engagement	Time between the first and last completed session	Full trial (3 months)	0-90
Depression practice – minutes	Percentage of minutes completed from the depression module out of the total time completed	Weekly	0-100%
Depression practice – sessions	Percentage of sessions completed from the depression module out of the total sessions completed	Weekly	0-100%
Mental health practice – minutes	Percentage of minutes completed from mental health-related modules out of the total time completed	Weekly	0-100%
Mental health practice – sessions	Percentage of sessions completed from mental health-related modules out of the total sessions completed	Weekly	0-100%

Variables	Scale Name	Items, α	Rating Scale	Range
<u>Predictors</u>				
Self-regulation (T0)	<i>Self-Regulatory Self-Efficacy Scale</i> (SRSE; Harrison & McGuire, 2008)	4 items $\alpha = .62$	1 (<i>Not well at all</i>) to 7 (<i>Very well</i>)	4-28
Behavioral self-efficacy (T1)	Developed for this research	1 item --	0 (<i>Not at all true</i>) to 4 (<i>Extremely true</i>)	0-4
Behavioral intention (T1)	Developed for this research	5 items $\alpha = .82$	1 (<i>Not likely</i>) to 5 (<i>Extremely likely</i>)	5-25
Routine variability (T1)	Developed for this research	10 items --	--	--
Perceived & expected benefit (T1)	Developed for this research	6 items $\alpha = .90$	0 (<i>Not at all true</i>) to 4 (<i>Extremely true</i>)	0-24
<u>Outcome</u>				
Depression	<i>Patient Health Questionnaire-9</i> (PHQ-9; Kroenke & Spitzer, 2002)	9 items $\alpha = .71$	0 (<i>Not at all</i>) to 3 (<i>Nearly every day</i>)	0-27

Due to the mixed findings and variability in adherence metrics, adherence patterns will be investigated in an exploratory manner. However, based on limited prior data, it is hypothesized that there will be a small proportion of students who never initiate Headspace use (Donkin et al., 2011; Kaltenthaler et al., 2008; Waller & Gilbody, 2009). Of those who do, adherence is expected to decline after the first month, and less than half of participants will show continued engagement into the final month of the trial.

Aim 2: Interplay of Adherence and Depression.

Additionally, the study will investigate the mutual relation between adherence and depression over the three-month trial, as well as the relative strength of these connections. It is hypothesized that higher levels of adherence will predict significant reductions in depressive symptoms, and reductions in depressive symptoms, in turn, will also predict increases in adherence. The strength of the effect of adherence on reductions in depression is predicted to be greater relative to the effect of depression on adherence.

Aim 3: Motivational Factors Predicting Adherence.

Finally, the current study will investigate whether motivational factors predict adherence patterns over time. Predictors to be examined include self-regulation (T0), behavioral self-efficacy (T1), behavioral intent (T1), routine variability (T1), and perceived and expected benefit (T1). Based on prior literature, it is hypothesized that greater levels of self-regulation, behavioral self-efficacy, and expected and perceived benefit, as compared to lower levels of these variables, will predict higher levels of adherence to Headspace over three months. Meanwhile, lower levels of routine variability as compared to greater variability will predict higher levels of adherence as well. Also based on prior literature indicating that intent is necessary but not sufficient for adherence, behavioral intent is predicted to have a non-significant relationship with adherence.

CHAPTER THREE

METHODS

Participants

The proposed study analyzed data from the Supported Mindful Learning (SMiLe) study, a three-month RCT assessing the effectiveness of a technology-based mindfulness program, Headspace, in improving the mental health of college students experiencing depressive symptoms. Headspace is an online/mobile app that delivers brief, guided mindfulness exercises. Headspace includes modules that typically include 10-30 sessions following a particular theme. For example, the app includes a “basics” module that aims to teach foundational mindfulness skills and principles, and other modules target specific experiences, such as depression, anxiety, happiness, focus, or relationships. Headspace also has single sessions that typically are intended to be used in a specific moment or situation, such as before an interview or while walking in nature. Users can customize the length of sessions, with shorter (1-3 minutes), mid-range (3-10 minutes), or longer (10-20 minutes) options.

Each semester across two years (i.e., four semesters), approximately 15 students who met the inclusion criteria, as described below, were randomized to one of four intervention conditions: Headspace with Peer Support, Headspace as Usual, Headspace as Usual without Orientation, and a Waitlist Control, which later became the Delayed Headspace as Usual group. The first two groups (i.e., Headspace with Peer Support and Headspace as Usual) attended an orientation session wherein participants were familiarized with the study procedures, basic

principles of mindfulness, and content of the Headspace app. Both groups then activated a code that allowed free access to all Headspace content for three months. Participants were encouraged to use Headspace daily, but ultimately engagement was self-guided. At this point in the orientation, participants in the Headspace as Usual group were dismissed, and did not have additional, organized contact with other study participants or the research staff beyond survey assessments and compensation. Meanwhile, those in the Headspace with Peer Support group stayed at the orientation session for a final section reviewing the online and in-person small group procedures.

In addition to using Headspace on their own, participants in the Headspace with Peer Support group joined a secret, closed Facebook group with the goal of enhancing social connection, motivation, and encouragement. Research staff posted quotes and prompts in the Facebook group approximately five times per week to motivate participants to share their own mindfulness experiences. Additionally, research staff posted group members' user statistics twice per week, which included each participant's total sessions and minutes completed, number of days from the past week that Headspace was used, and the general content that was completed. This same content (i.e., daily quotes and user statistics), as well as a brief explanation of the psychological and physical benefits of mindfulness, was emailed as a digest twice per week, with links to Headspace and the Facebook group.

Based on participant feedback during exit interviews, the third semester of the study added three in-person small group sessions occurring every other week during the first two months of the trial (i.e., 2, 4, and 6 weeks after the orientation and code activation) for the Headspace with Peer Support group. Sessions followed a general structure wherein research staff gave a brief introduction and reminder of the purpose of the small group sessions (i.e., for

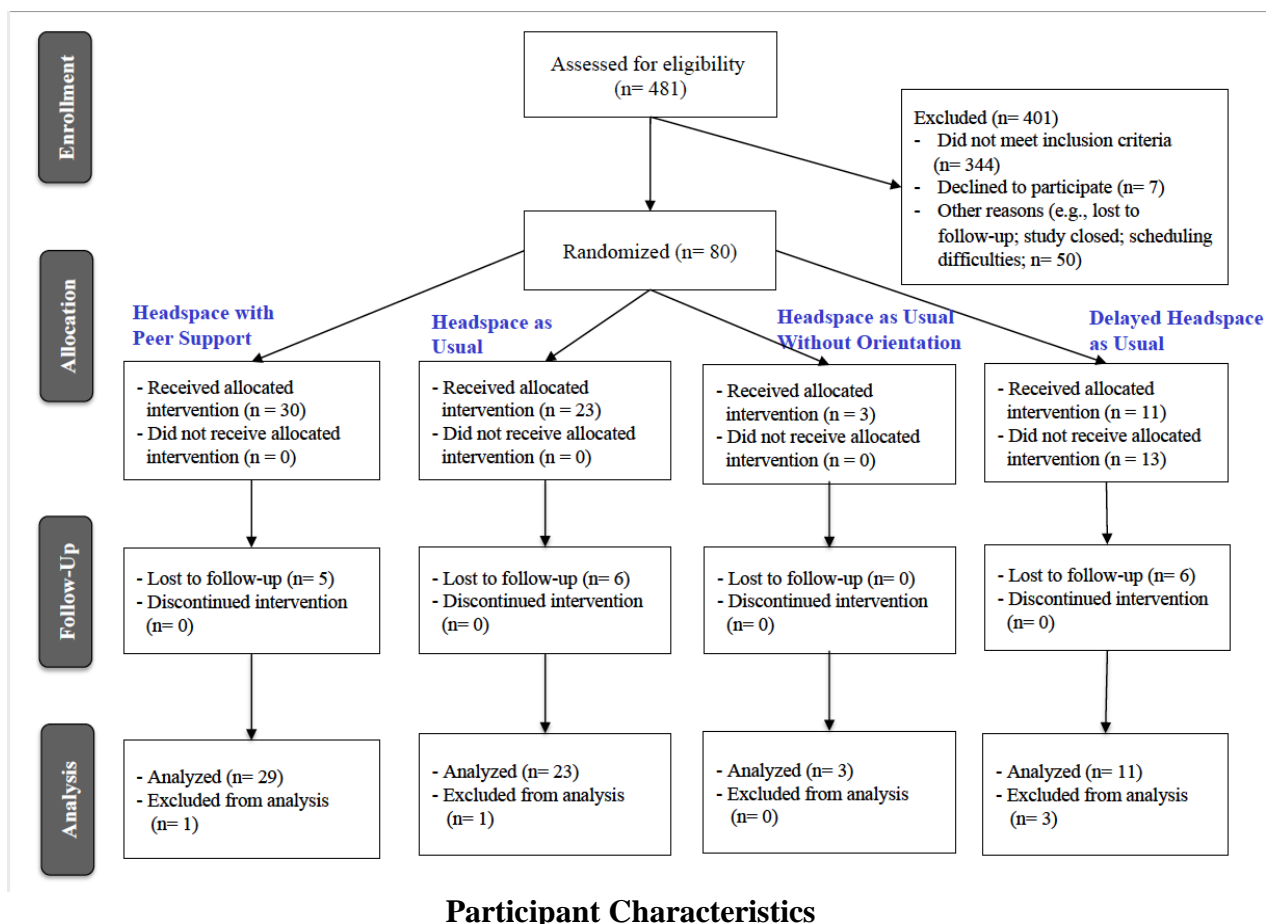
participants to connect and share their experiences with mindfulness) and of any goals that were set by participants in the prior session. Then participants were free to discuss their experiences with Headspace and mindfulness, share their successes and challenges, and talk about their shared experiences as college students, with minimal direction from research staff. At the end, research staff highlighted themes from the discussion, answered any logistical questions, and helped participants to set new group and individual goals for the next small group session.

The Headspace as Usual without Orientation and the Waitlist Control group did not attend the orientation session and also did not have contact with other study participants. The Headspace as Usual without Orientation group started the study at the same time as the other participants but did not attend the orientation session, and met separately with research staff to activate their access code to Headspace. For the Waitlist Control group, participants had the opportunity to meet with research staff and activate the same free access code for Headspace after the final assessments of the trial (i.e., three months after baseline). These participants, who are referred to as the Delayed Headspace as Usual group, followed the same procedures as the Headspace as Usual without Orientation group, except that their codes were accessed later at the end of the initial 12-week trial.

A total of 80 undergraduate students were recruited from a mid-sized, Midwestern university using listserv emails, flyers on campus, and Sona postings. An unequal allocation randomization procedure was followed wherein different colored markers were placed in a bag to represent the study groups, with predetermined, differing number of markers for each group depending on enrollment targets, and students blindly chose a marker. Thirty participants were assigned to Headspace with Peer Support (38%), 23 were assigned to Headspace as Usual (29%), 3 were assigned to Headspace as Usual without Orientation (3%), and 24 were assigned to

Waitlist Control (30%). Of the Waitlist Control participants, 11 later engaged in the Delayed Headspace as Usual group at the end of the three-month trial. Given the proposed study hypotheses about Headspace engagement and outcomes, only data from those participants in the four groups that utilized Headspace (i.e., Headspace with Peer Support, Headspace as Usual, Headspace as Usual without Orientation, and Delayed Headspace as Usual) were included in the analyses ($N = 67$; see Figure 2 CONSORT Diagram). One participant was excluded due to missing Headspace data; thus, the final sample included 66 participants. The current study does not examine differences between the randomization groups because such analyses are beyond the scope of this study. Further, the current sample size is underpowered to explore group differences in the proposed analyses. Preliminary data on differences in adherence and outcomes across randomization groups have been presented (Conley et al., 2019; Huguenel et al., 2019), and such findings will be published separately in the future.

Figure 2. CONSORT Diagram of Enrollment Procedures and Numbers



Participants for the proposed study were 18 to 27 years old ($M= 19.1$, $SD= 1.56$) at baseline, and 89% ($N= 59$) of participants identified as female, 6% ($N= 4$) as male, 2% ($N= 1$) as non-binary, and 2% ($N= 1$) as transgender. Seventy-three percent ($N= 48$) of participants identified as heterosexual, 20% ($N= 13$) as bisexual, 5% ($N= 3$) as gay, 3% ($N= 2$) as “other” (e.g., pansexual), and 0% ($N= 0$) as lesbian. Participants were ethnically and racially diverse, with 62% ($N= 41$) identifying as Caucasian, followed by Hispanic or Latinx (17%; $N= 11$), Asian American (12%; $N= 8$), Other (12%; $N= 8$; i.e., Asian, East Asian, Middle Eastern, Arab), Native Hawaiian or Other Pacific Islander (2%; $N= 1$), and African American (2%; $N= 1$). Six-percent ($N= 3$) of the sample selected more than one ethnic / racial category. Students self-reported their

annual family income, with 8% ($N= 5$) reporting less than \$25,000, 17% ($N= 11$) between \$25,000 - 50,000, 18% ($N= 12$) between \$50,000 - 75,000, 17% ($N= 11$) between \$75,000 - 100,000, 23% ($N= 15$) between \$100,000 - 150,000, 9% ($N= 6$) between \$150,000 - 200,000, and 9% ($N= 6$) over \$200,000.

There were no differences between the Headspace with Peer Support, Headspace as Usual, Headspace as Usual without Orientation, and Delayed Headspace as Usual groups at TO on age, $F(3,62) = .026$, $p = .994$, gender $\chi^2(12) = 9.29$, $p = .678$, sexual orientation, $\chi^2(9) = 7.82$, $p = .553$, parental income, $\chi^2(18) = 29.88$, $p = .064$, or baseline depressive levels, $F(3,62) = .276$, $p = .842$. As there was only one participant in the study who identified as Native Hawaiian or Other Pacific Islander, this demographic variable was unevenly distributed, $\chi^2(3) = 21.32$, $p < .001$. Otherwise, there were no differences between the groups in terms of ethnic/racial identities.

Inclusion Criteria

Interested participants completed an online screening survey through Opinio to determine eligibility. To participate in the study, individuals had to be Loyola University of Chicago undergraduate students, at least 18 years old, and endorsing clinically significant levels of depressive symptoms as measured by the Patient Health Questionnaire-9 (PHQ-9; Kroenke & Spitzer, 2002). An 8-item version of the scale was used for screening purposes wherein the item assessing suicidality was removed, per IRB request. Scores of 10 or higher on the PHQ-8 were required for inclusion, which is indicative of clinically significant depressive symptoms (Kroenke et al., 2009). Individuals were excluded if they had a history of neurological conditions or head trauma (e.g., concussions, seizures), were currently engaged in psychological treatment (medication or therapy), had regular practice of mindfulness in the past six months (which is an exclusion criterion common in other mindfulness studies; e.g., Van Dam et al., 2018), had prior

use of the Headspace app within the past six months, and reported that they were unwilling to join the peer support group if randomized to the Headspace with Peer Support condition.

Measures

Participants completed self-report measures at four time-points during the study: pre-trial baseline (T0), one month after code activation (T1), two months after code activation (T2), and three months after code activation (T3). Each survey was administered through the electronic survey tool Opinio and consisted of various measures of psychological functioning and well-being, as well as experiences with mindfulness, the Headspace app, and study features (e.g., the orientation session, the peer support group). Given the naturalistic design of the study, surveys were not always completed at exact one-month intervals. The following are the ranges of survey completion for each time-point from the start of the intervention: T1, 24-36 days ($M= 30.08$ days); T2, 55-66 days ($M= 60.34$ days); T3, 86-110 days ($M= 94.17$ days). Despite this assessment variability, the chosen analysis approach (i.e., HLM; described below) is designed to accommodate unbalanced data as long as the time variable is measured and modeled consistently.

Additionally, the majority of participants completed an electroencephalography (EEG) recording session at pre-trial baseline (T0) and again after two months of Headspace use (T3); however, the EEG data are not included in the present study. Participants were compensated monetarily or with Sona course credit for the completion of surveys and EEG sessions. Of the 66 participants, all participants (100%) completed the survey at T0, 61 (92%) completed the survey at T1, 63 (95%) completed the survey at T2, and 52 (79%) completed the survey at T3.

Adherence.

With participant consent, researchers from Headspace, Inc. emailed user data associated with the free access codes activated by participants. For each session of Headspace that was completed by a participant, the following information was recorded: date, time of day, session module (e.g., Basics), session number within the module (e.g., session 1), session duration in minutes, session platform (i.e., iOS, Android, Desktop), and the corresponding participant access code. All time data was converted from Coordinated Universal Time to local Central Time zone for analyses.

Adherence metrics for the current study included *cumulative number of minutes and sessions* completed across the three-month trial. *Cumulative modules* completed was calculated by summing the number of full 10-session modules completed by each participant by the end of the trial (e.g., 10 sessions of the Self-Esteem module). The metric of *loyalty* was created by calculating the number of sessions completed each week of the three-month trial. *Regularity* describes the number of days within each week wherein a participant completed at least one session. *Continued engagement* was created by calculating the duration of time between the first and the last completed session across the trial. Finally, adherence related to content included *depression practice*, or the proportion of time and sessions (calculated separately) of the total that were from the depression-related module each week, as well as *mental health practice*, or the proportion of time and sessions (calculated separately) of the total that were from modules related to mental health each week (see Appendix A for content that was characterized as relating to mental health).

Self-Regulation.

The Self-Regulatory Self-Efficacy scale (SRSE; Harrison & McGuire, 2008; see Appendix B) is a 4-item questionnaire assessing how well one can employ various self-efficacy skills. Responses were scored from 1 (*Not well at all*) to 7 (*Very well*), with higher total scores indicating higher levels of self-efficacy. Sample items include “how well can you motivate yourself to keep trying difficult tasks?” and “how well can you start over when what you are trying is not working?” Participants completed the scale at T0, and it yielded adequate internal consistency in the current sample ($\alpha = .63$).

Behavioral Self-Efficacy.

Self-efficacy in using mindfulness was assessed by 1 item administered at T1 that asked participants to rate the truth of the statement, “I am confident about using mindfulness on my own in daily life.” Responses were scored from 0 (*Not at all true*) to 4 (*Extremely true*), with higher scores representing greater behavioral self-efficacy.

Behavioral Intent.

Intention for future mindfulness practice was captured by a 5-item scale at T1 created for the current study that asked participants to rate how likely they were to engage in various mindfulness practices in the future (see Appendix B). Responses were scored from 1 (*Not likely*) to 5 (*Extremely likely*), with higher scores representing greater intention to practice mindfulness in the future. Sample items asked participants how likely they would be in the future to “use Headspace (not considering cost)” and “do mindfulness exercises on my own.” The scale produced adequate internal consistency in the current sample ($\alpha = .77$).

Routine Variability.

Participants' routine of practice was captured through variability in the time of day that sessions were completed. Between-session variability was measured by the difference between the time of day that sessions were completed (session 2 time - session 1 time) + (session 3 time - session 2 time) + ... + (session z time - session y time), which was then averaged across the z number of sessions completed in each week. This approach to calculating variability and consistency in behaviors has been used in health-related literature, such as capturing sleep variability (Sánchez-Ortuño et al., 2011; Suh et al., 2012). A higher variability score indicated less routine or consistency in the time of day that a participant utilized Headspace, whereas lower scores indicated greater routine and consistency.

Expected and Perceived Benefit.

Perceived and expected benefit of mindfulness practice was measured at T1 through a 6-item scale created for the current study asking participants about their possible benefit from using Headspace (see Appendix B). Five items in the scale corresponded to perceived benefit, whereas one item corresponded to expected benefit. Responses are scored from 0 (*Not at all true*) to 4 (*Extremely true*), with higher scores representing greater perceived and expected benefit from mindfulness practice. Sample items include “the skills I am learning are valuable and beneficial” and “I expect to see even more benefit and value in the second half of the program.” The scale produced adequate internal consistency in the current sample ($\alpha = .88$).

Depression.

The Patient Health Questionnaire-9 (PHQ-9; Kroenke & Spitzer) is a 9-item questionnaire assessing how often one has been bothered by various depressive symptoms over the past two weeks. Responses were scored from 0 (*Not at all*) to 3 (*Nearly every day*), with

higher total scores indicating more symptoms of depression. Sample symptom-based items include “little interest or pleasure in doing things” and “poor appetite or overeating.” The scale has been validated for non-clinical samples (Martin et al., 2006), and yielded adequate internal consistency in the current sample ($\alpha = .71$ at T0).

Data Analysis Plan

Preliminary Analyses.

Descriptive statistics and correlations among variables in the study were explored prior to main analyses. Data also was examined through descriptive statistics and frequencies to determine data distribution, including the presence of skewness and outliers. Particular attention was paid to possible skew in depression scores at the end of the study trial (T3) given that PHQ-9 score distributions tend to be positively skewed in the general population (Cannon et al., 2007; Kocalevent et al., 2013; Rief et al., 2004; Tomitaka et al., 2018). In accordance with past literature, PHQ-9 total scores with a skewness greater than 1.0 will be corrected with a square root transformation (Jensen et al., 2013; McKechnie et al., 2014; Wang et al., 2012). If the data continue to be skewed due to a large proportion of 0 scores, then total scores will be converted to count data in order to use Poisson distributions. In such a case, all PHQ-9 item scores of 0 and 1 will be changed to 0, or absence of a clinically relevant symptom based on DSM-5 time-course criteria for depressive symptoms, and scores of 2 and 3 will be changed to 1, or the presence of clinically relevant symptom (APA, 2013). Item scores will then be summed to yield a total between 0 and 9.

Analytic Plan for Aim 1: Adherence Patterns.

To examine adherence patterns over the three-month trial, adherence metrics will be presented numerically and visually. For each metric, the mean, standard deviation, and range will

be reported. For cumulative minutes, cumulative sessions, and cumulative modules, data will be plotted in line graphs to visually depict adherence across each day of the trial (x-axis representing days and y-axis representing cumulative adherence). For cumulative minutes and sessions, separate graphs will be created for each of the randomization groups with all individual data points plotted to retain variability. However, given the lack of variability within the metric of module completion, all participant data will be presented in a single graph. Additionally, for all cumulative metrics (i.e., minutes, sessions, modules), data will be summarized in histograms stacked by month (i.e., Month 1, Month 2, and Month 3), with a bar for each participant and the bar's height representing cumulative adherence.

Bar graphs will be created to capture metrics of loyalty and regularity across each of the 13 weeks of the trial, with all participant data collapsed into a single graph. Histograms also will be created to depict adherence at Month 1, Month 2, and Month 3 for metrics of mental health practice in minutes, mental health practice in sessions, depression practice in minutes, and depression practice in sessions. Continued engagement will be examined numerically, and summarized in a histogram. For each of the histograms, adherence values will be presented on the x-axis, and number of participants will be presented on the y-axis, with values collapsed into ranges for data simplicity. Although some of the adherence data will be displayed in separate figures by randomization group, this is only to present the data in a streamlined manner; examining differences between the groups is beyond the scope of the current study. Given the small size of the Headspace as Usual without Orientation group ($N=3$), these participants will be combined with the Headspace as Usual group for Aim 1 visual representations.

Analytic Plan for Aim 2: Interplay of Adherence and Depression.

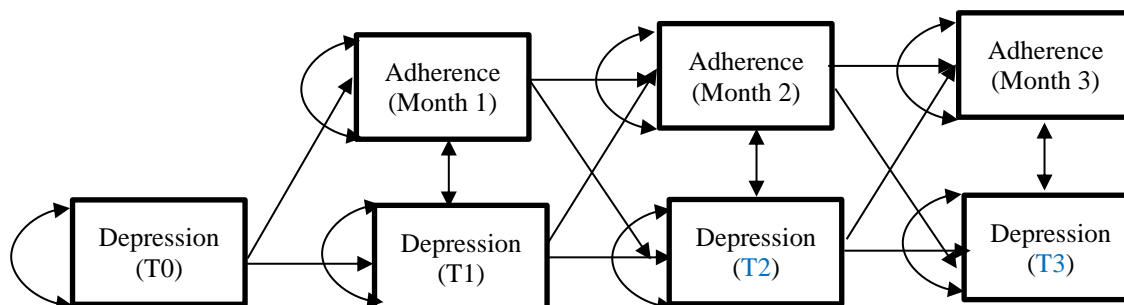
Using structural equation modeling, cross-lagged panel models (CLPM) will be used to examine the directional influence between adherence and depression levels over time. As compared to cross-sectional analyses, CLPM allows for the evaluation of inter-individual change in variables and cross-lagged correlations provide evidence for causal relations between variables longitudinally (Cole & Maxwell, 2003; Kearny, 2016; Selig & Preacher, 2009). Autoregressive coefficients yielded from the CLPM analyses will be used to examine the relative strength of significant paths (Kearny, 2017). Models also will include pathways wherein each variable predicts subsequent occurrences of the same variable, which allows for the direct effect of each predictor to be examined while controlling for the effect of previous timepoints (Cole & Maxwell, 2003; Selig & Preacher, 2009). All participant data will be included in the models, and analyses will not be separated by randomization group.

To reduce the number of analyses performed and possible Type I error, a procedure will be followed to determine which metrics of adherence will be further examined in Aims 2 and 3, with the aim of including no more than four adherence metrics in the subsequent analyses. First, adherence data from Aim 1 will be visually inspected, and adherence metrics with limited variability in scores (i.e., coefficient of variation (CV) <1.0) will not be included in subsequent analyses. Next, the inter-correlation matrix will be examined, and for metrics with a correlation of absolute value of 0.30 (i.e., moderate correlation) or greater, only one of the metrics will be retained for subsequent analyses. If these two steps do not reduce the number of adherence metrics sufficiently, then an exploratory factor analysis will be performed to examine the presence of broader factors that may encompass multiple metrics. Finally, the medical and

psychotherapy literature will be reviewed and the metrics with the most theoretical and research support will be retained, and the committee will be consulted if further reduction is needed.

Depending on the number of adherence metrics retained from the preliminary multiple regression analyses, a maximum of 9 CLPM analyses are possible (9 adherence metrics [excluding continued engagement] x depression). Models will be tested using MPlus Version 7.3 (Muthén & Muthén, 1998-2012; see Figure 3) to examine the inter-relation between adherence and depression at monthly intervals across the three-month trial. Model fit will be evaluated using goodness-of-fit-statistics. Fit indices of root mean square error of approximation (RMSEA, $\leq .08$; Browne & Cudeck, 1992), comparative fit index (CFI, $> .90$; Marsh et al., 2004), Tucker-Lewis index (TLI, $> .90$; Marsh et al., 2004; Tucker & Lewis, 1973), and standardized root mean square residual (SRMR, $< .08$; Hu & Bentler, 1998) will be used to evaluate model fit. RMSEA and SRMR are indices of absolute fit since they compare the proposed model to a perfect fit, whereas TLI and CFI examine incremental fit since they assess whether a modified model would represent an improvement relative to the proposed model. Additionally, modification indices will be requested for the model to determine whether model fit would be improved by including additional parameters. Following the guidelines proposed by Bentler (1995), at least five participants are needed for each estimated parameter of the model. Thus, the current model, with 20 estimated parameters, would be adequately powered by a sample size of at least 130.

Figure 3. Model for Aim 2: Depiction of Adherence and Depression as Time-Varying Covariates in a Cross-Lagged Panel Model



Note. Cross-lagged paths between adherence and depression are expected to be negative relations, whereas linear paths within variables are expected to be positive relations

Analytic Plan for Aim 3: Motivational Factors Predicting Adherence.

Multi-level modeling via Hierarchical Linear Modeling (HLM; Bryk & Raudenbush, 1992) will be used to identify motivational factors that may predict adherence rates. HLM accounts for multiple engagement data points within each participant, which would otherwise violate the independence assumption of traditional multiple regression techniques.

Depending on the adherence metrics retained from Aim 1, a maximum of 9 models (due to the exclusion of continuous engagement) will be explored. A 2-level model will be applied, with time nested within usage data and assessments (Level 1), and assessments nested within participants (Level 2). Given that the current study is not examining differences between the randomization groups, participant data will not be nested within groups. Level 2 time-invariant predictors at the first available timepoint (T0 or T1) will be used to predict subsequent adherence slope trajectories (Month 1 to Month 3, or Month 2 to Month 3, respectively). Level 2 predictors will include self-regulation, behavioral self-efficacy, behavioral intention, routine variability, and perceived and expected. Time will be measured in weekly intervals, with adherence data collapsed across each week of the trial. All five predictor variables will be entered

simultaneously into the conditional model. By mean-centering variables, results will allow researchers can explore whether increases in the motivational variables, as compared to the sample mean, predict differing rates of adherence across the trial.

Published Monte Carlo simulations were reviewed to assess the third aim's power to detect the hypothesized relations between motivational predictors and adherence within a 2-level nested model. Meinck and Vandenplas (2012) conducted a Monte Carlo simulation to explore the effect of varying sample sizes and fit indices in accurately detecting a predictive relation between variables. Even at the smallest cluster size of 50 and within-cluster sample size of 5, parameters were estimated accurately; however, the slope of random intercepts was most negatively affected by the small same size (Meinck & Vandenplas, 2012). Ultimately, the effect of sample size depended on the parameter of interest. Small sample size can result in biased parameter estimates, and so it is recommended to maintain a minimum cluster size of 100 and within-cluster sample size of 10 (Meinck & Vandenplas, 2012). Thus, the cluster size of the current sample is small and may produce biased parameter estimates.

CHAPTER FOUR

RESULTS

Aim 1: Adherence Patterns

The first aim was to explore patterns of adherence to Headspace across the three-month trial. The mean, standard deviation, and range were calculated for each of the adherence metrics on a monthly and weekly level (see Table 2 and Table 3, respectively). Raw adherence data were used for all adherence pattern calculations and visual depictions.

Table 2. Descriptive Statistics Summarizing Adherence Metrics by Month

Metric	<i>Month 1</i> M (SD) Maximum*	<i>Month 2</i> M (SD) Maximum*	<i>Month 3</i> M (SD) Maximum*	<i>Total</i> M (SD) Maximum*
Cumulative minutes	107.33 (89.58) 325.00	87.86 (88.99) 300.00	12.18 (31.89) 190.00	207.38 (183.08) 728.00
Cumulative sessions	14.06 (10.24) 35.00	10.29 (9.97) 37.00	1.32 (3.04) 19.00	25.67 (20.51) 81.00
Cumulative modules	0.39 (0.63) 2.00	0.42 (0.72) 3.00	0.06 (0.30) 2.00	0.88 (1.33) 5.00
Loyalty	3.66 (2.63) 8.75	2.51 (2.24) 7.78	0.50 (0.80) 4.60	2.22 (1.89) 7.04
Regularity	2.78 (1.98) 6.75	2.15 (1.93) 6.75	0.47 (0.72) 4.00	1.80 (1.54) 5.83
Mental health practice – minutes	0.21 (0.27) 0.99	0.27 (0.33) 1.00	0.08 (0.14) 0.60	0.32 (0.31) 1.00
Mental health practice – sessions	0.19 (0.25) 0.97	0.24 (0.31) 1.00	0.07 (0.12) 0.60	0.27 (0.27) 1.00
Depression practice – minutes	0.03 (0.13) 0.97	0.02 (0.12) 0.88	0.00 (0.04) 0.30	0.04 (0.14) 0.91
Depression practice – sessions	0.02 (0.12) 0.92	0.02 (0.12) 0.88	0.00 (0.04) 0.30	0.02 (0.08) 0.52

Note: Maximum values only are presented since the minimum for all metrics was 0.0.

Table 3. Descriptive Statistics Summarizing Adherence Metrics by Week

Metric	Wk 1 <i>M</i> (SD) Max.*	Wk 2 <i>M</i> (SD) Max.*	Wk 3 <i>M</i> (SD) Max.*	Wk 4 <i>M</i> (SD) Max.*	Wk 5 <i>M</i> (SD) Max.*	Wk 6 <i>M</i> (SD) Max.*	Wk 7 <i>M</i> (SD) Max.*	Wk 8 <i>M</i> (SD) Max.*	Wk 9 <i>M</i> (SD) Max.*	Wk 10 <i>M</i> (SD) Max.*	Wk 11 <i>M</i> (SD) Max.*	Wk 12 <i>M</i> (SD) Max.*	Wk 13 <i>M</i> (SD) Max.*
Loyalty	5.11 (3.70) 15.00	3.82 (3.04) 14.00	2.91 (2.93) 15.00	2.80 (2.88) 11.00	3.07 (3.00) 16.00	2.92 (2.86) 11.00	2.42 (2.58) 10.00	1.62 — 2.33 9.00	1.53 (2.03) 6.00	0.45 (1.29) 8.00	0.29 (0.84) 4.00	0.14 (0.65) 4.00	0.07 (0.51) 4.00
Regularity	3.42 (2.31) 7.00	3.17 (2.22) 7.00	2.32 (2.11) 7.00	2.21 (2.29) 7.00	2.44 (2.25) 7.00	2.44 (2.19) 7.00	2.18 (2.14) 7.00	1.54 (2.08) 7.00	1.41 (1.81) 6.00	0.44 (1.08) 6.00	0.30 (0.76) 4.00	0.15 (0.64) 4.00	0.04 (0.37) 3.00
Mental health practice – minutes	0.18 (0.30) 1.00	0.21 (0.33) 1.00	0.25 (0.38) 1.00	0.22 (0.37) 1.00	0.29 (0.40) 1.00	0.25 (0.39) 1.00	0.32 (0.41) 1.00	0.22 (0.40) 1.00	0.22 (0.40) 1.00	0.10 (0.29) 1.00	0.05 (0.21) 1.00	0.01 (0.09) 0.73	0.00 (0.00) 0.00
Mental health practice – sessions	0.15 (0.26) 1.00	0.19 (0.31) 1.00	0.23 (0.36) 1.00	0.19 (0.33) 1.00	0.25 (0.36) 1.00	0.23 (0.36) 1.00	0.29 (0.39) 1.00	0.21 (0.38) 1.00	0.20 (0.38) 1.00	0.09 (0.27) 1.00	0.05 (0.21) 1.00	0.01 (0.08) 0.67	0.00 (0.00) 0.00
Depression practice – minutes	0.03 (0.15) 0.87	0.01 (0.12) 1.00	0.02 (0.13) 1.00	0.04 (0.17) 1.00	0.03 (0.17) 1.00	0.02 (0.14) 1.00	0.02 (0.12) 1.00	0.01 (0.06) 0.50	0.01 (0.06) 0.50	0.01 (0.12) 1.00	0.00 (0.00) 0.00	0.00 (0.00) 0.00	0.00 (0.00) 0.00
Depression practice – sessions	0.02 (0.11) 0.67	0.01 (0.12) 1.00	0.02 (0.13) 1.00	0.04 (0.14) 1.00	0.03 (0.17) 1.00	0.02 (0.14) 1.00	0.02 (0.12) 1.00	0.01 (0.06) 0.50	0.01 (0.06) 0.50	0.01 (0.12) 1.00	0.00 (0.00) 0.00	0.00 (0.00) 0.00	0.00 (0.00) 0.00

Wk= week; *M*= mean; SD= standard deviation; Max. = maximum

Note: Maximum values only are presented since the minimum for all adherence metrics was 0.0.

In terms of cumulative minutes, participants practiced an average of 107 minutes during the first month of the trial, with a range of 0 to 325 minutes. By the second month, adherence decreased to an average of 88 minutes over the month with a range of 0 to 300 minutes. The most drastic change occurred in the third month of the trial, wherein adherence dropped to an average of 12 minutes, with a range of 0 to 190 minutes. Visual inspection of the line graph and histogram of cumulative minutes across the trial reveals a similar picture, with fewer minutes of mindfulness completed as the trial progressed (Figures 4-9). Further, some participants, all of whom were in the Delayed Headspace as Usual group, never initiated use, and others completed a low number of minutes early in the trial and then discontinued. Overall, many participants did not complete any minutes of mindfulness in the third month of the trial.

Figure 4. Line Graph of Cumulative Minutes for the Headspace with Peer Support Group

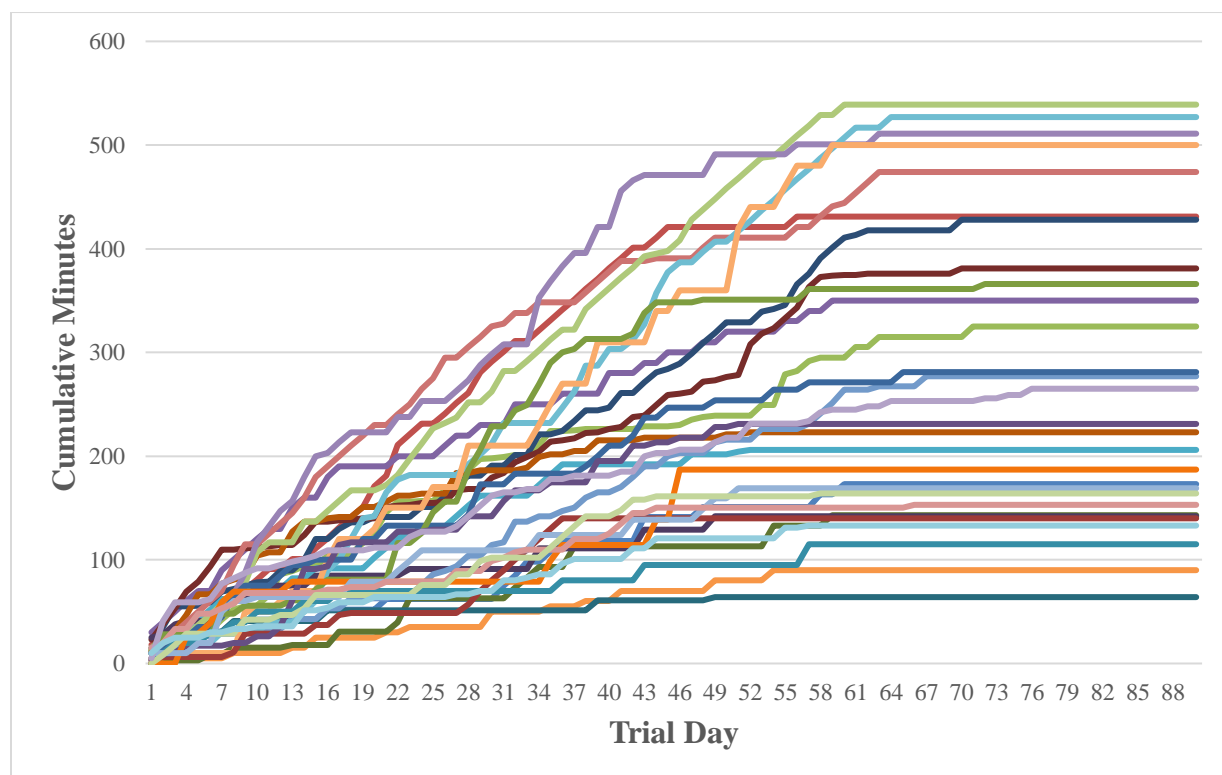


Figure 5. Line Graph of Cumulative Minutes for the Headspace as Usual Group

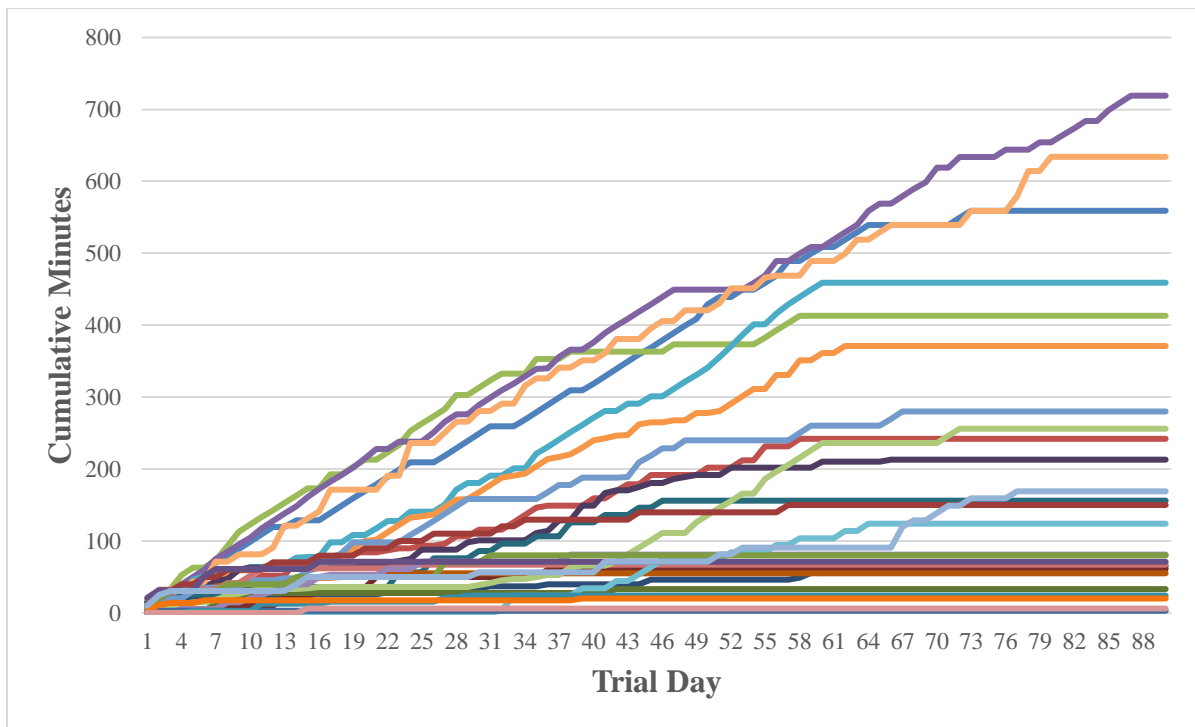


Figure 6. Line Graph of Cumulative Minutes for the Delayed Headspace as Usual Group

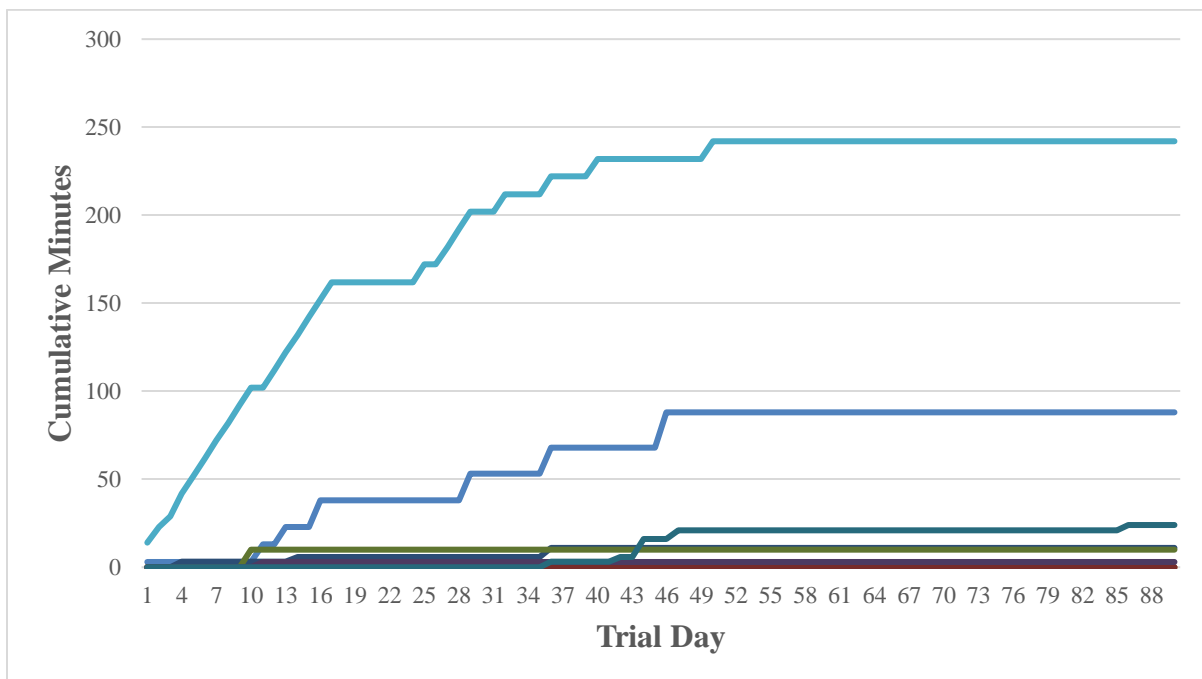


Figure 7. Histogram of Cumulative Minutes for the Headspace with Peer Support Group

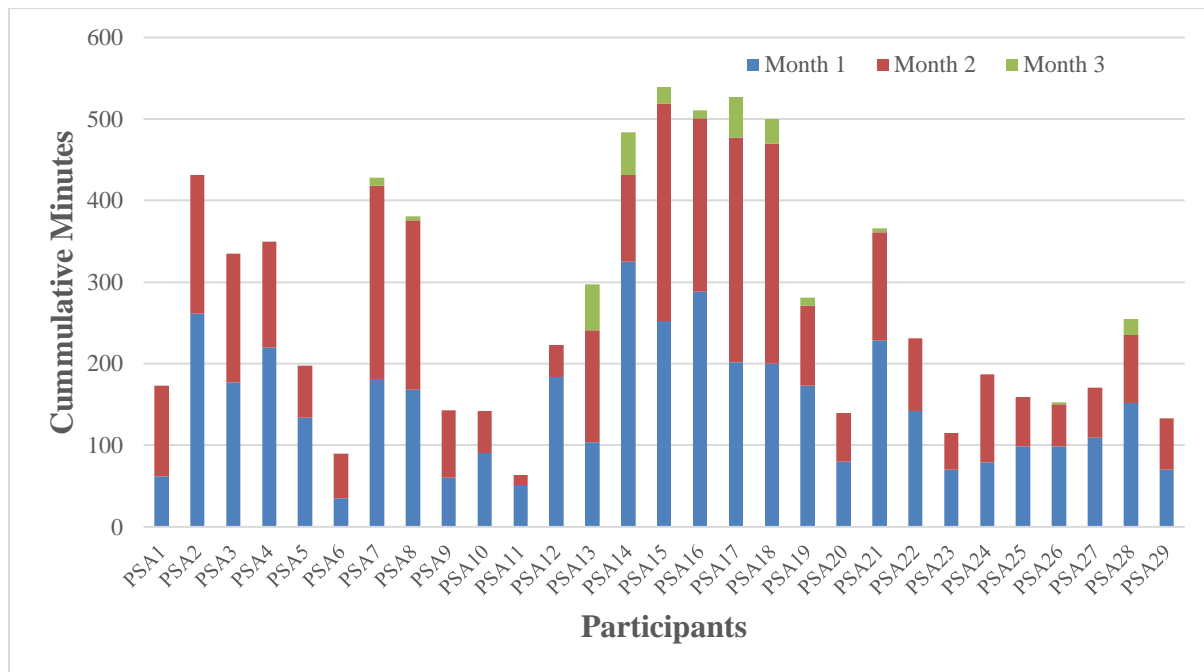


Figure 8. Histogram of Cumulative Minutes for the Headspace as Usual Group

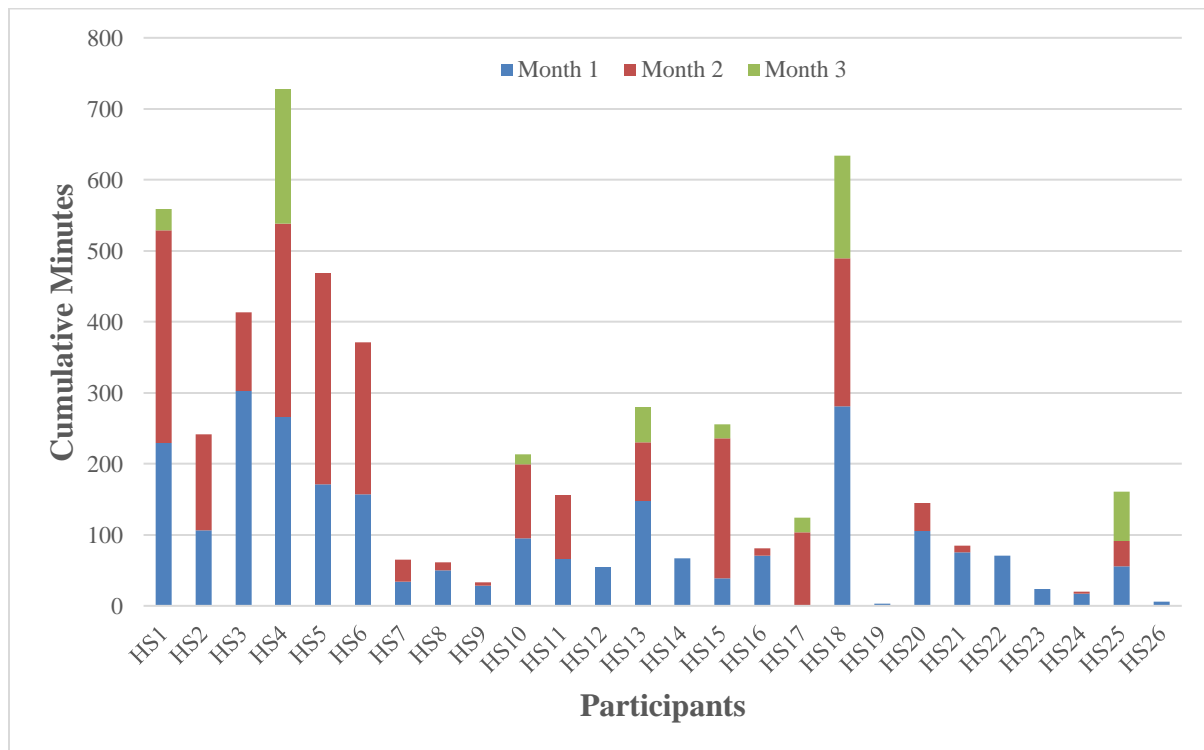
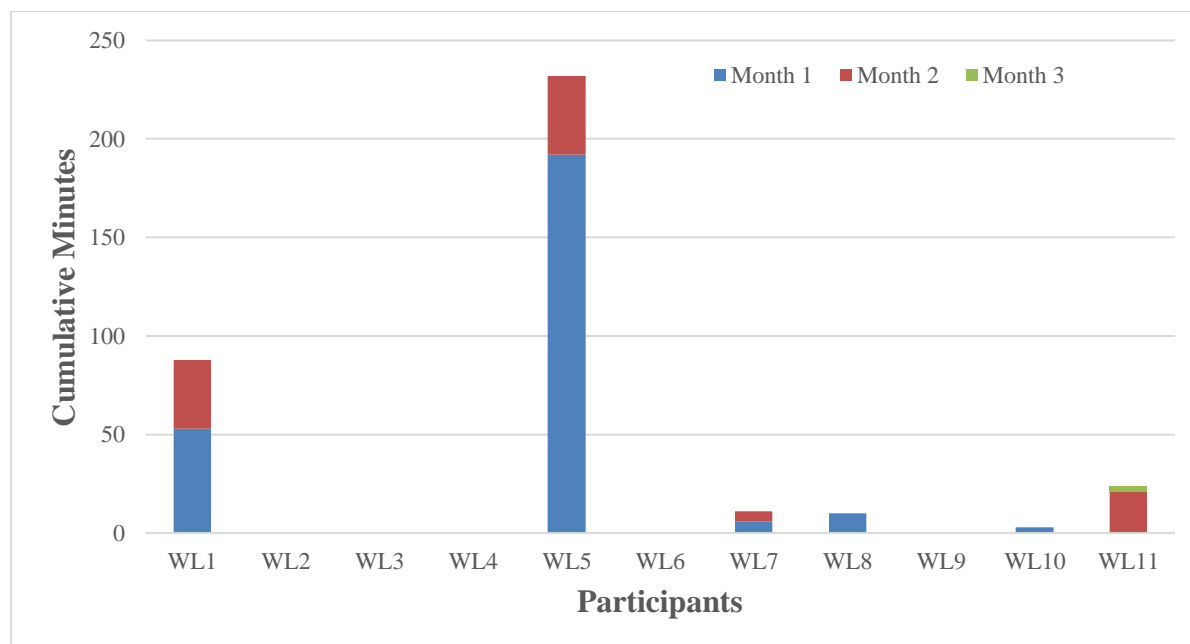


Figure 9. Histogram of Cumulative Minutes for the Delayed Headspace as Usual Group



Similar trends were depicted when focusing on cumulative sessions completed (Figures 10-15). Across the three months, the average number of sessions completed in each month declined from 14 (35 session range), to 10 (37 session range), and to 1 (19 session range). Visual inspection of the line graphs and histograms of cumulative sessions shows that some participants, all again from the Delayed Headspace as Usual Group, never completed any Headspace sessions. Meanwhile, others completed sessions early on but discontinued after the first month. Finally, few participants continued completing sessions into the final month of the trial.

Figure 10. Line Graph of Cumulative Sessions for the Headspace with Peer Support Group

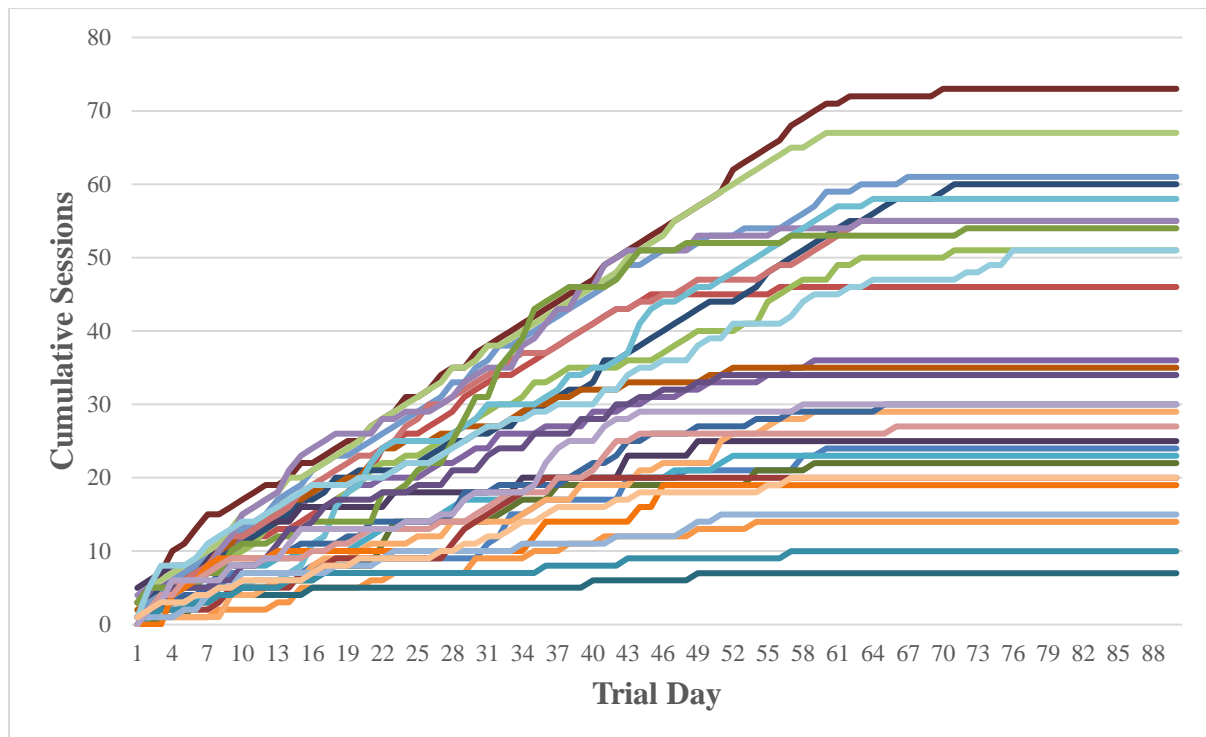


Figure 11. Line Graph of Cumulative Sessions for the Headspace as Usual Group

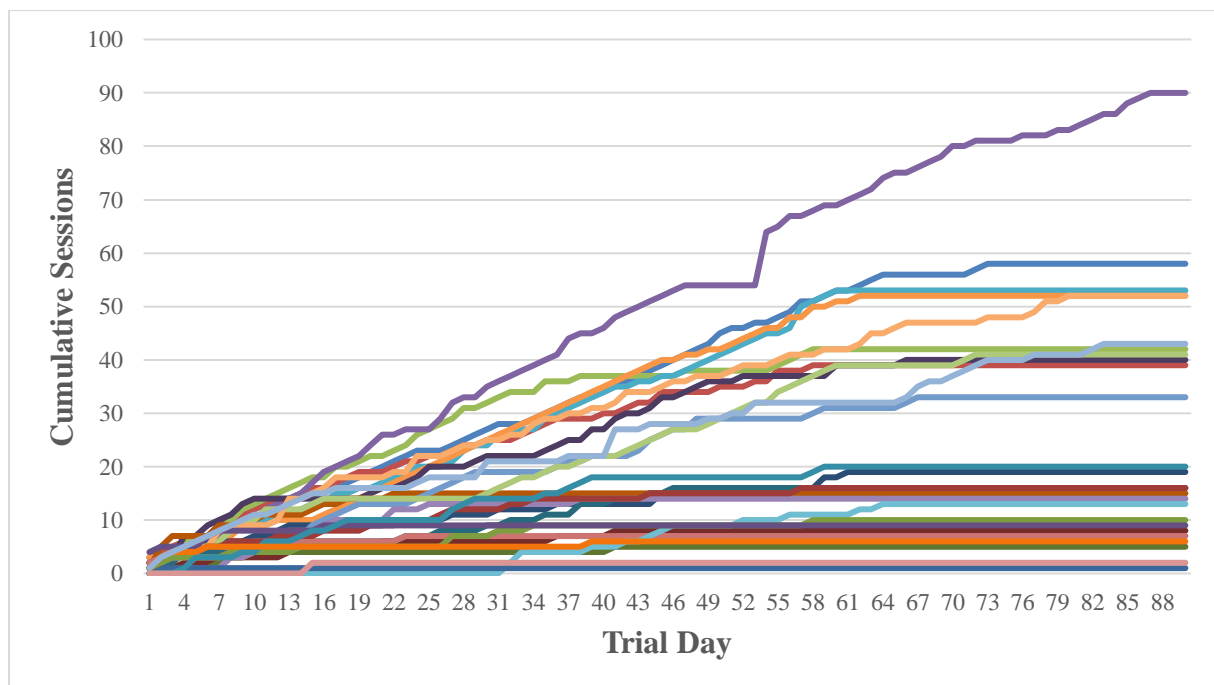


Figure 12. Line Graph of Cumulative Sessions for the Delayed Headspace as Usual Group

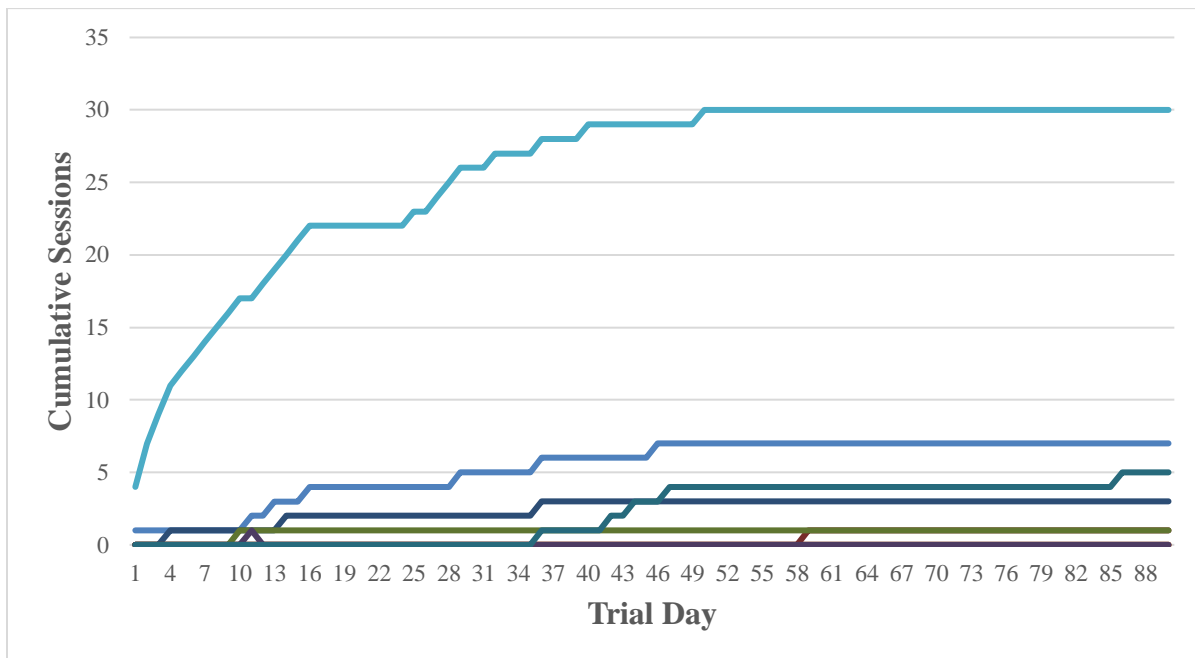


Figure 13. Histogram of Cumulative Sessions for the Headspace with Peer Support Group

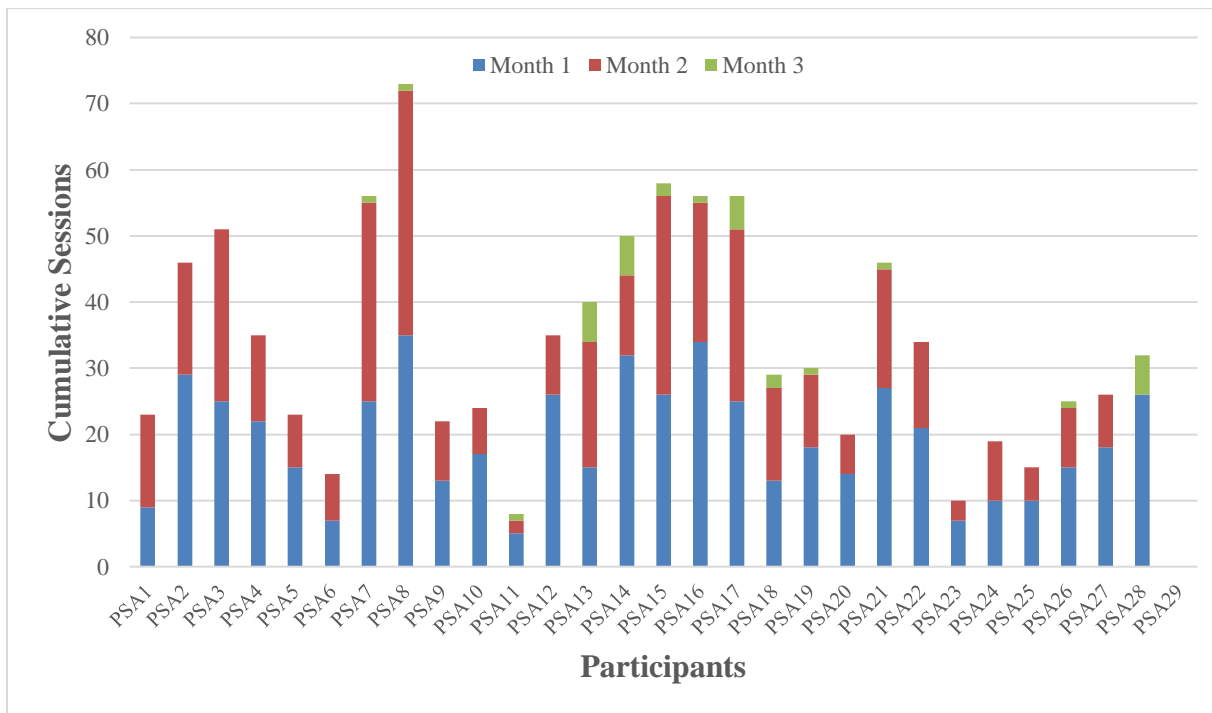


Figure 14. Histogram of Cumulative Sessions for the Headspace as Usual Group

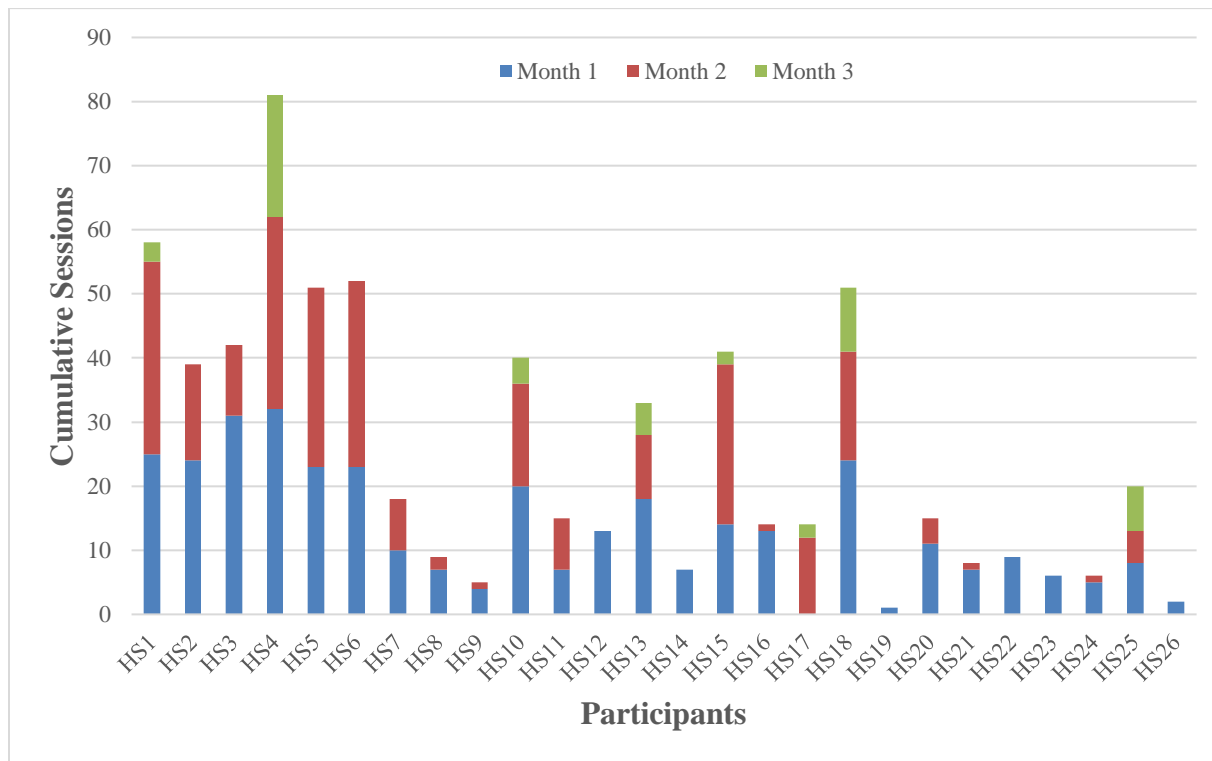
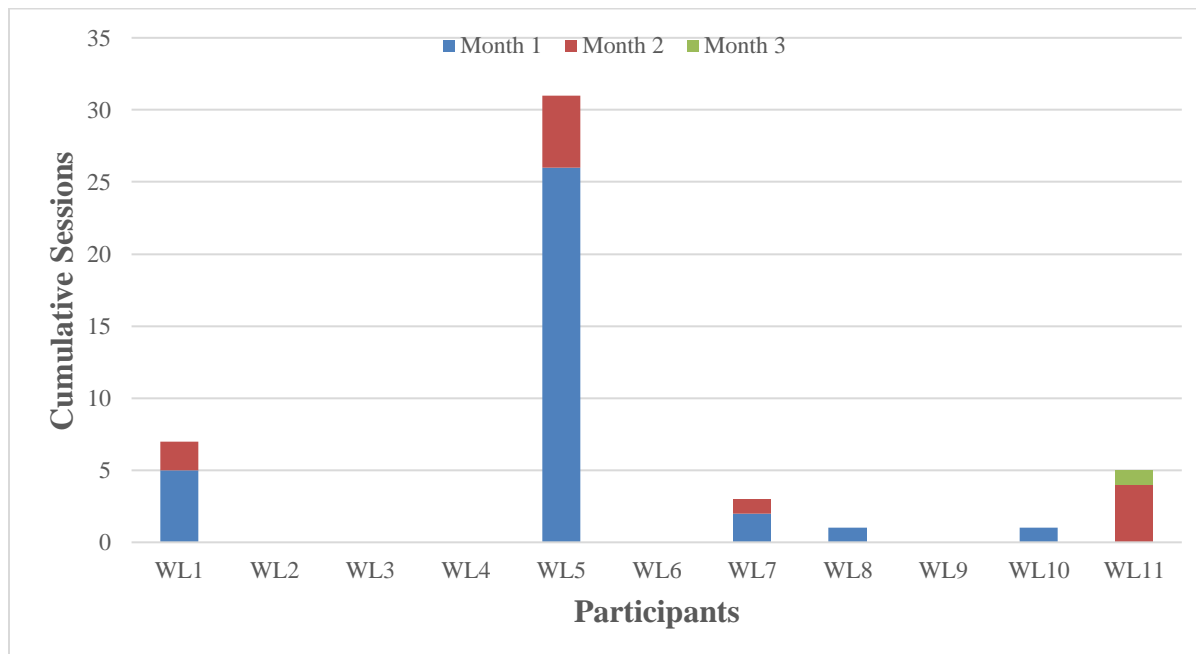


Figure 15. Histogram of Cumulative Sessions for the Delayed Headspace as Usual Group



Completed modules remained fairly low throughout the trial, with an average of 0.4 modules completed during the first two months, which then dropped further to an average of 0.1 modules in the final month. Module completion clustered more within the first month of the trial, and the range extended to 5 modules completed across the three-month trial (Figures 16-17); however, the majority of participants (59.1%) did not complete any modules by the end of the trial.

Figure 16. Line Graph of Cumulative Modules for All Participants

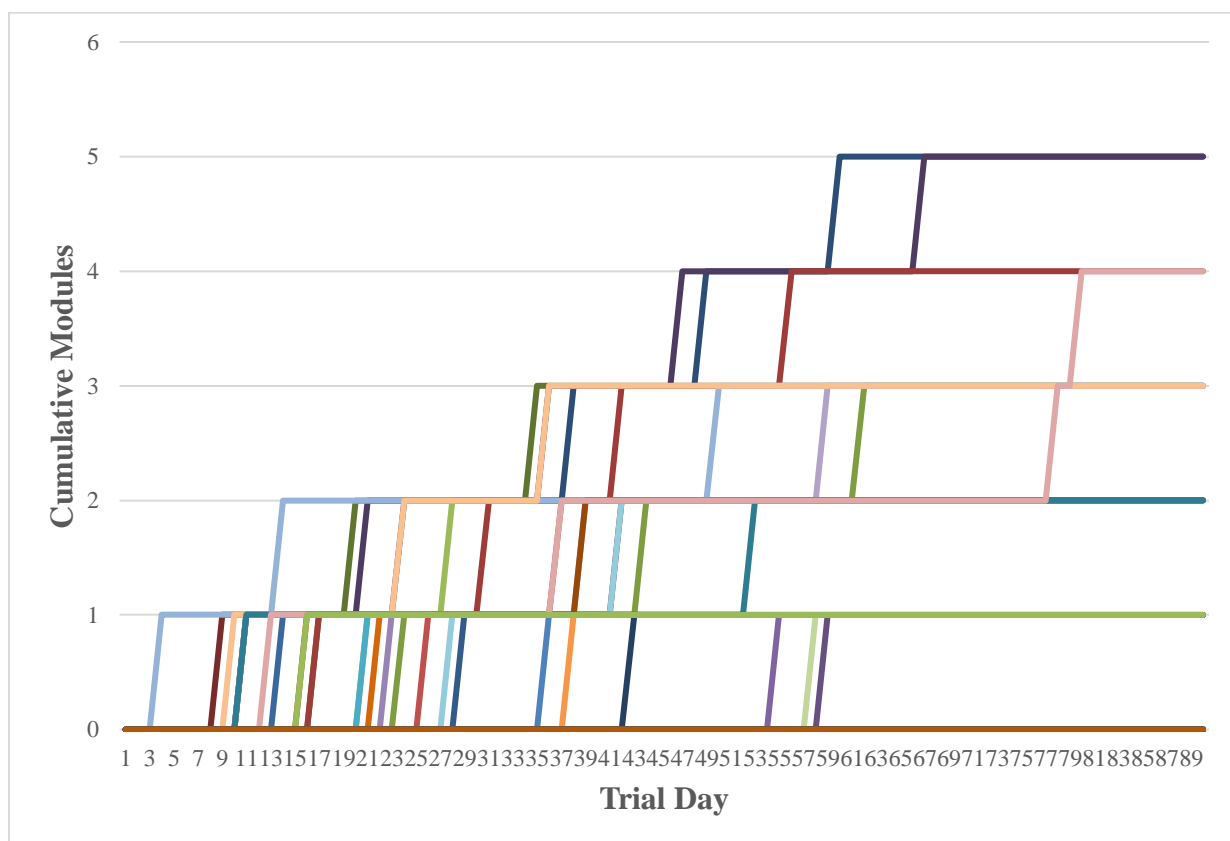
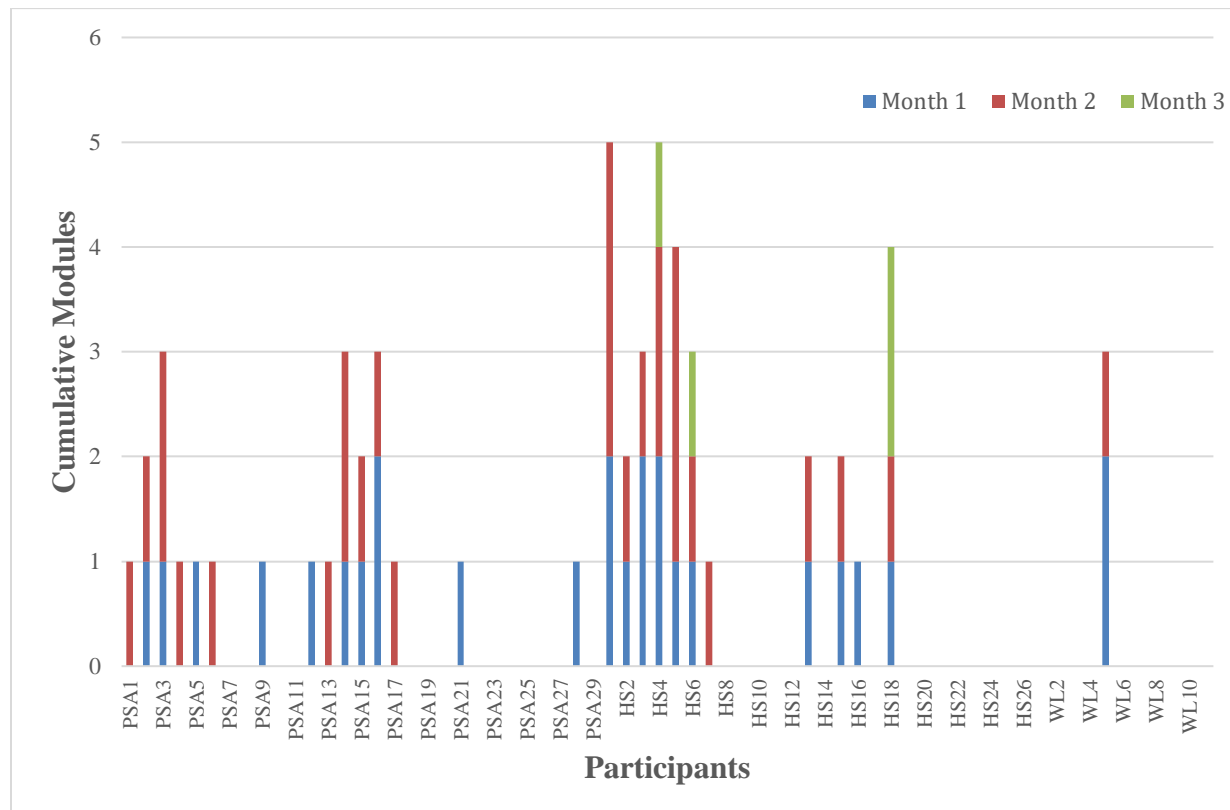
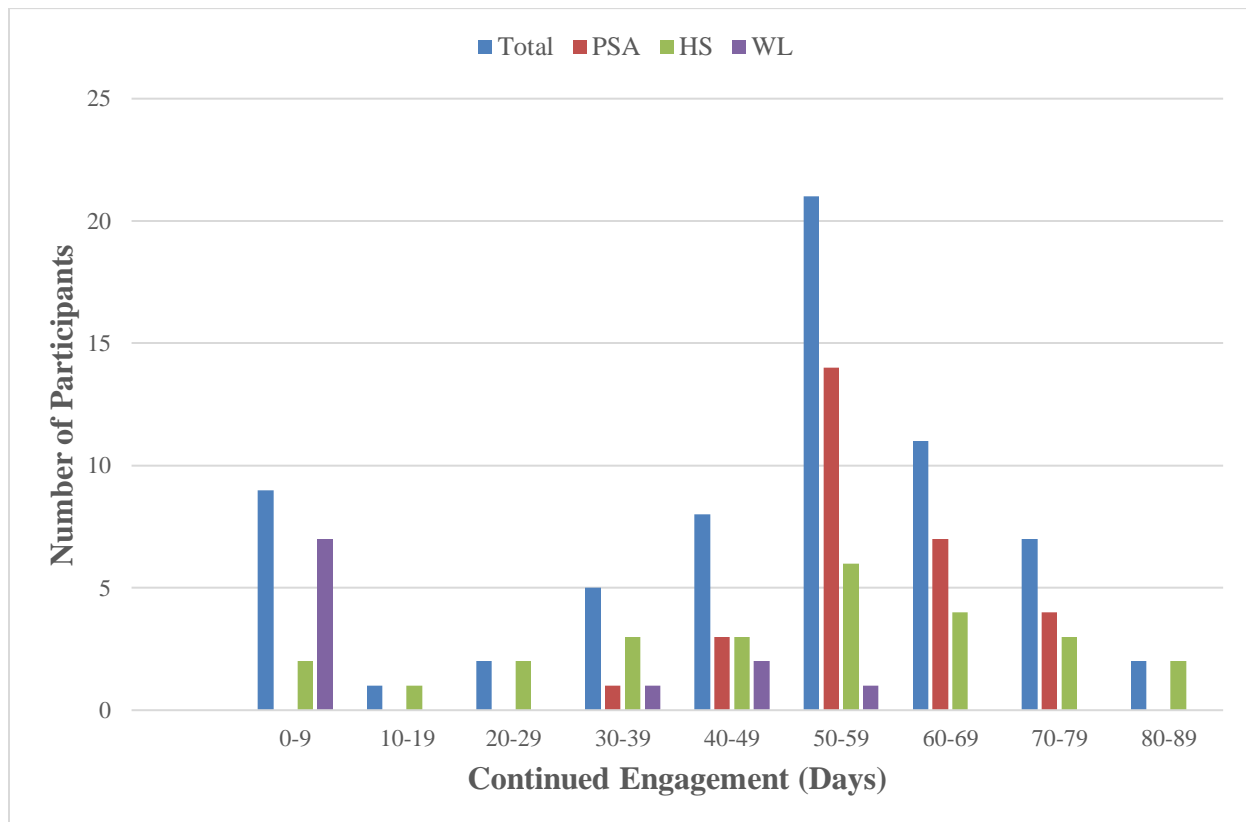


Figure 17. Histogram of Cumulative Modules for All Participants



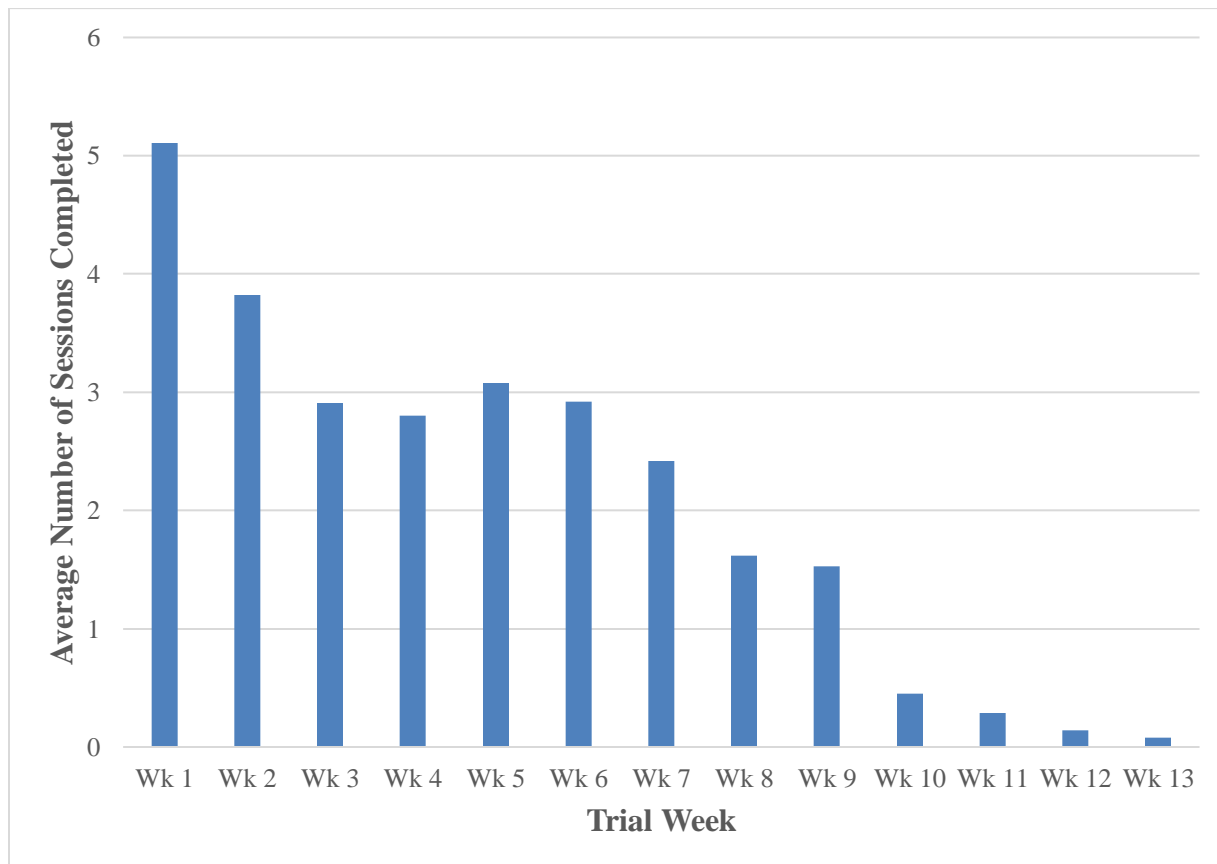
In terms of continued engagement (Figure 18), the largest portion of participants fell into the range of using Headspace across a span of 50 to 59 days. Importantly, a number of participants—particularly from the Delayed Headspace as Usual group—used the app fewer than 9 days, with some never initiating use. Further, only two participants out of 66 continued using the app into the final week of the trial, both of whom were randomized to the Headspace as Usual group. While group differences are not explicitly examined, it is notable that the longest engagement for those in the Delayed Headspace as Usual group fell into the 50 to 59 days range.

Figure 18. Continued Engagement for All Participants



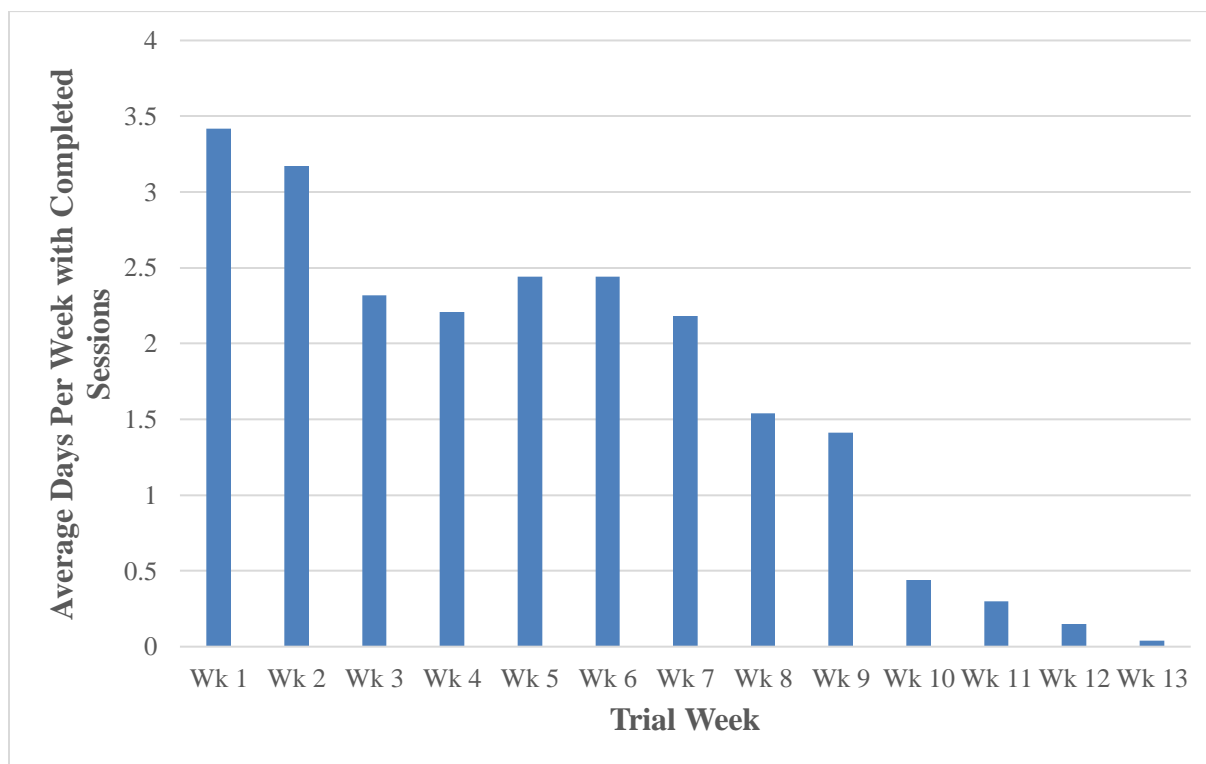
Metrics of loyalty and regularity were calculated at both monthly and weekly levels (see Table 2 and 3, respectively). Loyalty calculations and bar graphs showed that the average number of completed sessions per week was the highest in the beginning of the trial, with an average of 5.1 sessions completed across the first week (Figure 19). From there, loyalty generally decreased, varying between an average of 2.4 to 3.8 sessions completed during weeks 2 through 7, then 1.5 to 1.6 sessions in weeks 8 to 9, and then dropped to less than an average of 0.5 sessions per week for the remainder of the trial (weeks 10 through 13).

Figure 19. Loyalty for All Participants



Adherence patterns for regularity showed that the average number of days per week with at least one session completed was the highest during the first week at 3.4 days, and similarly was 3.2 during the second week of the trial (see Table 3; Figure 20). From weeks 3 through 7 of the trial, the average number of days per week with completed sessions ranged from 2.2 to 2.4, and declined to an average of 1.4 to 1.5 days in weeks 8 and 9. For the remainder of the trial (weeks 10 through 13), regularity was below 0.5 days per week.

Figure 20. Regularity for All Participants



As shown in Table 3, participants' completion of mental health content varied between an average of 18 to 29% of their total completed minutes in the beginning of the trial through week 6 (see also Figure 21). Minutes of mental health practice then peaked at 32% of total content during week 7, and decreased through the end of the trail, with less than 10% of completed minutes qualifying as mental health-focused for the final weeks (weeks 10-13). A similar pattern was found for mental health practice when it was captured by sessions instead of minutes (see Table 3; Figure 22). Fifteen to 25% of completed sessions had a mental health focus across the first six weeks of the trial. Mental health practice again peaked during week 7 at 29% of completed sessions, and then similarly decreased through the end, with less than 10% of sessions relating to mental health during weeks 10 through 13.

Figure 21. Mental Health Practice in Minutes for All Participants

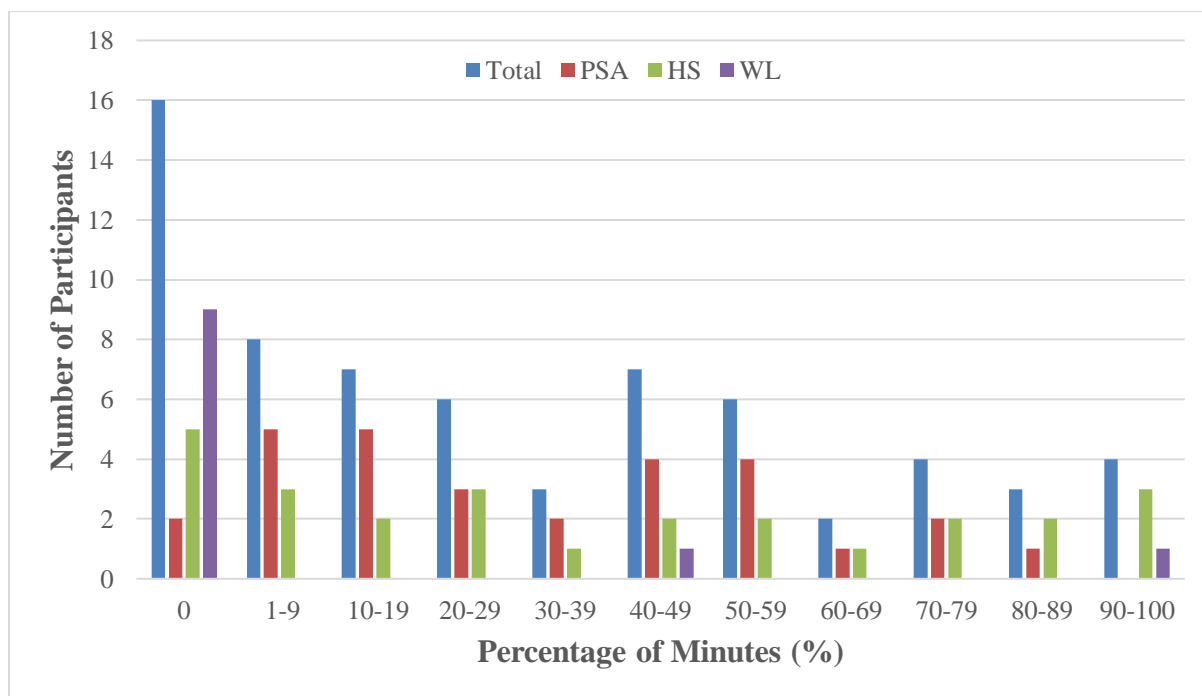
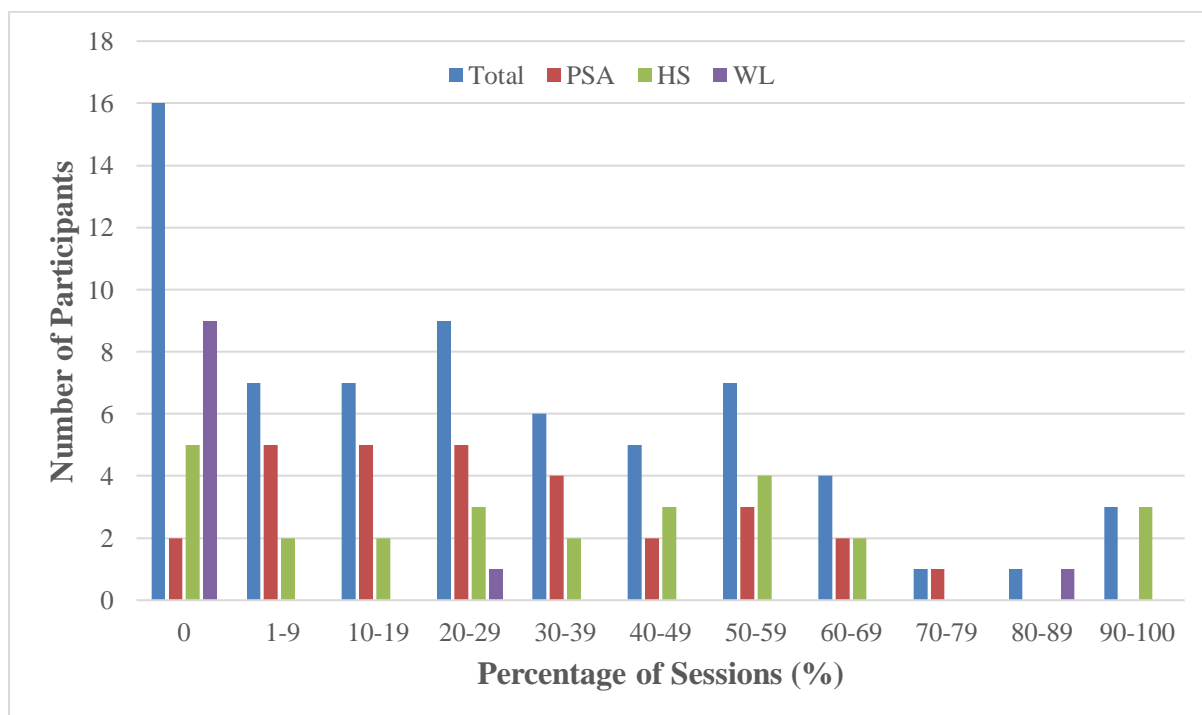


Figure 22. Mental Health Practice in Sessions for All Participants



Finally, Tables 2 and 3 show that the pattern for depression practice as captured by both minutes and sessions is identical with the exception for week 1 (3% vs. 2% of completed content, respectively), so they will be described together. Depression practice remained low throughout the trial with little variability (Figures 23 and 24). This adherence metric ranged between 1 to 3% across the first three weeks, peaked at 4% during week 4, and then decreased to 2 to 3% from weeks 5 through 7. Depression practice then lowered to 1% of total content for weeks 8 through 10, and then to 0% through the end of the trial.

Figure 23. Depression Practice in Minutes for All Participants

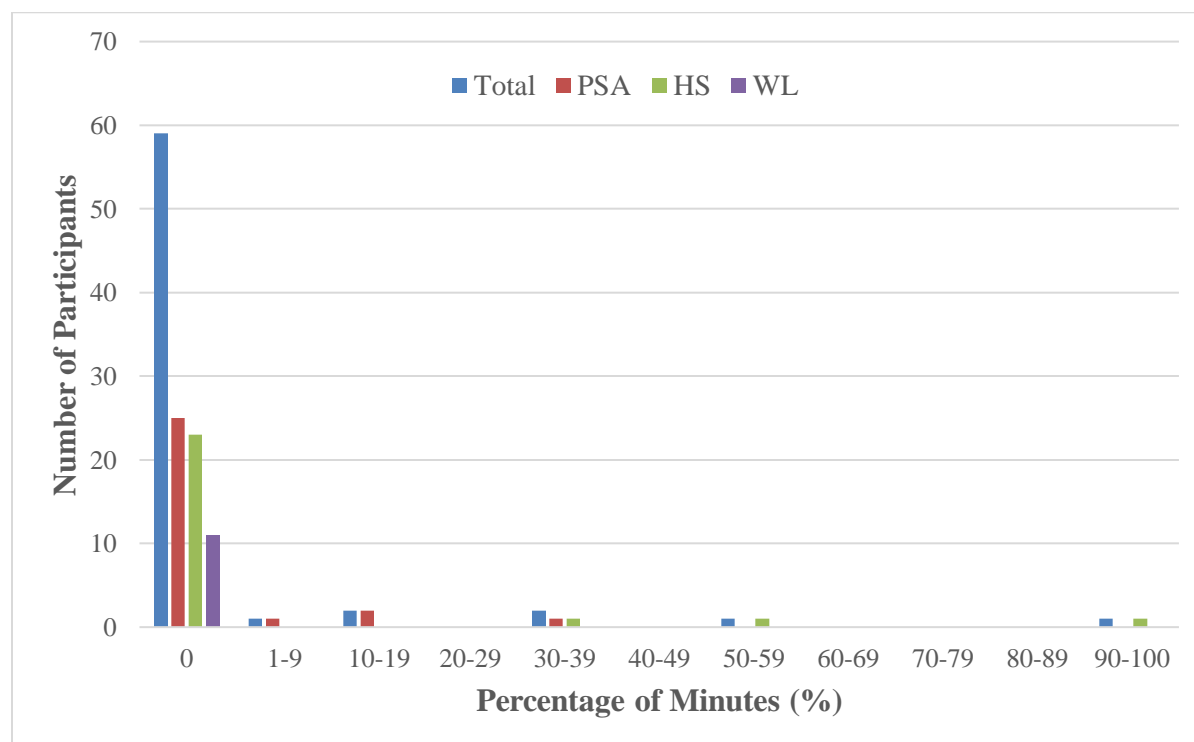
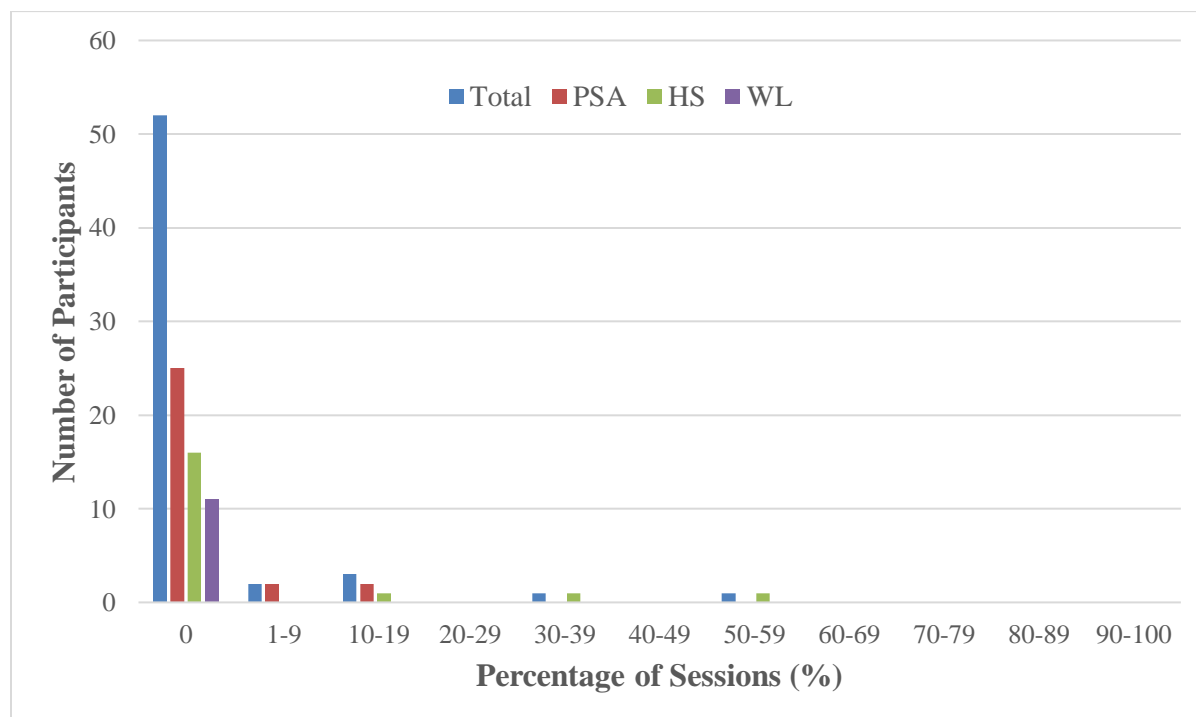


Figure 24. Depression Practice in Sessions for All Participants



Aim 2: Interplay of Adherence and Depression

The second aim of the study was to examine the connection between MHapp adherence and depression over time, and to better understand the directionality of that relation using cross-lagged panel models (CLPMs). However, to limit Type I error, the number of adherence metrics retained in Aim 2 was first reduced by investigating variability in the data (i.e., coefficient of variation < 1.0) and inter-correlations between variables (i.e., correlations of absolute value of 0.30 or greater). The metric of mental health practice in sessions was eliminated since the means across the weeks of the trial were nearly exact to those of mental health practice in minutes. Similarly, the metric of depression practice in sessions was eliminated since the means across the weeks of the trial were nearly exact to those of depression practice in minutes. Next, analyses revealed a strong correlation between cumulative minutes and cumulative sessions ($r = .926$), thus only the metric of cumulative minutes was retained for the CLPM. Further, metrics of

loyalty and regularity were highly correlated as well ($r = .913$), and so only the metric of loyalty was retained for the CLPM. Finally, the metrics of cumulative minutes and loyalty were highly correlated ($r = .906$), thus loyalty was eliminated from the CLPM analyses. Therefore, the final set of adherence metrics evaluated in the CLPMs included four variables: cumulative minutes, cumulative modules, mental health practice in minutes, and depression practice in minutes.

In examining distributions of relevant variables, PHQ-9 total scores had adequate skew statistics for T0 to T2 (skew = 0.44 – 0.62), but T3 scores were positively skewed (skew = 1.10). Skew for PHQ-9 total scores at T3 was adequately addressed with a square root transformation (skew = -0.193), and the transformed T3 data was used for Aim 2 analyses. A number of adherence metrics were highly skewed (> 1.00) due to the large proportion of zeroes, including cumulative modules T0-T3 (skew = 1.37 - 5.38), mental health practice T0-T3 (skew = 1.34 - 2.11), and depression practice T0-T3 (skew = 6.67 - 8.12). For Aim 2 and Aim 3 analyses, skew was addressed within the analyses by utilizing Poisson distributions.

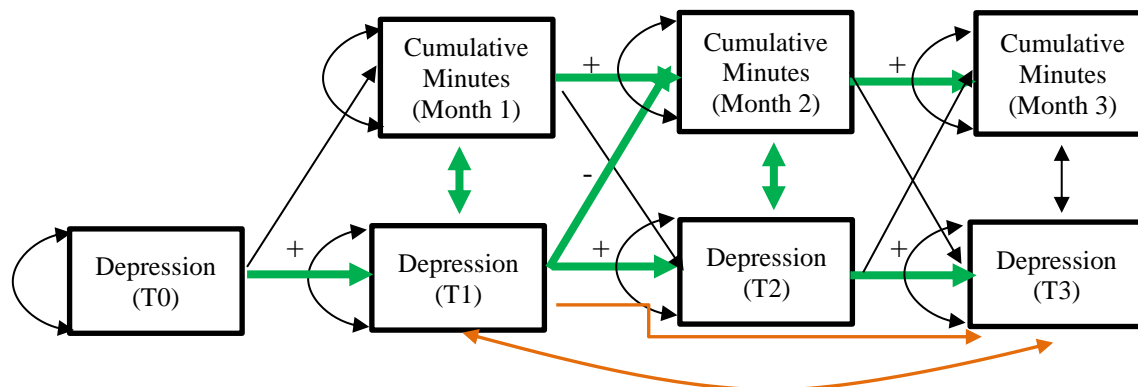
CLPM with Cumulative Minutes.

It was hypothesized that there would be a bidirectional relation between cumulative minutes completed and depression symptoms, but the strength of the effect of adherence on depression (i.e., more completed minutes predicting lower levels of depressive symptoms) would be greater relative to the effect of depression on adherence (i.e., lower levels of depressive symptoms predicting more completed minutes). All goodness-of-fit statistics, except SRMR and chi-square, reflected poor model fit (RMSEA = 0.192; CFI = 0.871; TLI = 0.660; SRMR = 0.072; $\chi^2(8) = 27.459, p < .001$). There were two modification indices that exceeded the minimum value, indicating that model fit may be improved by entering additional pathways. As such, a modification index regressing depression at T1 on depression at T3, as well as covarying

depression levels at T1 with T3, were added to the model (see Figure 25). With these additions, RMSEA and TLI remained unacceptable (RMSEA = 0.108; TLI = 0.893), but goodness-of-fit statistics CFI and SRMR were improved and yielded adequate fit (CFI = 0.969; SRMR = 0.052; $\chi^2(6) = 10.611, p = .101$). The Satorra-Bentler scaled difference chi-square test showed that the nested model represented a significant improvement from the previous one ($\Delta\chi^2(2) = 10.675, p < .01$; Bryant & Satorra, 2013; Satorra & Bentler, 2001).

Results illustrated in Figure 25 indicated that baseline (T0) depression significantly predicted depression at T1 ($b = 0.463, SE = 0.175, p < .01$), but did not significantly predict cumulative minutes in Month 1 ($b = -0.405, SE = 2.571, p = .875$). Depression at T1 significantly predicted both subsequent depression at T2 ($b = 0.700, SE = 0.090, p < .001$) and cumulative minutes completed in Month 2 ($b = -3.208, SE = 1.478, p < .05$). Meanwhile, cumulative minutes in Month 1 significantly predicted cumulative minutes completed in Month 2 ($b = 0.673, SE = 0.102, p < .001$), but not depression at T2 ($b = -0.005, SE = 0.006, p = .351$). Depression at T2 significantly predicted depression at T3 ($b = 0.298, SE = 0.142, p < .05$), but was not predictive of cumulative minutes completed in Month 3 ($b = -0.030, SE = 0.263, p = .909$). Finally, cumulative minutes in Month 2 significantly predicted cumulative minutes in Month 3 ($b = 0.100, SE = 0.026, p < .001$), but did not predict depression at T3 ($b = -0.002, SE = 0.005, p = .674$). Depression and cumulative minutes covaried significantly at T1 ($b = -131.814, SE = 53.200, p < .05$), T2 ($b = 48.247, SE = 23.711, p < .05$), but not at T3 ($b = -0.304, SE = 7.227, p = .966$).

Figure 25. CLPM Model with Results for Depression and Cumulative Minutes Completed



Note: Pathways in green were significant and are marked with a +/- sign to reflect the directionality of the relation. Pathways in orange were added based on modification indices.

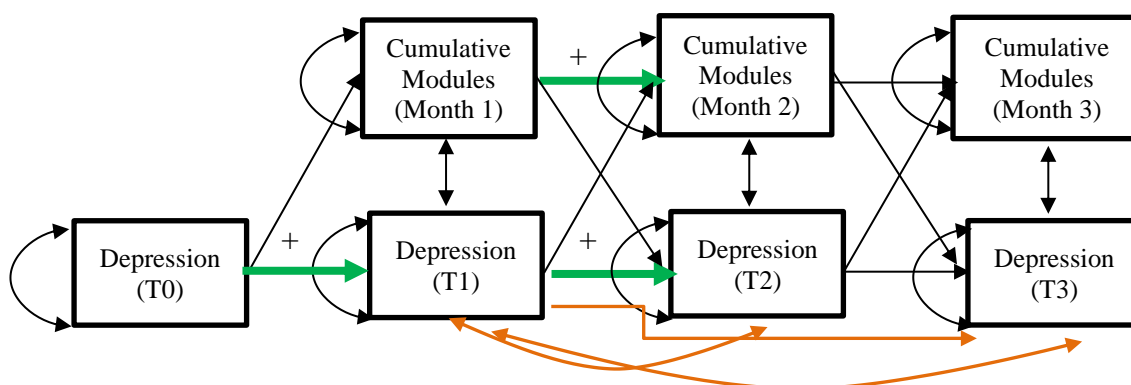
CLPM with Cumulative Modules.

It was hypothesized that there would be a bidirectional relation between cumulative modules completed and depression symptoms, but that the strength of the effect of adherence on depression (i.e., more completed modules predicting lower levels of depressive symptoms) would be greater relative to the effect of depression on adherence (i.e., lower levels of depressive symptoms predicting more completed modules). All goodness-of-fit statistics, except SRMR and chi-square, reflected poor model fit (RMSEA = 0.205; CFI = 0.841; TLI = 0.584; SRMR = 0.069; $\chi^2(8) = 30.136, p < .001$). There were five modification indices that exceeded the minimum value, indicating that model fit would be improved by entering additional pathways. Modification indices regressing depression at T1 on depression at T3, covarying depression levels at T1 with T3, and covarying depression levels at T2 with T3 were added to the model (see Figure 26). Modification indices regressing depression at T3 on depression at T1 and T2, separately, were not added since it did not make sense theoretically to regress later timepoints onto earlier ones. With these changes, RMSEA remained unacceptable (RMSEA = 0.090), but goodness-of-fit indices of CFI, TLI, and SRMR were improved and yielded adequate fit (CFI =

0.981; TLI = 0.919; SRMR = 0.042; $\chi^2(5) = 7.703, p = .173$). The Satorra-Bentler scaled difference chi-square test showed that the nested model represented a significant improvement from the previous iteration ($\Delta\chi^2(3) = 30.919, p < .001$; Bryant & Satorra, 2013; Satorra & Bentler, 2001).

Results illustrated in Figure 26 indicated that baseline (T0) depression significantly predicted depression at T1 ($b = 0.508, SE = 0.140, p < .001$), but did not significantly predict modules completed in Month 1 ($b = -0.013, SE = 0.015, p = .393$). Depression at T1 significantly predicted subsequent depression at T2 ($b = 0.720, SE = 0.086, p < .001$) but did not predict cumulative modules completed in Month 2 ($b = -0.017, SE = 0.011, p = .122$). Cumulative modules completed in Month 1 significantly predicted modules completed in Month 2 ($b = 0.719, SE = 0.133, p < .001$), but not depression at T2 ($b = -0.288, SE = 0.807, p = .721$). Depression at T2 neither predicted depression at T3 ($b = -0.426, SE = 0.640, p = .505$) nor cumulative modules completed in Month 3 ($b = -0.002, SE = 0.003, p = .556$). Finally, cumulative modules completed at Month 2 neither predicted modules in Month 3 ($b = 0.079, SE = 0.052, p = .131$) nor depression at T3 ($b = 0.057, SE = 0.718, p = .937$). Depression and cumulative modules completed did not significantly covary at any timepoint (T1: $b = -0.268, SE = 0.454, p = .554$; T2: $b = 0.319, SE = 0.248, p = .198$; T3: $b = -0.004, SE = 0.026, p = .869$).

Figure 26. CLPM Model with Results for Depression and Cumulative Modules Completed



Note: Pathways in green were significant and are marked with a +/- sign to reflect the directionality of the relation. Pathways in orange were added based on modification indices.

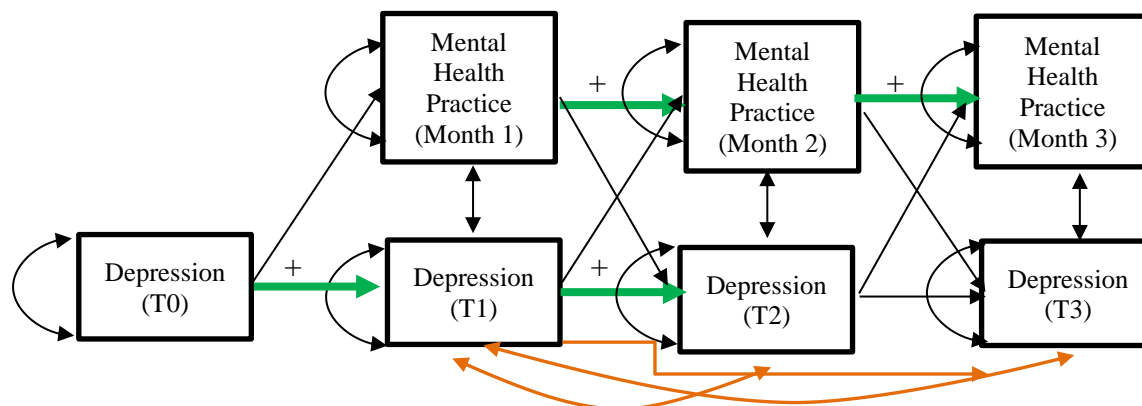
CLPM with Mental Health Practice in Minutes.

It was hypothesized that a bidirectional relation would emerge between the proportion of mental health practice completed and depression levels, but that the strength of the effect of adherence on depression (i.e., more completed mental health content predicting lower levels of depressive symptoms) would be greater relative to the effect of depression on adherence (i.e., lower levels of depression predicting more mental health content completed). All goodness-of-fit statistics, except SRMR, reflected poor model fit (RMSEA = 0.232; CFI = 0.790; TLI = 0.449; SRMR = 0.078; $\chi^2(8) = 36.322, p < .001$). There were five modification indices that exceeded the minimum value, indicating that model fit would be improved by entering additional pathways. Modification indices regressing depression at T1 on depression at T3, covarying depression levels at T1 with T3, and covarying depression levels at T2 with T3 were added to the model (see Figure 27). Modification indices regressing depression at T3 on depression at T1 and T2, separately, were not added to the model since it did not make sense theoretically to regress later timepoints onto earlier ones. With these changes, RMSEA and TLI remained unacceptable (RMSEA = 0.188; TLI = 0.636), but goodness-of-fit indices of CFI and SRMR were improved

and yielded adequate fit (CFI = 0.913; SRMR = 0.055; $\chi^2(5) = 16.700, p < .01$). The Satorra-Bentler scaled difference chi-square test showed that the nested model represented a significant improvement from the previous iteration ($\Delta\chi^2(3) = 21.479, p < .001$).

Results illustrated in Figure 27 indicated that baseline (T0) depression significantly predicted depression at T1 ($b = 0.506, SE = 0.140, p < .001$), but did not predict mental health practice completed in Month 1 ($b = 0.005, SE = 0.007, p = .444$). Depression at T1 significantly predicted subsequent depression at T2 ($b = 0.716, SE = 0.085, p < .001$) but not mental health practice in Month 2 ($b = -0.009, SE = 0.006, p = .128$). Mental health practice completed in Month 1 significantly predicted subsequent mental health practice in Month 2 ($b = 0.710, SE = 0.114, p < .001$), but was not predictive of depression at T2 ($b = -2.493, SE = 2.110, p = .237$). Depression at T2 neither predicted depression at T3 ($b = 0.072, SE = 0.894, p = .936$) nor mental health practice in Month 3 ($b = -0.001, SE = 0.003, p = .672$). Finally, mental health practice in Month 2 predicted practice in Month 3 ($b = 0.143, SE = 0.054, p < .01$), but did not predict depression at T3 ($b = 0.776, SE = 2.028, p = .702$). Depression and cumulative modules completed did not significantly covary at any timepoint (T1: $b = -0.143, SE = 0.177, p = .419$; T2: $b = -0.058, SE = 0.104, p = .579$; T3: $b = -0.023, SE = 0.047, p = .626$).

Figure 27. CLPM Model with Results for Depression and Mental Health Practice (Minutes)



Note: Pathways in green were significant and are marked with a +/- sign to reflect the directionality of the relation. Pathways in orange were added based on modification indices.

CLPM with Depression Practice in Minutes.

It was hypothesized that there would be a bidirectional relation between the proportion of depression practice completed and depression symptoms, but that the strength of the effect of adherence on depression (i.e., more completed depression content predicting lower levels of depressive symptoms) would be greater relative to the effect of depression on adherence (i.e., lower levels of depressive symptoms predicting more completed depression content). Results revealed that completed depression practice in Month 1 was observationally equivalent to depression levels at T2, thus the model could not be identified, and goodness-of-fit statistics could not be produced. When this parameter was adjusted in the model, identification issues continued to arise due to the observational equivalence between depression practice and levels of depressive symptoms across multiple timepoints (e.g., Month 2 depression practice and depression levels at T3).

Aim 3: Motivational Factors Predicting Adherence

The final aim of the study was to identify motivational factors that may predict adherence slopes using multi-level modeling in HLM. For this aim, completed minutes and modules were

non-cumulative so that the slope of adherence (i.e., increases and decreases in non-cumulative data, as opposed to increases and plateaus in cumulative data) could be accurately captured across time. Five variables were entered into the HLM models to predict the slope of each adherence metric (i.e., minutes, modules, mental health practice, depression practice): self-regulation, behavioral self-efficacy, behavioral intention, routine variability, as well as perceived and expected benefit. Given the varying ranges and scales of the predictors, they were converted to z -scores to allow for standardized comparisons across predictors. Through the analyses, comparisons were made between participant scores that fell above and below the sample mean for each predictor variable. Adherence metrics of cumulative modules (skew = 1.37 - 5.38), mental health practice (skew = 1.34 - 2.11), and depression practice (skew = 6.67 - 8.12) were skewed with a high proportion of zeroes, so over-dispersed Poisson distributions were used for those models. Given that Poisson distributions describe probability models, event rate ratios (ERR) are reported to represent rates of occurrence. Specifically, an ERR of 1.00 indicates that the rates of adherence between the two groups are equivalent. An ERR above 1.00 indicates *increased* rates of adherence for participants who report levels of the predictor variable that are above the group mean, and an ERR below 1.00 indicates *decreased* rates of adherence for participants reporting levels of the predictor variable that are above the group mean.

The variance of the intercepts and slopes for each adherence metric was significant, indicating that there was sufficient change in Headspace use over time. However, the slope of mental health practice was not significant ($\chi^2(50) = 53.10, p = .356$). As such, the results for mental health practice are not included since they were not interpretable.

Minutes.

Examining slope effects, routine variability was significantly associated with changes in weekly minutes completed ($\beta_{15} = -.011, p = .046$). As displayed in Table 4, those who reported greater routine variability than the group mean completed Headspace minutes at 0.99 times the rate of other participants (ERR = 0.99). Self-regulation at T0 ($\beta_{11} = .001, p = .797$; ERR = 1.00), behavioral self-efficacy at T1 ($\beta_{12} = -.003, p = .717$; ERR = 1.00), behavioral intention at T1 ($\beta_{13} = .003, p = .659$; ERR = 1.00), and perceived and expected benefit at T1 ($\beta_{14} = -.001, p = .871$; ERR = 1.00) were not significantly linked to minutes completed over time.

Modules.

When examining slope effects, self-regulation at T0 was significantly associated with changes in weekly modules completed ($\beta_{11} = -.084, p < .001$). As displayed in Table 4, participants who reported higher baseline levels of self-regulation than the group mean completed modules at 0.92 times the rate of other participants (ERR = 0.92). Further, perceived and expected benefit at T1 significantly predicted module completion ($\beta_{14} = -.059, p < .001$). Participants reporting greater perceived and expected benefit than the group mean completed modules at 0.94 times the rate of other participants (ERR = 0.94). Finally, routine variability was also significantly associated with changes in modules completed ($\beta_{15} = -.025, p < .001$). Participants exhibiting more routine variability than the group mean completed modules at 0.98 times the rate of other participants (ERR = 0.98). Meanwhile, behavioral self-efficacy at T1 ($\beta_{12} = -.016, p = .143$; ERR = 0.98) and behavioral intention at T1 ($\beta_{13} = .002, p = .814$; ERR = 1.00) were not significantly linked to the number of modules completed over time.

Depression Practice.

In terms of slope effects, levels of self-regulation at T0 were significantly associated with changes in depression practice over time ($\beta_{11} = .334, p = .002$). As displayed in Table 4, participants reporting higher levels of self-regulation than the group mean completed depression content at 1.40 times the rate of other participants (ERR = 1.40). Further, behavioral self-efficacy at T1 was associated with changes in depression practice over time as well ($\beta_{12} = -.785, p < .001$). Those reporting higher levels of behavioral self-efficacy than the group mean completed depression content at 0.46 times the rate as other participants (ERR = 0.46). Additionally, behavioral intention at T1 predicted the slope of depression practice across the trial ($\beta_{13} = .376, p < .001$). Participants with higher levels of behavioral intention than the group mean completed depression content at 1.46 times the rate as other participants (ERR = 1.46). In terms of perceived and expected benefit at T1, levels were associated with changes in depression practice ($\beta_{14} = .885, p < .001$), with those reporting higher levels of perceived and expected benefit than the group mean completing depression content at 2.42 times the rate as other participants (ERR = 2.42). Finally, routine variability was not significantly linked to changes in depression practice across the trial ($\beta_{15} = -.016, p = .704$; ERR = 0.98).

Table 4. HLM Results of Effects of Motivational Predictors on Longitudinal Adherence

	Minutes			Modules			Depression practice		
Slope Effects	Coef.	SE	ERR	Coef.	SE	ERR	Coef.	SE	ERR
Intercept	0.116***	0.005	1.122	-0.296***	0.005	0.744	5.010***	0.063	149.910
Self-regulation (T0)	0.001	0.005	1.001	-0.084***	0.004	0.920	0.334**	0.104	1.396
Behavioral self-efficacy (T1)	-0.003	0.009	0.997	-0.016	0.011	0.984	-0.785***	0.062	0.456
Behavioral intention (T1)	0.003	0.006	1.003	0.002	0.007	1.002	0.376***	0.041	1.457
Routine variability (T1)	-0.011*	0.006	0.989	-0.025***	0.003	0.976	-0.016	0.042	0.984
Perceived and expected benefit (T1)	-0.011	0.006	0.999	-0.059***	0.005	0.943	0.885***	0.191	2.423

Note: Coef. = coefficient; SE= standard error; ERR= event rate ratio; * $p < .05$; ** $p < .01$; *** $p < .001$

CHAPTER FIVE

DISCUSSION

Prior research has begun to support the utility and effectiveness of MHapps in addressing critical gaps and disparities in mental health treatment, with mindfulness-based apps particularly benefiting depressive symptoms (Firth et al 2017; Lattie et al., 2019a; Linardon et al., 2019; Ly et al., 2015). The current study extends previous work by exploring MHapp adherence (specifically Headspace) with a variety of measures in order to capture different aspects of engagement. Further, advanced statistical approaches were used to examine the interplay between adherence and depression, as well as to identify motivational factors that may promote MHapp engagement. Overall, these aims begin to shed light on the “dosing” of MHapps in terms of better understanding naturally occurring patterns of use over time, how such patterns may influence change in mental health symptoms, and how adherence may be promoted through individual characteristics.

Importantly, the present study also provides insight into the use of a MHapp for college students specifically. College students represent a group in particular need of mental health resources as rates of depression have consistently risen over the last decade, yet only half of students with psychological needs access treatment. Further, the collegiate years commonly coincide with the developmental stage of emerging adulthood, which encapsulates transition and instability in a range of life domains. The need for expanded mental health services for this

population is evident, and MHapps may be uniquely beneficial for college students given their familiarity and comfort with technology.

Aim 1 Findings

The first aim was to investigate patterns of adherence to Headspace over the three-month trial through the use of various metrics. This allowed researchers to capture adherence patterns more comprehensively and in a nuanced manner. Given that prior work has captured adherence in limited ways, this aim was largely exploratory. However, based on the available literature, it was hypothesized that a proportion of students would never initiate Headspace use. Of those who did, it was predicted that adherence would decline after the first month, with less than half of students still using the app within the final month of the trial.

In total, mindfulness practice completed by participants ranged widely from 0 to 728 minutes ($M = 207$, median = 158) and 0 to 81 sessions ($M = 20$, median = 22). Looking across each month of the trial, the number of minutes and sessions completed decreased from the first month (Minutes: $M = 107$, median = 80; Sessions: $M = 14$, median = 13) to the second month (Minutes: $M = 88$, median = 61; Sessions: $M = 10$, median = 9), and then dropped more drastically in the final month (Minutes: $M = 12$, median = 0; Sessions: $M = 1$, median = 0). These trends were highlighted in the visual representations of adherence, with completed minutes and sessions plateauing for almost all participants by the end of the second month. This was mirrored in the metric of continued engagement, with the largest proportion of participants using Headspace for a span of 50 to 59 days. In fact, two-thirds of the participants ($N = 44$) did not complete any Headspace content in the final month of the trial, which aligns with study hypotheses. Additionally, 8% of participants ($N = 5$) never initiated Headspace use, which also

was consistent with hypotheses. Interestingly, all of the participants who never began using Headspace were in the Delayed Headspace as Usual group. Further, an additional 18% of participants ($N = 12$) discontinued using the app within the first month of the trial, two-thirds of whom ($N = 8$) stopped within the first week. Finally, the measure of continued engagement revealed that only 3% of participants ($N = 2$) used Headspace during the final week of the trial. Overall, the present adherence patterns reinforce the narrative within the field of MHapp research in that adherence rates are variable but generally decline quickly over time (Baumel et al., 2019; Linardon & Fuller-Tyszkiewicz, 2020; Torous et al., 2019).

Findings related to adherence patterns provide further evidence for MHapp limitations that are commonly cited in the literature, namely early discontinuation for some participants (Chittaro & Vianello, 2016b) and declining adherence over time (Christensen et al., 2009; Economides et al., 2018; Huckvale et al., 2020). Further, research examining adherence to MHapps for depression, specifically, shows that a large percentage of interested users never ultimately download the MHapp, with rates as high as 58% (Arian et al., 2016). Such themes emerge within the larger landscape of apps as well. A recent review of 12,000 apps highlighted the difficulties of maintaining user engagement as a quarter of users never returned to an app after the first use, and retention beyond 10 sessions is fairly low at 32% (Localytics, 2019). In fact, 2019 had the lowest retention rates for apps since the study began collecting data in 2012. Given that it is a leading app in the areas of wellness and mental health, Headspace engagement data have been specifically examined from a marketing and development perspective. Data show that despite Headspace's 20 million downloads per year—making it the most downloaded wellness app—over 90% of those who downloaded the app discontinued its use within 30 days

(Neura, 2020). This is the norm within the landscape of MHapps, with Headspace's overall retention rate of 8% representing a slight improvement compared to competing MHapps, which have average retention rates of 6-7% after one month (Neura, 2020).

The current study's finding that 66% of participants discontinued Headspace use before the final month of the trial is a higher rate than that of other trials (Donkin et al., 2011; Kaltenthaler et al., 2008; Waller & Gilbody, 2009). However, the current pattern of discontinuation is consistent with research positing that adherence diminishes when there is less structure or guidance for MHapp use (Cheung et al., 2018; Economides et al., 2018; Emmerik et al., 2017; Flett et al., 2019). At the end of the second month, the supportive accountability features of the Headspace with Peer Support group (i.e., small group sessions; messages from research staff on social media and email) ended. Similarly, participants in all study arms were invited at that time to complete a more time-intensive post-assessment (T2) session as compared to the midpoint survey (T1) and final survey (T3), in that it involved an EEG recording and completing study measures in the lab. Both the ending of the peer support features for applicable students and the occurrence of the in-person, more intensive assessment may have inadvertently communicated an ending of the formal study or a marked a change from monitored, prescriptive use to open, self-guided use. As such, the decrease in adherence after the second month may reflect the power of supportive accountability since participants may have felt more motivated to be adherent to the MHapp when they believed others (i.e., research staff) were monitoring their progress. Further, patterns also may reflect participants' external, rather than internal, motivations for MHapp use in that they may have felt obligated to support the research study by using Headspace.

Although group comparisons are beyond the scope of the current study, it is noteworthy that those who never initiated Headspace use were all randomized to the Delayed Headspace as Usual group, who waited for three months in the waitlist condition before receiving access to Headspace. This emphasizes the detriment of imposing an extended wait-period before providing individuals access to resources in which they expressed interest. The need to “strike while the iron is hot” in order to capitalize on initial interest and motivation has been well-researched in relation to the effect of waitlists for FTF therapies (Ho et al., 2015; Ofonedu et al., 2017; Redko et al., 2006; Westin et al., 2014). Those studying app development and marketing similarly emphasize the critical period that occurs immediately after downloading an app, wherein engaging potential users as soon after they express interest (i.e., app download) is essential to longer term retention (Localytics, 2019; Neura, 2020). The current finding reinforces the benefit of MHapps in that they subvert the barrier of extended wait times for accessing resources, particularly on college campuses where there are discrepancies between the number of students interested in mental health resources and clinicians available to provide such services (AUCCCD, 2016).

Meanwhile, module completion (i.e., completing sets of 10 sessions within a certain topic) over the trial ranged from 0 to 5 ($M = 1$), with consistent rates across the first and second months ($M = 0.4$), but then dropping in the third month ($M = 0.1$). Visual depictions of these trends highlight the clustering of module completion within the first month; however, more than half of participants (59%) did not complete any modules during the trial. This is an important insight into the ways in which college students engage with MHapps since many apps are designed to organize content by modules to promote skill learning and mastery. Low rates of

module completion and users' dislike of being restricted by modules have been reflected in other MHapp studies as well, with users expressing preference to move between content freely and to have greater control of their app use (Garrido et al., 2019; Ip et al., 2016; Pinto et al., 2016). Interestingly, prior to the start of this trial, Headspace was designed such that users were required to first complete one of the "Basics" modules before being able to access other content. The reasoning for this was to help users learn foundational mindfulness skills and to allow them to become familiar with the app (Headspace Inc, n.d.). In the larger field of MHapps, module completion has been linked to improvements in psychological outcomes (Donkin et al., 2011; Manwaring et al., 2008), but it is not clear whether progressing through modules is akin to completing courses of evidence-based treatments in FTF therapy. Follow-up analyses from this study would benefit from examining the relation between module completion and mental health outcomes or skill-learning.

Looking on a weekly level, both loyalty (i.e., average number of sessions completed each week) and regularity (i.e., average number of days each week with a completed session) were highest during the first week of the trial (average of 5.1 sessions per week and 3.4 days per week, respectively). Loyalty and regularity rates followed similar patterns in that they declined by the second week, plateaued through the second month, and then dropped further across the final month of the trial. These patterns align with prior research wherein college students reported using MHapps once a week or less, despite perceiving a benefit from them (Kern et al., 2018).

When considering habit development and the weekly use of MHapps, it is important to acknowledge students' busy and constantly changing schedules. During college, it is the norm to have schedules that vary widely day-to-day as a result of differing class times, extracurricular

activities, and work or family obligations. Examining the present study's data, students' use of Headspace tended to occur at similar times of day across sessions, with an average routine variability of 4.2 hours (range= 0.1-8.1 hours). While it may not be realistic for students to engage with Headspace at the same time each day in order to establish a more regular habit, it appears that students can commit to a particular quadrant of the day in which to practice mindfulness (e.g., morning, afternoon, evening, night). Further, when recommending a MHapp to an interested individual—but particularly college students or those with inconsistent schedules—taking time to discuss methods for developing the habit of a mindfulness practice may be beneficial. Habit development was briefly discussed during the orientation session for the current study, but a greater emphasis on this, as well as ways to navigate a changing schedule, may be warranted. For example, instead of choosing a specific time of day to use Headspace, individuals may be guided to anchor the new activity to a pre-existing and regular part of their day, such as deciding to use Headspace after brushing their teeth or during lunch. Interestingly, prior research using data from the current study identified that the largest percentage of completed sessions (40%) occurred at night (i.e., between 11PM and 4AM; Huguenel et al., 2019). This suggests that bedtime was used as an anchor for Headspace use, which also was reflected in qualitative data attained through exit interviews and small group sessions in the Headspace with Peer Support.

Since the initiation of this study, Headspace has incorporated a greater focus on supporting habit development. When users open the app for the first time, they are now presented with various questions that prompt them to set specific goals and think through the scheduling of those goals, such as choosing a time of day to meditate or choosing from a list of

activities to which Headspace could be anchored. Additionally, users are prompted to set reminders and schedule notifications to encourage their engagement. Through this process, users are given a sense of ownership over their new mindfulness practice and there is an expectation that the MHapp will engage with them through notifications and reminders (Neura, 2020). While these features generally aim to support habit development, the effect of app-based outreach (e.g., reminders, notifications) is dependent on their timing and availability of the user. Given students' inconsistent schedules, it is likely that reminders and alerts to use Headspace will be delivered at times when students are simply not available, such as during a class or club meeting (Neura, 2020). In those cases, students become accustomed to ignoring the notifications and may even experience them as aversive over time. Ultimately, given that many things compete for students' time and attention, an essential element to boost user engagement from a marketing perspective is for MHapps to engage with users at the right time (Neura, 2020).

Finally, approximately one-third of completed Headspace content, on average, had a mental health focus (e.g., happiness, depression, anger, anxiety). The greatest proportion of mental health content was completed during the seventh week of the trial, which coincided with the end of the academic semester (i.e., 2 to 4 weeks before final exams). This timing suggests that participants selected content in a reactive manner in response to increased stress as end-of-semester deadlines approached. Interestingly, approximately one-quarter of participants ($N = 16$) never completed any mental health-related content over the course of the trial, despite the study's focus on recruiting students experiencing depressive symptoms. Similarly, the completion of depression-specific content remained very low throughout the trial. Several participants followed through the depression module more fully, completing 10 to 39% of their total Headspace

content from that module, but such a pattern was rare. From a stages of change perspective, some students may recognize that they struggle with mental health symptoms and would benefit from mental health resources, but are not yet ready or motivated to engage in treatment specific to those concerns (Prochaska & DiClemente, 1983). MHapps may be one way of familiarizing students to therapeutic skills, such as mindfulness, in a broad and palatable way. Ideally, the experience of learning and using mindfulness skills could serve as a stepping-stone to seeking more targeted mental health content or formal FTF mental health services in the future.

Aim 2 Findings

The second aim of the study focused on the interplay between adherence and depression over the trial by investigating the relative strength of such pathways. It was hypothesized that adherence would negatively predict depression levels, and lowered depression would in turn predict higher levels of subsequent adherence. Further, the relative strength of the effect of adherence on depression was expected to be greater than that of the effect of depression on adherence. To limit the number of analyses conducted, adherence metrics were consolidated, resulting in four models—cumulative minutes, cumulative modules, mental health practice (minutes), and depression practice (minutes).

After adding new pathways to improve model fit, models yielded mixed adequacy of goodness-of-fit statistics. With this in mind, only one cross-lagged pathway was significant across all models of adherence. For the metric of cumulative minutes, depression levels at the end of the first month significantly predicted minutes of Headspace completed during the second month of the trial, with higher levels of depression linked to fewer minutes completed. These findings are largely contrary to study hypotheses, which expected adherence to have a greater

effect on depression than vice versa. The current finding indicate that depressive symptoms serve as a significant barrier to users' ability to engage with the MHapp, which is concerning since users must be able to engage with a MHapp in order to benefit from it. However, the lack of impact of adherence on depression suggests that improvements in mental health may not occur in a dose-dependent manner. Instead, individuals may vary in the amount of mindfulness practice and exposure that is needed for them to learn and then implement the skills in relevant situations.

While prior work has begun to examine the differential effect of various adherence metrics on mental health outcomes, the bidirectional relation—the effect of mental health symptoms on subsequent adherence—had not been explored. Limited research has focused on the impact of baseline symptom levels on subsequent adherence, finding that one SD increase in baseline depression scores was associated with a 23% reduction in subsequent MHapp adherence (Arean et al., 2016). Symptoms including low motivation, anhedonia, and fatigue could make it difficult for users to initiate use after downloading a MHapp. Even after download, symptoms may continue to complicate engagement, particularly for mindfulness practice. For example, difficulty concentrating, rumination, and negative thought patterns (e.g., “What’s the use? This won’t help me.”) may make it challenging to fully engage with the exercises and could lead to a negative experience with the MHapp, both of which may deter subsequent use. The notion of depressive symptoms negatively affecting treatment adherence has been identified in research for FTF medical and psychological treatments (Broadbent et al., 2008; DiMatteo et al., 2000; Gonzalez et al., 2011; Shen et al., 2008). Despite MHapps' ability to eliminate aspects of FTF services that may be impediments for those experiencing depression, such as garnering the energy to travel to in-person sessions or harnessing one's concentration for a 45-minute therapy

session, the lack of accountability inherent of MHapps may be particularly detrimental for users with depressive symptoms.

Interestingly, connections between adherence and depression did not emerge for the other adherence metrics; in fact, even relations between the same variables at different timepoints (e.g., T2 depression and T3 depression) were inconsistent over time and across models. Most commonly, adherence and depression during the second month did not significantly predict levels of the same variable, respectively, during the third month. The effect of T2 depression on T3 depression varied across models since the amount of variance accounted for by those variables would have changed across models as a result of the different adherence metrics included (Selig & Preacher, 2009). Further, the stability of regression coefficients, and related error, was likely negatively affected by the study's small sample size (Hamaker et al., 2015). Meanwhile, the model for depression practice could not be identified since the parameter values of depression practice and depressive symptom levels were observationally equivalent across multiple timepoints. In other words, depression practice at Months 1 and 2 yielded equivalent data and probability distributions as depressive levels at T2 and T3. When parameters are observationally equivalent, they are reduced to the same form within the model and conclusions about relations between the variables cannot be drawn (Hershberger & Marcoulides, 2006).

While depression scores in the second and third months of the trial had adequate variability (Month 2: $M = 8.37$, $SD = 5.42$, range 0-21; Month 3: $M = 6.13$, $SD = 4.58$, range 0-20), adherence metrics of module completion and depression practice did not, particularly in the latter months of the trial (Modules completed month 2: $M = 0.42$, $SD = 0.73$, range 0-3; Modules completed month 3: $M = 0.06$, $SD = 0.30$, range 0-2; Depression practice (minutes) month 2: $M =$

2.54, $SD = 13.75$, range 0-80; Depression practice (minutes) month 3: $M = 0.45$, $SD = 3.66$, range 0-30). Although the skew and large proportion of zeroes for these metrics in the second and third months of the trial were accounted for in analyses, it makes sense that the very limited variability in some adherence metrics could contribute to their lack of meaningful connection to depression scores over time.

Aim 3 Findings

The third aim of the current study examined whether motivational factors predicted adherence patterns across the three-month trial. It was expected that higher levels of self-regulation, behavioral self-efficacy, and expected and perceived benefit would predict higher levels of adherence, whereas lower levels of routine variability were expected to predict higher levels of adherence. Behavioral intent was not predicted to have a significant relation with adherence. Higher levels of perceived and expected benefit predicted reductions in module completion ($ERR = 0.94$) as well as increases in depression practice ($ERR = 2.42$). Meanwhile, greater routine variability resulted in slight reductions in completed minutes ($ERR = 0.99$) and modules ($ERR = 0.98$). Further, higher levels of self-regulation predicted reductions in module completion ($ERR = 0.92$) and increases in depression content ($ERR = 1.40$). Finally, higher levels of behavioral self-efficacy at the end of the first month predicted reductions in depression practice ($ERR = 0.46$), whereas higher levels of behavioral intent at the end of the first month predicted increases in depression practice ($ERR = 1.46$).

Although the motivational variable of perceived and expected benefit exhibited connections across adherence outcomes, such relations were not consistently positive. Participants who had perceived higher levels of benefit by the end of the first month and

expected more benefit to come in the remaining months of the trial exhibited greater increases in depression practice at almost 2.5 times the rate of other participants. Given that participants recruited for this study reported clinically elevated depressive symptoms, those who perceived a benefit from Headspace use early on may have felt encouraged to see whether its depression-focused content would help with their personal mental health experiences as well. Since perceived and expected benefit did not predict rates of change in total completed minutes, the change in depression practice rates was not simply driven by participants' liking of mindfulness more generally. Meanwhile, higher levels of perceived and expected benefit predicted reductions in the rate of module completion. These participants' beneficial experience with Headspace may have motivated them to sample a wider range of content in the remaining two months of the trial before losing their free access to the app. Overall, these findings replicate those from a prior study involving Headspace wherein positive expectations—both at the beginning of the study and after use began—predicted increased engagement (Laurie & Blandford, 2016), and extend them by exploring which aspects of adherence are enhanced. Prior work that did not find a significant link between expected benefit and completed minutes of mindfulness, is consistent with the current results and highlights the importance of examining multiple metrics of adherence (Ribeiro et al., 2018).

The findings related to routine were more consistent in that participants with greater variability in the routine (i.e., less routine consistency) completed Headspace minutes and modules at slightly lower rates. The small reduction in rates suggests that although routine of MHapp use has a significant effect on adherence patterns, it may not be the variable with the largest impact. These findings align with research concluding that lack of routine is associated

with worse adherence to Headspace (Laurie & Blandford, 2016); however, it runs contrary to studies examining treatment adherence more broadly, which characterizes routine as a critical factor for improving adherence (Brooks et al., 2015; Leventhal et al., 2016; Tanenbaum et al., 2015). Further, it makes intuitive sense that regularity would be linked to foundational metrics of adherence (i.e., is the app being used or not; minutes and modules completed) rather than the specific type of content completed (i.e., depression practice). Ultimately, although routine may be helpful in improving adherence, it may not be sufficient as an isolated variable to produce a large impact. Also, routine may be a less critical variable for MHapps since individuals typically have access to their phone at almost all times of the day. Treatments that are less convenient and accessible during one's day, such as taking medication, may benefit from the establishment of a routine, whereas more convenient and accessible tools, such as MHapps, may not benefit as greatly given the seemingly limitless access to smartphones. Of note, results related to routine variability may have been affected by the overall dose (minutes of practice) of mindfulness that each participant received, since participants could have the same routine variability score but very different amounts of completed sessions or minutes of Headspace. When routine predicted rate of cumulative minutes completed, the dosage of mindfulness practice was controlled for through the modeling of minutes over time, but this was not the case for other HLM models of adherence (i.e., cumulative modules and depression practice).

Meanwhile, participants reporting higher levels of self-regulation exhibited decreased rates of module completion but 1.4 times the rate of depression practice. The reduction in module completion despite greater perceived control of oneself was surprising initially; however, participants who sense that they are more in control of their decisions and motivations may feel

that they can confidently move across content without the external structure of modules. The predictive relation between self-regulation and depression content is notable. Although all participants reported clinical levels of depressive symptoms, those with greater degrees of perceived control over themselves may have been able to focus on the most applicable content and filter out the multitude of other options available within the Headspace app.

Finally, behavioral self-efficacy and intention each had one significant connection to rates of adherence. Greater levels of behavioral self-efficacy, or one's confidence in using mindfulness skills in daily life, predicted rates in depression practice that were reduced by half. Participants who feel confident in their mindfulness skills may be drawn to engage with a wider range of content in the MHapp, as opposed to limiting themselves to a single module like depression. Given that modules in Headspace tend to focus on the development of a single mindfulness skill or exercise to support learning (e.g., visualization within the depression module), participants who have more confidence in their skills may find this to be repetitive and instead seek a variety of modules or single sessions instead. Conversely, higher degrees of behavioral intention predicted increases in depression practice by almost 1.5 times the rate of other participants. From the perspective of motivational interviewing, fostering intention is foundational to increasing motivation, readiness for change, and the actual implementation of change behaviors (Rollnick & Miller, 1995). Similar to perceived and expected benefit, the intention to practice mindfulness in the future may also reflect readiness for change and commitment to the study's advertised focus on mitigating stress and feelings of sadness, and thus greater willingness to complete depression content during the trial.

Implications and Conclusions

The results of the current study have important implications for the ways in which clinicians, researchers, and college staff may approach MHapp use with interested students and recommendations they may make for optimizing their benefits. MHapps are touted as a promising means of providing resources to those in need, and their effectiveness in reducing symptoms and improving well-being outcomes has been a focus of research in this area. However, poor adherence is consistently identified as a limitation and few studies have explored the longitudinal link between adherence patterns and change in mental health outcomes in more detail. Further, studies aiming to improve adherence rates have examined modifiable study-level factors, such as creating more accountability within the MHapp interface or intervention program, but few have investigated person-level factors that may affect adherence.

Adherence emerges as an issue for college students as well, as evidenced by the current study wherein almost 10% of the sample never initiated use of the MHapp, another 20% of the sample discontinued MHapp use after one month, and an additional 35% discontinued MHapp use after two months. Professionals working with students should be aware from the outset that adherence is likely to diminish, and they can openly discuss this pattern with students in a nonjudgmental manner to allow for problem-solving. Further, this study suggests that students are less likely to follow through with content that builds on prior sessions, with less than half of the current participants (approximately 40%) completing any modules over three months. Finally, professionals should be aware that a student's identification or acknowledgement of psychological concerns (e.g., depressive symptoms) does not necessarily translate into readiness or interest in engaging with content that is tailored to that particular issue.

Although it is beyond the scope of the present study to explore the effect of the trial's supportive accountability features on adherence, current findings provide evidence for the need of such features. The most common recommendation for improving retention and engagement with mental health technologies is to incorporate human, guided support (Baumesiter et al., 2014). However, research examining the effect of human support on adherence and outcomes is mixed. Some studies indicate that technologies incorporating guidance from mental health professionals have stronger effects on mental health outcomes than completely self-directed technology use, though such findings represent small effect sizes and vary across mental health outcomes (Andersson & Titov, 2014; Baumeister et al., 2014; Linardon et al., 2019; Mohr et al., 2013c; Wright et al., 2019). Meanwhile, meta-analytic work has found that interventions delivered solely through MHapps had a significantly greater effect on depression than MHapps that incorporated in-person human, virtual human, or computer-based support (Firth et al., 2017). More recent studies exploring the benefit of supportive accountability features did not include a comparison condition of MHapp use without support, so it is difficult to assess the additive benefit of such features (Graham et al., 2020; Stiles-Shields et al., 2019). However, research in this area appears to converge on the finding that guided interventions, or those that include some degree of human or non-human (e.g., "chat bots") support improves rates of adherence as compared to non-guided interventions (Baumesiter et al., 2014). Overall, adherence and retention are major limitations of MHapp use, and determining the optimal ways in which to support these processes will be critical in future research (Andersson & Titov, 2014).

An important finding to highlight from this study is that students' depressive symptoms at the end of the first month predicted fewer completed minutes of Headspace during the

subsequent month. It is notable that depressive symptoms did not impact other adherence metrics, suggesting that mental health symptoms affected the overall dosage of mindfulness but not the particular content that was completed (i.e., depression practice). Professionals should be conscientious of depressive symptoms as a barrier to engagement, and to have an open dialogue with students about the ways in which symptoms related to energy, motivation, concentration, and mood may interfere with their consistent use of a MHapp (Arean et al., 2016). Similarly, the severity of depressive symptoms should be carefully considered as clinicians engage in treatment-planning and decision-making surrounding the use of MHapps. Despite the effectiveness of mindfulness-based MHapps in reducing depressive symptoms, as established by prior literature (e.g., Bostock et al., 2018; Economides et al., 2018; Flett et al., 2019; Lee & Jung, 2018; Ly et al., 2015), college students experiencing higher levels of depressive symptoms may require additional support and accountability to maintain engagement.

Limited research has begun exploring the interaction between symptom severity and users' ability to engage with and benefit from MHapps. RCTs and meta-analyses indicate that the largest reductions in symptoms occur for those experiencing mild to moderate depressive symptoms, indicating that that severity range may be best suited for the use of MHapps (Arean et al., 2016; Firth et al., 2017). Similarly, mindfulness-based apps have shown to be uniquely beneficial for mild depressive symptoms as compared to other types of MHapps (i.e., a behavioral activation MHapp; Ly et al., 2015). As such, it may not be clinically appropriate to recommend that individuals use MHapps in a stand-alone manner when addressing severe symptoms of depression (Firth et al., 2017; Nicholas et al., 2019; Weisel et al., 2019). This aligns with concerns regarding the management of severe depression symptoms, namely suicidality,

with MHapps from a safety perspective (Huckvale et al., 2020). Alternatively, students experiencing more severe depressive symptoms may benefit from a more formal course of treatment (e.g., FTF cognitive behavioral therapy, medication) to target their most interfering symptoms, and once the severity of their symptoms has been mitigated, they may be better able to engage with, and benefit from, a MHapp.

Ultimately, the current results are aligned with research suggesting that mental health technologies may be most effective when integrated into a stepped-care approach (Andersson & Titov, 2014; Firth et al., 2017; Green & Iverson, 2009; Linardon et al., 2019; Nicholas et al., 2019). Consistent with other stepped-care approaches for the treatment of depression (Scogin et al., 2003), MHapps would be appropriate as initial interventions, along with bibliotherapy, for mild to moderate depression. If symptoms did not improve, then the individual would move to the next level of care, such as psychopharmacology and/or FTF therapy (Nicholas et al., 2019; Scogin et al., 2003). Importantly, MHapps with adequate research support may also be integrated into higher levels of care (psychopharmacology and/or psychotherapy) to bolster treatment progress and symptom remission. This is consistent with data gleaned from focus groups, which find that the majority young adults would prefer for technology to be used in conjunction with, rather than as a replacement to, FTF treatments (Montague et al., 2015). Re-imaging a stepped care approach with the integration of MHapps may be particularly critical for college students given the challenges in addressing the volume and severity of needs on campuses in recent years (Berry et al., 2017).

Finally, study results indicate that some internal motivational factors could be targeted to improve adherence rates, which may be particularly relevant for clinicians who aim to

incorporate MHapps into their therapeutic practices. Notably, students who perceived Headspace as generally beneficial engaged with content that was applicable to their unique concerns (i.e., depression practice) at significantly higher rates. Similarly, students perceiving greater control in their lives (i.e., self-regulation) and greater intention to practice mindfulness in the future completed depression content at higher rates than other students as well. These findings suggest that using motivational interviewing skills, such as goal-setting and exploring the benefits and risks of changing behavior, may help to bolster individual motivation and in turn the completion of relevant content. Additionally, making clear connections between the content offered in MHapps and students' symptoms may also prompt students to engage in content that is applicable to their symptoms and goals.

As technology continues to advance and MHapps become increasingly utilized and incorporated into FTF treatments, it will be critical for mental health and higher-education professionals to have a deeper understanding of them. This study highlights the need for proactive discussions about adherence and intentionally building readiness for change before students begin using MHapps. As such, skills to enhance motivation (e.g., motivational interviewing) may be crucial, particularly for students experiencing mental health symptoms that directly impede MHapp engagement. To improve engagement, professionals should focus on building students' sense of control while using the MHapp, explicitly discuss the benefits that the student has experienced from the MHapp and those that may be to come, and engage in future goal-setting to foster intention. Further, just because MHapps are accessible to virtually all students given the ubiquity of smartphones does not mean that MHapps are appropriate tools for all students. Clinicians should consider students' symptom severity, motivation, and treatment

needs as they determine whether MHapps—alone or in conjunction with other treatment modalities—may be clinically indicated. It will be important for future research to continue exploring the connections between adherence patterns and mental health outcomes to shed additional light on *how* students should engage with MHapps to receive the greatest benefit.

Strengths, Limitations, and Future Directions

The current study addresses the need for a clearer, more comprehensive understanding of adherence to MHapps over time, and builds on prior work by examining the longitudinal interplay between mental health symptoms and adherence, and identifying motivational characteristics that may enhance adherence. The inclusion of a variety of adherence metrics is a strength of the study given that past examinations have typically included single measures of adherence and explored patterns in broad strokes, rather than exploring changes across shorter time intervals (e.g., weekly comparisons). Although research has called for a closer investigation of adherence, few studies actually have incorporated such recommendations (Bostock et al., 2018; Economides et al., 2018; Flett et al., 2019). Similarly, another strength of the current study is its use of a MHapp that internally records user data, which improves the validity of adherence data as compared to studies that rely on self-report measures of engagement (Cavanagh et al., 2013; Wahbeh et al., 2011).

Additionally, this research utilized advanced statistical approaches, including structural equation modeling techniques, that allow for the more nuanced examination of relationships over time and can support causal conclusions. To our knowledge, this is the first investigation into the effect of depressive symptoms on subsequent MHapp adherence at regular intervals throughout a trial. Finally, research has typically included college student participants as a convenience

sample, whereas the current study intentionally selected this sample from a theoretical perspective. Given the high rates of mental health concerns among the college student population as well as the ubiquity of smartphone and app use, MHapps may be uniquely appealing and beneficial for this group. Thus, it was intentional and meaningful to examine how this developmental stage and context may affect MHapp adherence.

Despite these strengths, there are also several limitations of the current study that should be addressed in future research. First, the current study included a sample that was predominantly cisgender female (89%), White (62%), first-year students (59%), and was collected from a single university. Thus, it is possible that the current findings do not generalize beyond this specific sample, making it difficult to extend results to other gender distributions, ages, ethnicities, education levels, and university contexts. Further, in exploring motivational factors that may predict adherence trajectories, this study utilized assessment items and scales that were created by the research group. While item and scale development occurred under the advisement of other experts in the field and yielded acceptable reliability in the current study, ultimately they are not validated measures and may not have adequately captured the intended constructs.

Further, the current study was under-powered to detect significant effects and results may have differed with a more robust sample size. For example, the HLM models that were conducted required a sample size of 130 for adequate power, whereas the current study was half of that size. While interesting findings still emerged, the advanced statistical techniques are better suited for larger sample sizes and the limited sample size of this study likely affected the findings. Future research would benefit from exploring similar research questions with a larger

group of participants. Additionally, a strength of the current study was its consideration of different metrics of adherence as opposed to condensing rich user data into a single variable. However, many of the adherence metrics were highly correlated, as seen when determining which to use in the models for Aim 1 and Aim 2 analyses. Similarly, some adherence metrics used in the current analyses may have been confounded by participants' total dose of mindfulness (i.e., completed minutes). For example, participants who completed few minutes of Headspace would inherently have low module completion scores as well. It would be interesting to use statistical techniques such as exploratory factor analysis to investigate the underlying structure and inter-relations of a similar set of adherence metrics.

Although apps provide methodological benefits by tracking mindfulness practice within the app interface, errors can occur that prevents data from being accurately recorded. For example, one participant was excluded from the current study because her Headspace usage data were not recorded for the first month of the trial, for reasons that were not clear to the study team. It is possible that similar, albeit smaller, data-tracking errors could have occurred in the app interface, of which the researchers would not be aware. Similarly, it is assumed that participants are engaged while using Headspace sessions; however, participants could fall asleep during practices or play sessions while they are not actually attentive and engaged (e.g., the app turning on in their backpack). In these cases, sessions would be recorded as completed practices without the researchers being aware that the participant was not engaged in the practice.

Importantly, the landscape of technology is quickly and constantly changing. Within the span of time that the current data were collected (i.e., 3 years), the interface of Headspace underwent several changes and developments that may have affected study results. Most

noteworthy was the introduction of sleep content, including sound recordings serving as white noise (e.g., “Rain Pipes”) and audio-recorded stories (e.g., “Sea Shapes”). Although research staff discussed this change during the orientation sessions—including the difference between mindfulness and relaxation—and advised students to focus on the actual mindfulness content, the sleep-related content was inter-mixed with mindfulness exercises in the app interface and were used by participants. Further, participants who did not attend the orientation session because of their randomization group did not receive this guidance from study staff. For the purposes of this study, the sleep content was included for metrics of cumulative sessions, loyalty, and regularity to capture the continued contact that the participant had with the MHapp. However, the sleep-related minutes were not included since the metric of cumulative minutes was intended to capture dosing of actual mindfulness practice. Although a relatively small proportion of students’ completed content came from the non-mindfulness sleep content (approximately 1%; Huguenel & Conley, 2019), these sessions may have contributed to misrepresentative routine variability scores. For example, engaging in sleep content before bed each night would yield a low routine variability score (i.e., more consistent engagement), but does not reflect habit development for mindfulness as a skill and practice. This may have affected the ways in which routine variability predicted rates of adherence in the third aim.

In terms of Headspace content, the current study only examined the ways in which completion of depression content related to other study variables. This made sense given the study’s focus on recruiting students with elevated depressive symptoms, but future research should explore the impact of other specific content on adherence outcomes as well. For example, the Basics, Anxiety, and Stress modules were most popular in the current study (24%, 19%, and

14%, respectively), whereas the Depression module was less frequently used despite guidance from research staff (6%; Huguenel & Conley, 2019). This may indicate that students feel more comfortable identifying with and engaging in content related to anxiety and stress as opposed to depression, which can be more stigmatized particularly for college students (Eisenberg et al., 2009; Lee, 2020). Further, the lower rates of completing depression content may reflect participants' dislike of a particular skill that was used in that module (e.g., visualizing liquid sunlight in their bodies) rather than a disinterest in targeting their depressive symptoms.

Finally, data from the current study was drawn from a trial involving multiple randomization conditions. Although it was beyond the scope of the current study to investigate group differences, it is likely that adherence and symptom outcomes differed across, and were affected by, the randomization groups. For example, the Headspace with Peer Support group included small group meetings and an online support group that were intended to boost adherence based on models of supportive accountability (Mohr et al., 2011). Related to this, it is possible that a greater proportion of participants in the Headspace with Peer Support group showed a reduction in adherence at the end of the second month due to the completion of the small group sessions and change from supported to more independent MHapp use. Meanwhile, the Delayed Headspace as Usual group, who waited for three months before engaging in the study and had limited interaction with other participants and research staff, were noted to have fully accounted for the participants who never initiated Headspace use. Similarly, the majority of participants assigned to the Waitlist Control condition (54%, $N = 13$) did not activate their Headspace access code at the end of the trial and continue their research involvement, or were lost to follow-up. Those who decided to continue in the study as Delayed Headspace as Usual

participants may have differed from those who did not in terms of motivational characteristics or symptomatology. Overall, it is clear that patterns in adherence varied across the randomization groups, and it will be meaningful for subsequent research to explore changes in adherence and symptoms across the groups. This will yield important information about the effectiveness of including different components of supportive accountability, such as small group sessions and outreach from study staff through emails and social media postings.

APPENDIX A
MENTAL HEALTH-RELATED CONTENT

Mental Health-Related Content

Modules:

- Depression / Handling Sadness
- Happiness
- Letting Go of Stress
- Managing Anxiety
- Reframing Loneliness
- Self-esteem
- Transforming Anger

Singles:

- Stressed

Minis:

- Burned Out
- Feeling Overwhelmed
- Finding Happiness
- Frustrated
- Flustered
- Losing Your Temper
- Panicking

APPENDIX B
STUDY MEASURES

The Self-Regulatory Self-Efficacy Scale

Please choose the answer that describes you best.

1	2	3	4	5	6	7
(Not well at all)		(Not too well)		(Pretty well)		(Very well)

1. How well can you motivate yourself to keep trying difficult tasks?
2. How well can you concentrate on learning new things?
3. How well can you start over when what you are trying is not working?
4. How well can you divide a large task into several smaller tasks?

Behavioral Intent Scale

You are about one month through the research study. After the assessment in one more month, how likely do you think you are to...

1	2	3	4	5
(Not likely)	(Possibly likely)	(Moderately likely)	(Very likely)	(Extremely likely)

1. Use Headspace (not considering cost).
2. Use any/some other mindfulness program or app (not considering cost).
3. Seek out a mindfulness group practice (e.g., at the Wellness center or elsewhere)
4. Do mindfulness exercises on my own.
5. Be more mindful in my everyday life.

Perceived & Expected Benefit Scale

Please consider your overall experience of the Loyola SMiLe Program (including the orientation, your Headspace practice, and your Loyola SMiLe group on Facebook if applicable) and rate how true each of the following statements is for you:

1	2	3	4	5
(Not at all)	(Slightly)	(Moderately)	(Very much)	(Extremely)

1. I am better able to cope with stress and negative thoughts / feelings because of this program.
2. The skills I am learning are valuable and beneficial.
3. This program has helped me to be more present in my life.
4. I expect to see even more benefit and value in the second half of the program.
5. The skills I am learning are important and relevant to my life.
6. The skills I am learning are having an impact in my life.

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VITA

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