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Access and Engagement of MoodTools, an mHealth Application for Depression

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by

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Under the Direction of Page Anderson, PhD

ABSTRACT

mHealth (mobile health) serves as a potential solution for circumventing barriers to traditional psychotherapy, but few studies evaluate mHealth technologies available in real-world settings with real-world users. This study evaluated the extent to which MoodTools, a self-help app for depression, circumvents barriers to traditional psychotherapy and engages users. App behavior from 159,00 Android users were assessed. Results showed that MoodTools could circumvent barriers to traditional psychotherapy, as it was downloaded in 198 countries, and the number of users was positively correlated with rates of unmet mental health need in the US. App use during and outside of traditional business hours were not significantly different. Regarding engagement, app sessions averaged 4 minutes and half of users returned to the app after their first session. There was no correlation between users' initial depressive symptom severity score and total amount of time spent in MoodTools. Implications and future directions are discussed.

INDEX WORDS: mHealth, Depression, Mental health, Mobile app, Smartphone, Engagement

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DEDICATION

This is dedicated to my family, peers, friends, and my partner. The backbone of my success is the community of eternally loving human beings who supported me along this path.

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LIST OF ABBREVIATIONS

AOR	Adjusted odds ratio
CBT	Cognitive behavioral therapy
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, 5th Edition
iCBT	Internet-based cognitive behavioral therapy
MBCT	Mindfulness-based cognitive therapy
mHealth	Mobile health
PCL-C	PTSD Checklist – Civilian Version
PHQ-9	Patient Health Questionnaire-9
PTSD	Post-traumatic stress disorder
RCT	Randomized controlled trial
SAMHSA	Substance Abuse and Mental Health Services Administration
SCID-IV	Structured Clinical Interview for the DSM-IV
SDK	Software development kit
SPI	Safety planning intervention
uMARS	User Version of the Mobile Application Rating Scale

1 INTRODUCTION

Depression is recognized as a leading cause of global disability. It is associated with not only personal suffering but also unemployment, poor physical health, poor social function, and suicide (Hawton et al., 2013; World Health Organization, 2017). Worldwide, depression affects 332 million individuals (World Health Organization, 2017), and depressive disorders are a leading cause of global burden of disease (Ferrari et al., 2013). For example, the 2010 Global Burden of Disease study found that major depressive disorder accounted for 8.2% of global years lived with disability and 2.5% of global disability adjusted life years (Ferrari et al., 2013). Within the United States, rates of depression remain high, with 9% of the population experiencing depression at any one time and a lifetime prevalence rate of 16.6% (Centers for Disease Control and Prevention, 2010; Kessler et al., 2005). Economic costs of depression are also substantial, with one analysis estimating $53 billion in annual economic burden in the United States alone (Greenberg et al., 1996; Wang, Simon, & Kessler, 2003).

1.1 Psychotherapy for the Treatment of Depression

Psychotherapy is one of the first-line treatments for depression. Many different types of psychotherapy have been studied for depression treatment efficacy, including cognitive-behavioral therapy, nondirective supportive therapy, behavioral activation, psychodynamic therapy, problem-solving therapy, interpersonal psychotherapy, and social skills training (Cuijpers, van Straten, Andersson, & van Oppen, 2008). Robinson, Berman, & Neimeyer (1990) compared the overall effectiveness of psychotherapy in comparison to no therapy and found an effect size of 0.73 (SD=.69), confirming that psychotherapy is effective in helping depressed individuals.

1.1.1 Cognitive-behavioral therapy

Cognitive-behavioral therapy (CBT) is an evidence-based treatment for depression (Chambless & Hollon, 1998) and remains one of the most scientifically supported models of psychotherapy. Of all types of psychotherapy, CBT is also the most commonly researched treatment for adult depression. The core of CBT focuses on evaluating, challenging, and modifying an individual's dysfunctional thoughts and beliefs in order to improve mood and behavior (Butler, Chapman, Forman, & Beck, 2006; Cuijpers et al., 2008). One meta-analysis conducted by Gloaguen, Cottraux, Cucherat, & Blackburn (1998) found that CBT was significantly better than waitlist/placebo and antidepressants for adult depression, with an effect size of 0.82 compared to waitlist or placebo and 0.38 compared to antidepressants. A more recent meta-analysis confirmed the finding, identifying a mean effect size of $g = 0.71$ for CBT compared to control groups (Cuijpers et al, 2013).

Behavioral activation is a component of CBT for the treatment of depression that aims to increase an individual's contact with sources of reward and to reengage with his or her life (Jacobson et al., 1996; Jacobson, Martell, & Dimidjian, 2001). It is also an evidence-based standalone treatment for depression (Chambless & Hollon, 1998). A review of meta-analyses and randomized controlled trials found that behavioral activation was superior to waitlist and treatment-as-usual control groups, and the effect size of behavioral activation was not different from CBT at post-treatment and follow up (Sturmey, 2009).

1.1.2 Psychoeducation

Psychoeducation refers to the intervention in which educational material is offered to individuals with psychological disorders (Donker, Griffiths, Cuijpers, & Christensen, 2009). Psychoeducation varies from passive interventions, such as the delivery of informational brochures or websites about depression (Christensen, Griffiths, & Jorm, 2004), to more active variants such as multi-session group interventions (Scogin, Jamison, & Gochneaur, 1989; Swan et al., 2004). This intervention may be delivered in book form (bibliotherapy; Cuijpers, 1997) or digitally (Christensen et al., 2004). A meta-analysis of passive psychoeducation interventions for depression and psychological distress revealed an effect size of 0.2 (95% CI [.01, .40]), indicating reduced symptoms of depression and psychological distress at post-intervention compared to attention, waitlist, or no intervention controls (Donker et al., 2009).

1.1.3 Mindfulness

Mindfulness is the practice of "openly attending, with awareness, to one's present moment experience" (Creswell, 2017). Mindfulness-based interventions, usually group-based interventions that incorporate mindfulness principles and techniques, have been effective at reducing depressive symptoms (Strauss, Cavanagh, Oliver, & Pettman, 2014; Teasdale et al., 2000). Specifically, mindfulness-based cognitive therapy (MBCT) is a group-based relapse prevention program designed for recurrently depressed individuals; evidence suggests that it is efficacious at reducing the risk of depression relapse (Teasdale et al., 2000). In a recent meta-analysis, mindfulness-based interventions were not different from evidence-based treatments at reducing disorder-specific symptoms at post-treatment ($d = -.004$) and follow up ($d = 0.09$), with consistent evidence in support of mindfulness for depression (Goldberg et al., 2018).

1.1.4 Safety planning

Individuals with depression are at elevated risk of suicidality. This risk increases with comorbid disorders (Bronisch & Wittchen, 1994; Schaffer et al., 2000) and across recurrent depressive episodes (Williams et al., 2006). Although it is not a treatment for depression, suicide safety planning can be used in adjunct with other psychotherapies for suicide prevention. Stanley

& Brown's (2012) safety planning intervention (SPI) provides individuals with a list of coping strategies and sources of support should suicidal thoughts emerge, with the goal of reducing immediate risk of suicidal crisis. SPI can be used in the context of outpatient or inpatient treatment and it is considered a best practice by the American Foundation for Suicide Prevention Best Practices Registry for Suicide Prevention (Stanley & Brown, 2012). Furthermore, SPI used in combination with structured telephone follow-up is considered acceptable and effective by both suicidal patients and staff in reducing suicidal behaviors among those who present to the emergency department (Chesin et al., 2017; Stanley et al., 2018).

1.2 Barriers to Psychotherapy

Despite effective psychotherapy options for the treatment of depression, certain obstacles prevent individuals from receiving services. Only half of Americans diagnosed with depression received some kind of treatment (González et al., 2010). Worldwide, the estimated treatment gap for depression is 56.3% (Kohn, Saxena, Levav, & Saraceno, 2004). It is necessary to understand why individuals do not seek evidenced-based mental health care in order to find methods for reducing the treatment gap and increasing access to care.

There are many barriers to receiving mental health treatment, such as low perceived need, structural barriers (e.g. affordability or shortage of mental health care providers), and attitudinal or evaluative barriers (e.g. stigma or desire to handle the problem on one's own) (Mojtabai et al., 2011). Mohr et al. (2006) identified and evaluated practical barriers (similar to structural barriers) and emotional barriers to psychotherapy in a primary care setting. Practical barriers included cost of psychotherapy, time constraints, transportation difficulties, and childcare or care for loved ones. Emotional barriers, similar to attitudinal or evaluative barriers, included discomfort talking about personal issues, concerns about being seen while emotional, talking about private topics with someone not known, and concerns about what others may think.

1.2.1 Low perceived need

Low perceived need refers to one's perception that seeking mental health treatment is unneeded. Sareen et al. (2007) analyzed three population-based mental health surveys across the United States, the Netherlands, and Ontario province in Canada. The rate of respondents who identified a perceived need for professional mental health treatment but did not seek out care was 6.5% (CI=5.9-7.2) from the Ontario Health Survey, 6.5% (CI=5.5-7.5) Netherlands Mental Health Survey and Incidence Study, and 7.1% (CI=6.2-8.0) from the National Comorbidity Survey. Additionally, Mojtabai et al. (2011) examined barriers to seeking and continuing treatment among the general public in the United States who had at least one psychiatric disorder (anxiety disorders, mood disorders, impulse control disorders, and substance use disorders) within the last 12-months. Results showed that 44.8% of respondents with a disorder who did not seek treatment reported low perceived need.

1.2.2 Attitudinal/evaluative barriers

According to Mojtabai et al. (2011), the desire to handle the problem on one's own was the most common reason among respondents with perceived need for both not seeking treatment and for dropping out of treatment. Attitudinal factors (e.g. stigma, and pessimism regarding effectiveness of treatment) were considered much more important barriers to seeking and maintaining treatment than structural barriers (e.g. inconvenience, inability to obtain an appointment). Across the three surveys analyzed by Sareen et al. (2007), the most commonly endorsed barriers were "I wanted to solve the problem on my own" and "I thought that the problem would get better by itself," indicating a mindset in which one acknowledges a need for professional mental health help but wants to solve the problem on one's own or wait until the symptoms resolve themselves over time. This form of attitudinal barrier may be one explanation for delayed treatment seeking behavior in individuals with a mental disorder. Wang et al. (2005) examined treatment contact behaviors after first onset of mental disorders using data from the National Comorbidity Survey Replication (Kessler & Merikangas, 2004). Although the majority of individuals with mood disorders eventually made contact with a treatment provider after disorder onset (cumulative lifetime probability of 88.1% for major depressive episode), most did not do so right away. For those with major depressive episodes, 37.4% of individuals made treatment contact within the first year of onset of the disorder; however, the median duration of delay until treatment contact was 8 years (Wang et al., 2005).

Socioeconomic factors can play a role in individuals' attitudes towards seeking treatment. Sareen et al. (2007) reported that across all three countries, individuals of lower income were significantly more likely than individuals of above-average income to endorse that "help probably would not do any good" (Adjusted Odds Ratio (AOR)=5.97, CI=1.77-20.11). Increasing age was significantly associated with lower likelihood of concerns about embarrassment from using mental health services (AOR=0.95, CI=0.90-1.00).

Finally, due to the nature of the disorder, depression acts as a barrier to treatment as well. Mohr et al. (2006) found that 74% of depressed respondents identified one or more barriers to psychotherapy compared to 51.4% of nondepressed respondents ($p=.008$). Depression was also associated with more emotional barriers. A replication of the 2006 study found similar results: greater levels of depression was associated with greater overall perceived barriers to psychological treatment (Mohr, Ho, et al., 2010). These results indicate that the presence of depression is both “an indicator for psychotherapy” but also a barrier to care in itself (Mohr et al., 2006).

1.2.3 Structural barriers

Structural barriers to mental health care include availability, accessibility, and affordability of care. In a survey of perceived barriers to psychological treatment, 24.6% of respondents identified cost as a barrier (Mohr, Ho, et al., 2010). Sareen et al. (2007) reported that across all three countries, the presence of a past-year mood disorder was associated with increased likelihood of endorsing a financial barrier (AOR=2.48, CI=1.03-5.98). Additionally, individuals with low income in the United States were more likely to endorse a financial barrier compared to those in Ontario or the Netherlands (AOR=2.43, CI=1.18-4.98).

Urban versus rural distinctions are operationalized differently across studies (Peen et al., 2010). Despite that, overall, individuals living in rural areas are less likely to receive evidence-based mental health care due to barriers in availability and accessibility of such care. For example, rural areas face a shortage of mental health providers (Ellis, Konrad, Thomas, & Morrissey, 2009). Mental health providers are more commonly found in high-population, urban areas, leaving over 60% of rural residents with a provider shortage (US Department of Health and Human Services, 2017). Additionally, 80% of masters-level social workers and 90% of psychologists and psychiatrists practice in metropolitan areas in the United States (Ellis et al., 2009). A discrepancy in service coverage may also be a reflection of the prioritization of mental health services by location. Specifically, common mental illnesses like mood and anxiety disorders are more prevalent in urban compared to rural areas, which may impact service allocation (Peen et al., 2010).

Other structural barriers persist in rural areas as well. For example, lack of local providers creates a larger travel burden on rural residents compared to those living in urban areas. Residents have to travel further and ensure that transportation is available for such a trip. Other factors include money for gas, requesting time off of work, and arranging for childcare (Weaver & Himle, 2017).

1.3 Leveraging the Internet for Treatment Delivery

With mental health becoming increasingly prioritized as a global health concern (Patel et al., 2016), the need for better, more accessible mental health treatments becomes urgent. In the last decade or so, mental health resources have largely been accessible through the World Wide Web. For example, one of the earliest web-based interventions available for public use was MoodGYM, a program created by Australian National University that taught cognitive behavior therapy skills to prevent and cope with depression. Due to the modular format of CBT, internet-based cognitive behavioral therapy (iCBT) interventions gained traction as a valuable modality for delivering evidence-based treatment. Karyotaki et al. (2017) conducted a meta-analysis of individual participant data from randomized controlled trials (RCTs) to examine the efficacy of self-guided iCBT for treating depressive symptoms. Self-guided iCBT was found to be significantly more effective compared to controls on depressive symptom severity ($\beta = -0.21$, Hedges $g = 0.27$) and treatment response ($\beta = 0.53$; odds ratio = 1.95; 95% CI [1.52, 2.50]; number needed to treat = 8). The authors concluded that self-guided iCBT could be considered an evidence-based first-step approach to treating depression symptoms in adults. Behavioral activation, a standalone treatment but also an important component of CBT for depression, has also shown “promising” evidence for efficacy in non-clinical settings, based on one meta-analysis of RCTs on internet-delivered behavioral activation (Huguet et al., 2018).

Similarly, internet-based services may reach broader populations than can be accessed through in-person methods. For example, a telephone survey of Texans after Hurricane Ike regarding post-disaster mental health distress found that although White participants were more likely to have considered and received in-person mental health services compared to African-American and Hispanic participants, all three racial groups reported same rates of accessing and using internet-based mental health interventions (Price, Davidson, Andrews, & Ruggiero, 2013). Their findings suggest that internet-based services may have a wider reach as well as greater accessibility for multicultural populations compared to that of in-person services. Muñoz et al. (2016) conducted a massively open online intervention for smoking cessation trial, which was available in Spanish and English for 30 months, and they observed that smoking quit rates for participants were 39.2%, 43.5%, 45.7%, and 50.3% at 1, 3, 6, and 12 months, respectively. Their results provided support that a widely accessible online-based intervention could provide a global population with evidence-based interventions for smoking cessation.

1.4 mHealth for Mental Health

As technology evolves, so do opportunities for its integration into the mental health landscape. Mobile health, also known as mHealth, is defined as any medical and health practice supported by mobile devices (van Heerden, Tomlinson, & Swartz, 2012). mHealth is a relatively new frontier for delivering mental health treatment (Kazdin & Blase, 2011), driven in part by rapid advances in smartphone technology and increasing global adoption of smartphones (Poushter, 2016; Smith, 2015). The Pew Research Center states that nearly two-thirds of Americans own a smartphone, whereas the total number of smartphone users around the globe in 2016 was an estimated 2.16 billion (Smith, 2015). Two-thirds of adults worldwide use the internet and smartphone ownership rates in emerging and developing countries are rising at a rapid rate (Poushter, 2016). Hence, mHealth interventions have the potential to reach close to one-third of the world's population.

mHealth apps have the potential to be used as a means for engagement, treatment facilitation, treatment maintenance, and connection between patient and health care professional (Price et al., 2014). Indeed, the number of mHealth-related publications has grown to reflect researchers' growing interest in using apps for mental health. Ownership, access, and use of mental health apps by consumers and health care organizations have grown as well (Firth et al., 2017). Due to the accessibility, convenience, widespread adoption of smartphones, mHealth interventions via smartphones offer the potential for cost-effective and evidence-based mental health services to the global community while circumventing traditional barriers to mental health care.

1.5 mHealth as a Potential Solution

Smartphone interventions for mental health, especially those in app format, have been on the rise with the goal of tackling a range of DSM-5 disorders, including post-traumatic stress disorder, obsessive compulsive disorder, and generalized anxiety disorder (Van Ameringen et al., 2017). Research has shown that interventions delivered in a mobile format can be efficacious in reducing depressive symptoms. Firth et al. (2017) conducted a meta-analysis of randomized controlled trials which suggested that depressive symptoms were reduced significantly more from smartphone application interventions than control conditions and that effects from smartphone-only interventions were greater than effects from interventions which incorporated human or computerized aspects in addition to the smartphone component. These findings are similar to those by Karyotaki et al. (2017) on self-guided iCBT interventions compared to controls. Not only are smartphone interventions effective, but they may be an increasingly preferred modality as well. Renn et al. (2019) found in a recent survey that the percentage of American adults who would consider trying in-person psychotherapy versus digital psychotherapy in the future were similar (73.2% and 72.0%, respectively). When forced to make a choice out of four treatment modalities—self-guided digital, peer-supported digital, expert-guided digital, or in-person psychotherapy—the majority of respondents (44.5%) preferred in-person psychotherapy, but a combined 53.8% of respondents said they were most likely to choose one of the three digital treatment modalities over in-person psychotherapy. Of the three digital modalities, self-guided digital treatment was most preferred (25.6%). These results suggest that preferences for digital treatment may have increased over the last few years, especially when comparing between previous survey studies that indicated a much higher preference for in-person treatment compared to internet-delivered treatment (Mohr, Siddique, et al., 2010; Travers & Benton, 2014).

In addition, smartphones offer the unique opportunity of putting mental health tools into the pockets of individuals with high and immediate need. Specifically, delivering mobile mental health care to less accessible, underserved populations becomes more efficient than ever. For example, 70% of Indigenous Australian people now own a smartphone compared to 66% of the overall Australian population (McNair Ingenuity Research, 2014). To address rates of youth suicide in Australian Indigenous communities, Tighe et al. (2017) designed a pilot study to evaluate the effectiveness of a self-help mobile app targeting, among others, depression and suicidal ideation. iBobbly is specifically aimed toward Indigenous youth in remote Australia. Participants who received iBobbly had statistically significant reductions in depressive symptoms ($d=0.71$, 95% CI [0.17, 1.23]) and distress ($d=0.65$, 95% CI [0.12, 1.17]) compared to those in the waitlist condition.

Smartphones can collect depressive symptom data in real-time and potentially with higher sensitivity compared to a paper-and-pencil assessment (Torous et al., 2015). Torous and colleagues (2015) evaluated the app Mindful Moods in a psychiatric outpatient sample and found that it was an effective tool for assessing symptoms of depression. More specifically, results revealed that the app significantly increased rates of disclosure relative to paper-and-pencil administered Patient Health Questionnaire (PHQ-9; Kroenke, Spitzer, & Williams, 2001) scores on depressive symptomology, including suicidal ideation.

Finally, mobile forms of intervention delivery may circumvent many of the structural barriers to treatment for depression, such as availability of mental health providers, inability to attend traditional in-person therapy during business hours, time, travel, and financial limitations (Moritz, Schröder, Meyer, & Hauschildt, 2013). Mohr and colleagues (2006) determined that 19.5% of participants who perceived barriers to psychological treatment cited time constraints, such as interference from daily responsibilities and difficulties getting time off work, as a barrier. Smartphones have the potential to disseminate effective interventions more cheaply, easily, and efficiently, and to make them more accessible to those who need them.

1.6 mHealth in the Real World

Although mHealth interventions have yielded promising usability, feasibility, and efficacy results, the majority of studies have been limited in various ways. One limitation is small sample size. Of the 18 studies included in the meta-analysis by Firth et al. (2017), the sample sizes ranged from 10 to 211. Another limitation is using research-only versions of interventions during the study, only to have the mHealth intervention unavailable to the public afterwards. Again, upon examining Firth and colleagues’ meta-analysis, only four (Headspace, PTSD Coach, Superbetter, and MyCompass) out of the 18 apps studied are currently available for public download. A third limitation is the use of incentives to increase participation in the study. While beneficial for data collection, it limits the generalizability of results to real-world settings. Lastly, mHealth interventions tend to be evaluated for feasibility or efficacy as a whole. Few studies report fine-grain user behavior, such as average length of time spent or most commonly visited features within an app, which would provide insight into what specific features or doses of an intervention contribute to symptom improvement.

Self-help internet-based interventions can contribute to the reduction of health disparities worldwide (Muñoz, 2010). Since smartphone-based interventions act on the same principles as internet-based interventions, they can similarly address disparities in global mental health. One method for doing so is the dissemination of mental health interventions that are publicly available and free for anyone in the world to use. Results from the massively open online intervention for smoking cessation (Muñoz et al., 2016) suggested the potential of this method for delivering evidence-based intervention to a global population.

In order to recognize ways in which mHealth, especially self-help, interventions increase access and circumvent barriers to treatment, it is crucial to understand how mental health apps are used in the general population. Examining real-life engagement of these apps not only increases ecologically valid understanding of mHealth use but also identifies areas of focus in functionality and design of apps for future research. However, many self-help or self-guided mHealth interventions reported in scientific journals are not publicly available for download. Only a handful of studies have examined how users in a general population engage with publicly available self-help mental health apps, as described below.

1.6.1 PTSD Coach

Developed in 2011, PTSD Coach is a free, publicly available, self-contained mental health tool for managing acute distress related to post-traumatic stress disorder (PTSD) that targets both military veterans and the broader civilian population (Kuhn et al., 2018). It was created in collaboration with the US Department of Veterans Affairs and the Department of Defense (Owen et al., 2015). The app contains four core sections. The Learn sections offers psychoeducation about PTSD, professional care, and impact of PTSD on family. The Track Symptoms section provides users the ability to self-monitor PTSD symptom severity, and it offers users feedback and recommendations for treatment. The Manage Symptoms section offers coping tools for PTSD-related acute stress. Finally, the Get Support section provides access to crisis support and allows users to add personal contacts as well. PTSD Coach has previously been found to be acceptable and moderately-to-very helpful for managing PTSD symptoms by veterans receiving PTSD treatment (Kuhn et al., 2014). Additionally, the app has shown to reduce PTSD symptoms in community samples after one month and three months of use (Kuhn et al., 2017; Miner et al., 2016).

Owen et al. (2015) assessed the reach, use, and impact of PTSD Coach using an aggregate analytics data service. iOS and Android user behavior data was collected from 153,834 downloads of the app. The methodology employed by Owen et al. (2015) is unique in its examination of real-life, population-based, aggregate usage data. The study examined (1) the reach of PTSD Coach over time, (2) user engagement with the app, and (3) reception and impact of the app in the general population. Reach was examined using descriptive statistics on basic user engagement metrics. App usage was characterized by differences between iOS and Android users with regards to app-related tasks, such as viewing one of the four content areas within the app. Reception was evaluated by analyzing user reviews from Apple and Google app stores. Finally, impact was evaluated by measuring changes in self-reported momentary distress scores.

Results showed that PTSD Coach was downloaded in 86 countries, with non-US downloads making up 12% of total downloads. On average, the total time spent using the app was 325 seconds and users used the app for 6.3 sessions before discontinuing use. The average score of self-reported PTSD symptoms, measured using the PTSD Checklist – Civilian Version (PCL-C; Weathers, Litz, Herman, Huska, & Keane, 1993), in both first-time user sessions and returning users' sessions were above the cut point for identifying a diagnosis of PTSD. In terms of user retention, 61.1% of users returned to the app after the first day it was installed. Usage rates declined over time, with 41.6%, 28.6%, 19.4%, and 10.6% of users returning to the app after 1, 3, 6, and 12 months after download, respectively. With regards to the time of day the app was used, most app usage occurred between 8:00 am and 10:00 pm during the user's time zone, peaking at 1:00 pm.

Authors examined PCL-C trauma symptom reduction between first-time sessions and return-visit sessions. The mean PCL score for first-time sessions (57.2, SD=15.7) was higher than that of return-visit sessions (55.1, SD=16.6), and the between-group difference was statistically significant (p=.024). Self-reported momentary distress levels were also collected. Results showed that return-visit users exhibited higher momentary distress levels compared to first-time users ($t(2956)=2.76$, $p=.0057$), suggesting that the app is being used in moments of need. The broad dissemination of PTSD Coach around the world points to its wide reach and potential public health impact, while attrition and user behavior data provide novel insight into real-world usage characteristics of a mHealth application for mental health.

1.6.2 IntelliCare

IntelliCare is a suite of thirteen smartphone apps developed at Northwestern University's Center for Behavioral Intervention Technologies. A free, publicly available mHealth intervention, the app suite is designed to employ various methods that are efficacious at improving depression and anxiety symptoms, such as elements from cognitive-behavioral therapy, positive psychology, and physical activity-based interventions (Lattie et al., 2016). The types of interactions differ by app; for example, apps may ask users to log or track information, complete checklists, follow guided exercises, or read didactic content.

Unlike PTSD Coach, which encompassed four core sections that was navigated from a main page, the IntelliCare app suite was designed to imitate smartphone apps that focused on singular functions. For example, Day to Day delivers information throughout the day to boost the user's mood and cultivate gratitude; Thought Challenger is an interactive cognitive restructuring tool; and Purple Chill offers users a library of audio recordings to teach relaxation and mindfulness practices. With one exception, IntelliCare apps focus on one behavioral or psychological strategy for reducing anxiety or depression. The thirteenth app, Hub, is a central hub for coordinating use across the twelve interactive apps. Additionally, Hub acts as a tool to harness data in order to "create an underlying analytic model that makes recommendations for further app use" (Lattie et al., 2016). The aim of the study by Lattie and colleagues (2016) was to evaluate feasibility through initial uptake and use patterns of IntelliCare, which was available for download on the Google Play store. Uptake and usage of the IntelliCare suite were measured by number of downloads and launches of each app.

Results revealed that 5,210 users downloaded one or more of the IntelliCare apps with 10,131 app downloads in total. Around one-third of users downloaded more than one app, while the mean number of app downloads per user was 1.94. Individuals who downloaded the IntelliCare Hub app (30.9%) downloaded more IntelliCare apps compared to those who did not ($X^2(11) = 1370.05$, $p<.001$). With regards to order and timing of downloads, the IntelliCare Hub was the most popular initial download, with one-fourth of all users downloading it first. Of the users who downloaded multiple IntelliCare apps, more than half (57.1%) downloaded their respective apps within a 24-hour period. With regards to app sessions, the modal number of sessions for each app was 1. The mean number of sessions for all interactive IntelliCare apps combined was 6.11 (SD = 17.18), whereas the mean number of sessions for each individual app ranged from 3.10 to 16.98. In terms of sustained user engagement, about half of all users continued to use IntelliCare apps for more than one day after initial download. The number of users decreased to approximately one-third after seven days after initial download. Among the twelve interactive apps, engagement rates at day 28 after initial download ranged from 12.02% to 23.30%. Daily Feats, an app that encourages users to incorporate meaningful, productive activities into the day, had the highest percentage of sustained user engagement over time (23.30% at 28 days).

Lattie and colleagues (2016) concluded that the general public will use multiple mental health apps from an app suite to meet their needs, and that the structure of the IntelliCare app suite may have the potential to introduce components of evidence-based treatments in a way that promotes usage and self-tailoring. They also noted “considerable variability” in the use of the IntelliCare apps, and they indicated that the variability in use could be due to usability issues or even competition from similar apps on the marketplace. Additionally, they alluded that the engagement numbers represent an early snapshot of IntelliCare use, as data was collected from users in the first year of IntelliCare’s release.

1.6.3 Wysa

Wysa is an artificial intelligence-based chatbot app aimed at “building mental resilience” and “promoting mental well-being using a text-based conversational interface” (Inkster, Sarda, & Subramanian, 2018). As a 24/7 chatbot service, Wysa uses self-help practices derived from CBT, dialectical behavior therapy, motivational interviewing, positive behavior support, behavioral reinforcement, and mindfulness to help users build emotional resiliency.

The study conducted by Inkster and colleagues (2018) investigated the effectiveness of Wysa at delivering positive psychology and mental well-being techniques for users with self-reported depressive symptoms, measured with the PHQ-9 (Kroenke, Spitzer, & Williams, 2001). A secondary aim was to understand users’ experiences during app use. Participants were allocated to one of two groups: high users and low users. Group status was determined by app engagement on and between 2 consecutive PHQ-9 screenings: high users engaged with the app on both screening days as well as once between those days, whereas low users only engaged with the app on the two screening days.

Region and time-zone analysis found that users (N=129) came from America (48.1%), Europe (26.4%), and Asia (18.6%). The high users group had significantly higher average symptom improvement (mean = 5.84, SD = 6.66) compared to the low users group (mean = 3.52, SD = 6.15). Qualitative analysis of users’ experiences in the app found that 67.7% of feedback responses found the app experience favorable. The authors concluded that initial findings on effectiveness and engagement of Wysa on users show promise but that further work is needed to validate these findings on a larger scale.

1.7 MoodTools for Depression

MoodTools is a free, publicly-available self-help app for reducing depressive symptoms. Since its release in 2014, MoodTools has been downloaded on iOS and Android devices over 480,000 times. Because it is available to the general public like PTSD Coach, IntelliCare, and Wysa, MoodTools offers the opportunity to examine how a mobile mental health app for depression is used by the general population.

MoodTools is a fully automated, self-help smartphone app for iOS (i.e. iPhone and iPad) and Android devices. All content is self-contained within the app and there is no therapist interaction. MoodTools contains six features called tools. The *Information* tool contains psychoeducation about depression. The *Test* tool contains the mobile form of the Patient Health Questionnaire (PHQ-9), a nine-item depression screening questionnaire that has been validated in paper form (Kroenke, Spitzer, & Williams, 2001) and in mobile form (Bush, Skopp, Smolenski, Crumpton, & Fairall, 2013). Users receive appropriate follow-up resources at the end of assessment if they meet various thresholds for depression severity and they can monitor symptoms by reviewing a history of previous assessment points. Users are also encouraged to track their symptom severity over time by re-taking the PHQ-9 once every two weeks. The *Thought Diary* tool features a diary entry derived from thought records (Beck, 2011) for the practice of thought restructuring. Users follow prompts to record negative thoughts, identify cognitive distortions within them, and reframe them in a more helpful or balanced manner. Entries can be saved for future review and editing. The *Activities* tool, based on behavioral activation therapy, offers self-prescribed or helpful activities that users can engage in to improve mood. The activities are fully customizable, and the history page allows users to see which activities provide the biggest boost in subjective mood. The *Videos* tool contains a curated list of

YouTube videos such as TED talks, guided meditations, and soothing sounds for mindfulness. Finally, the *Safety Plan* tool offers an informational guide on coping with suicidal thoughts, allows users to fill out a safety plan, and provides quick access to local urgent care, emergency departments, and national crisis hotlines. MoodTools was published on Google Play for Android devices in June 2014 and on Apple App Store for iOS devices in 2015.

2 PURPOSE

The purpose of the study is to evaluate the extent to which MoodTools (1) circumvents barriers to traditional psychotherapy and (2) engages users.

Aim 1. To characterize MoodTools users and MoodTools sessions, we examine:

- Number of users across the globe.
- Number of users in cities versus non-cities in the United States.
- Initial and ongoing user retention.
- App session characteristics.
- App session content.

Aim 2. To evaluate the potential of MoodTools to circumvent barriers to traditional psychotherapy, we examine:

- The number of times individuals use the app during and outside of traditional business hours of psychotherapy practice.

and test the following hypotheses:

- **Hypothesis 2a**: The number of MoodTools users will be positively associated with U.S. states with higher rates of unmet mental health need.
- **Hypothesis 2b**: MoodTools use, defined by frequency of app sessions, between traditional business and non-business hours will not be equal, such that use during non-business hours will be greater than use during business hours.

Aim 3. To evaluate the potential of MoodTools to engage users, we examine and test the following hypothesis:

- **Hypothesis 3**: There will be a positive correlation between PHQ-9 scores and MoodTools engagement time, such that individuals with higher initial PHQ-9 scores are more likely to spend more time in the app than individuals with lower initial PHQ-9 scores.

3 METHODS

3.1 Data Source

Data was derived from mobile analytics data from all unique downloads of the Android version of MoodTools between March 1, 2016 and February 28, 2018. Due to the de-identification and data aggregation process, no demographic or personally identifying information was tied to individual user data.

3.2 Procedure

This study was approved by the Institutional Review Board at Georgia State University as Designation for Not Human Subjects Research.

User engagement with MoodTools was measured through Google Analytics. The Google Analytics software development kit (SDK) was integrated into Android versions of MoodTools in order to collect behavioral and user engagement data from users. Google Analytics was used to securely capture aggregate usage data and retention information across time, as well as to capture key app-related events (e.g. viewing home pages, visiting app content, taking a depression symptom severity questionnaire, and obtaining questionnaire scores). No identifying information was available for any user of the app. All usage measures were stored in aggregated, anonymized data files on Google Analytics' storage database.

Using Google Analytics SDK, we captured basic user engagement measures (e.g. number of downloads, active users, session length, number of sessions, duration of each session, total length of time spent in app), rates of user retention across time, location data, and app-related events. Additionally, user-level app engagement data, which included an individual's minute-by-minute session interactions as well as all PHQ-9 scores recorded within MoodTools, were collected from all users who had taken the PHQ-9 within the app at least once.

3.3 Measures

In addition to basic user engagement, user retention, and location data, we measured self-report data on depression symptoms through the PHQ-9. The nine-item PHQ-9 is a widely used self-report measure of depression, and it has been demonstrated to be reliable (Cronbach's alpha=0.86-0.89) and valid, as a PHQ-9 score of greater than 10 had a sensitivity of 88% and specificity of 88% for major depression (Kroenke, Spitzer, & Williams, 2001). Table 3.01 shows diagnostic cut-off scores for the PHQ-9.

Table 3.1 PHQ-9 Score Diagnostic Interpretations

PHQ-9 Score	**Interpretation**
0 – 4	Minimal depression
5 – 9	Mild depression
10 – 14	Moderate depression
15 – 19	Moderately severe depression
20 – 27	Severe depression

3.4 Data Analysis

All data analyses were conducted using SPSS 24, SPSS 26, Microsoft Excel, and Python.

4 RESULTS

4.1 Aim 1: Characterizing MoodTools Users and Sessions

4.1.1 Number of users across the globe

Between March 1, 2016 and February 28, 2018, MoodTools on the Android platform was used by 158,930 people from 198 countries. Appendix C displays the percentage breakdown of users by continent, subcontinent, and country. The app was downloaded across the Americas (50.46%), Europe (26.46%), Asia (15.48%), Oceania (4.82%), and Africa (2.61%). When categorized by subcontinents, more than half of all users were from Northern America and Northern Europe (46.537% and 13.324%, respectively). Countries with the highest percentage of users included the United States (40.83%), United Kingdom (10.64%), India (8.47%), Canada (5.60%), and Australia (4.02%). Users whose location could not be determined by Google Analytics were identified as “Not Set” (0.18%).

4.1.2 Number of users in cities versus non-cities in the United States

To evaluate the ratio of downloads between cities and non-cities in the United States, we defined “city” as any urban area of 50,000 or more people (i.e. Urbanized Area) as classified by the U.S. Census Bureau (2010). Users who downloaded the app from places that didn’t meet classification as an Urbanized Area was considered “non-city” for the purposes of this analysis. Results showed that even though 71.23% of the United States population reside in cities (U.S. Census Bureau, 2012), only 56.87% of all users who downloaded MoodTools from the United States were from cities.

4.1.3 Initial and ongoing user retention

Retention was evaluated in two ways: initial retention and ongoing retention. Initial retention was defined as the rate of users that return to the app at any point after their first app session. Ongoing retention was operationalized as the number of users that used the app one, two, three, etc., times after download.

MoodTools had an initial retention of 52.36%, indicating that a little more than half of all users returned to the app at any point after their first app session. *Figure 4.1* shows a funnel of *n* number of sessions that have been initiated across all sessions. For example, across all 525,000 app sessions initiated by all users, 161,000 were the users' very first session, 83,000 were their second session, and 52,000 were their third session. In addition, around 2,100 users initiated >200 app sessions over the two-year duration of the study.

4.1.4 App session characteristics

Across all sessions, the average session duration was 4 minutes 0 seconds. On average, users spent 11 minutes and 59 seconds across 2.78 sessions in MoodTools over the span of 90 days after initial app download. *Figure 4.2* displays a breakdown of app session durations across all sessions. Out of 524,629 total sessions, about one-third lasted between 0 and 10 seconds, one-third lasted between 11 to 180 seconds, and the remainder of sessions lasted more than 181 seconds.

Figure 4.3 displays the number of days between the close of one session and the opening of another for all app sessions ever initiated (*n* = 524,629). Over half of all app sessions were initiated within the same day. Furthermore, less than 1% of sessions took place more than 3 months after a previous session.

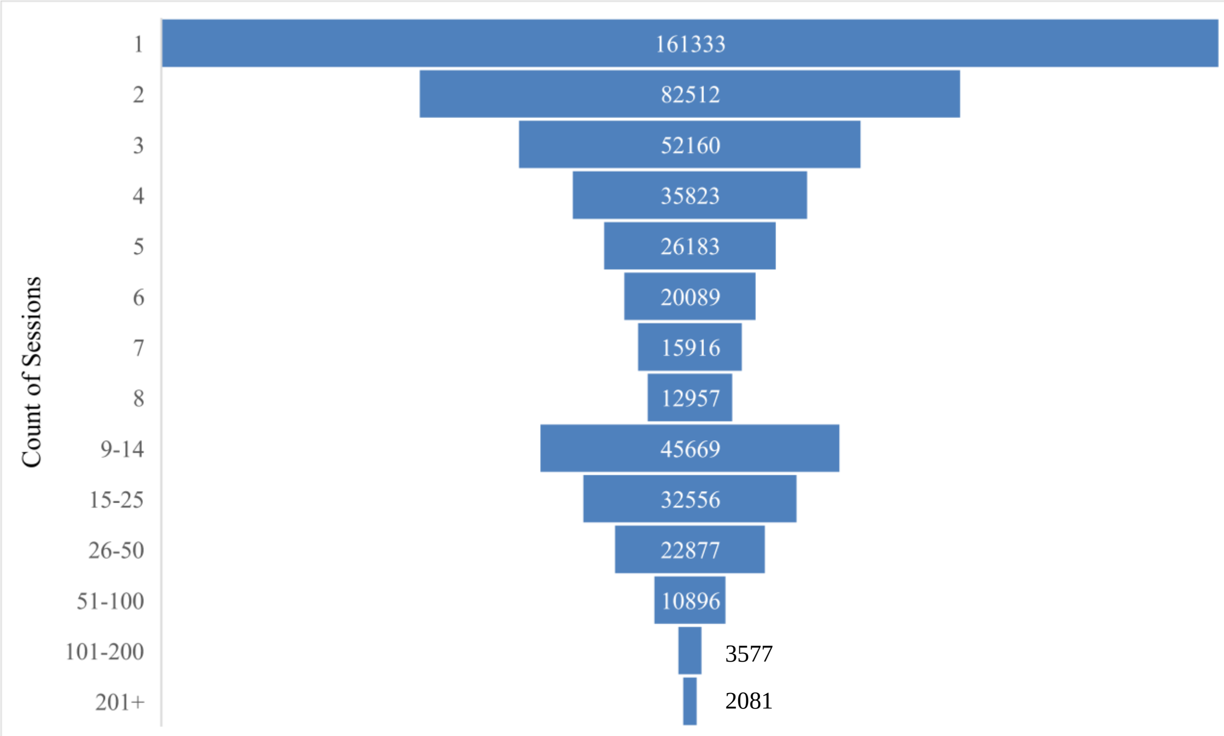

Figure 4.1 Frequency of MoodTools Session Counts

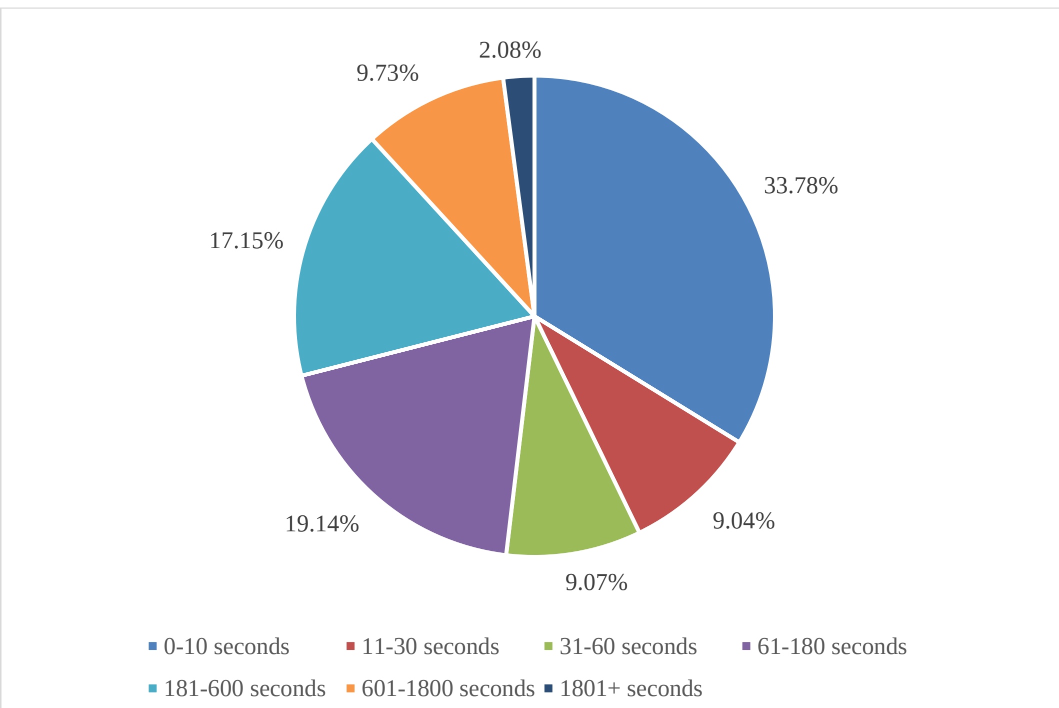

Figure 4.2 Duration of MoodTools Sessions Across All Sessions

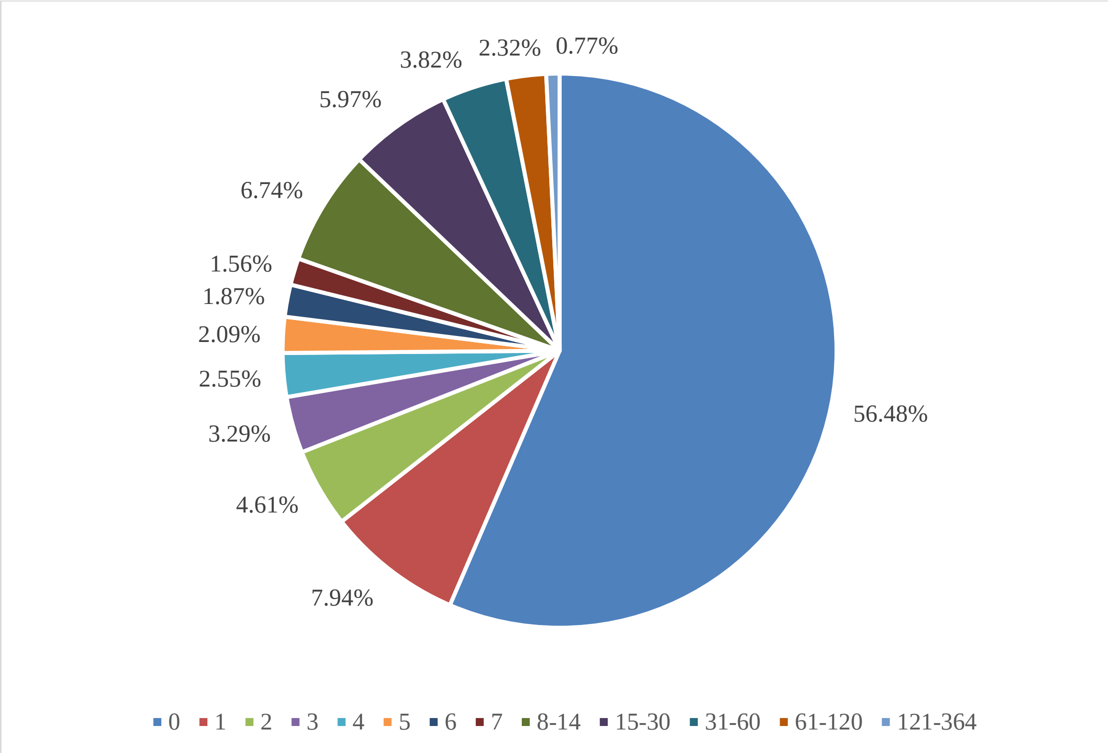

Figure 4.3 Number of Days Between Initiating MoodTools Sessions

4.1.5 App session content

Data analysis captured how often users visited specific screens within MoodTools on an aggregate level. MoodTools contains six tools accessible through a home page. If a user opens the main screen to any of the six tools, this would be defined as accessing that particular tool. *Table 4.1* shows total screen views, percentage of screen views, average number of screen views per session, and average time spent on screen for each of the six tools' main screens. Overall, the Thought Diary tool and Test tool were tied for most frequently accessed tools, each making up 24.32% of all main screens viewed across all sessions for all users (*n* = 1,618,277 screens). The Information tool (i.e. psychoeducation about depression) was the least frequently accessed (7.70%). In addition, the average time spent on the New Diary Entry screen, which all users accessed through the Thought Diary tool in order to complete a digital thought record, was 3 minutes and 5 seconds (185 seconds). The average time spent writing a Thought Diary entry was 3 minutes and 5 seconds (185 seconds).

Table 4.1 Screen Views by Tool

Tool Name	Total Screen Views	% of Screen Views	Average # of Screen Views per Session	Average Time on Screen (sec)
Thought Diary	393,549	24.32	2.24	12.25
Test	393,487	24.32	2.00	5.71
Activities	331,961	20.51	2.35	10.08
Safety Plan	236,449	14.61	2.32	14.20
Videos	138,164	8.54	1.40	5.76
Information	124,667	7.70	1.23	11.34

4.2 Aim 2: Circumventing Barriers to Mental Health Care

4.2.1 Relation between MoodTools use and unmet mental health need

The potential of MoodTools to circumvent barriers to traditional psychotherapy was examined by evaluating the relation between the rate of MoodTools users per 100,000 people to rates of adults with any mental illness reporting unmet need for treatment across all 50 states in the US. The rate of MoodTools users was controlled for using state population such that:

$$Rate = \frac{\#\ of\ MoodTools\ users\ from\ Mar\ 2016\ to\ Feb\ 2018}{State\ population\ in\ 2010\ Census} \times 100000$$

State population sizes were obtained from the 2010 United States Census (U.S. Census Bureau, 2012). The dataset for rates of unmet need for treatment was derived from the Substance Abuse and Mental Health Services Administration's (SAMHSA) National Survey on Drug Use and Health (U.S. Department of Health and Human Services, 2018) and coded by Mental Health America (2018). Adults with any mental illness was defined as having a diagnosable mental, behavioral, or emotional disorder, other than a developmental or substance use disorder, as assessed by the Structured Clinical Interview for the DSM-IV (SCID-IV); unmet need was defined as feeling a perceived need for mental health treatment/counseling that was not received (Mental Health America, 2018; U.S. Department of Health and Human Services, 2018).

All statistical assumptions were met for the Pearson's r correlation. For MoodTools users, data were normally distributed (skewness and kurtosis under +/- 0.5, Shapiro-Wilk p=0.17). Data were also normally distributed for rates of unmet need (skewness and kurtosis under +/- 0.5, Shapiro-Wilk p=0.72). As predicted, there was a moderate positive correlation between the number of MoodTools users per 100,000 people and rate of adults with any mental illness reporting unmet need per state (r=.368, 95% CI [.098, .638], p=.009).

4.2.2 Use of MoodTools during business and non-business hours

The potential of MoodTools to circumvent barriers to traditional psychotherapy was examined by evaluating the number of times that individuals use MoodTools outside of traditional business hours of psychotherapy practice. This was examined for four culturally Western countries that shared similar business hour schedules (i.e. 9:00 am to 5:00 pm): United States, United Kingdom, Canada, and Australia. For each country, we recorded the frequency of app sessions that were initiated during each hour in the day, for a total of 24 hours. Because some countries occupied multiple time zones, MoodTools data was calculated to the local time zone for each individual state or province. For states or provinces that occupied multiple time zones, a weighted average was used to determine the local time zone, such that the time zone that had a majority of MoodTools users (>60%) was used to represent the whole state or province.

Appendix D displays the histograms of app sessions by hour-of-day for the United States, United Kingdom, Canada, and Australia. The histograms demonstrate the frequency of MoodTools sessions by hour-of-day in 1) states or provinces with only one time zone and 2) all states or provinces. This is done for each country except the United Kingdom, since the UK occupies only one time zone. Across all countries, 37.96% of MoodTools sessions were initiated during business hours (i.e. 9am-5pm), while the majority (62.04%) of sessions were initiated outside of business hours. The hour with the highest session count was 10:00 pm, making up 6.80% of all sessions. The hour with the lowest session count was 4:00 am, making up 1.23% of all sessions.

A chi-square test of independence was performed to test the hypothesis that MoodTools use will be higher during non-business hours than business hours. A Shapiro-Wilk test showed a significant departure from normality ($W(96) = 0.742$, $p < .001$). Therefore, a Mann-Whitney U test was performed. Due to violating the assumption that the shape of the distribution between groups are the same, the Mann-Whitney U test compared mean ranks of MoodTools use rather than medians. The test compared MoodTools use between business hours (9:00am-4:59pm) and non-business, non-sleep hours (5:00pm-12:59am). MoodTools use during non-business, non-sleep hours were not significantly different than use during business hours ($U = 402.5$, $p = .141$).

4.3 Aim 3: User Engagement

A Pearson's r correlation was conducted to test the association between users' first PHQ-9 test score (Test Score) and total amount of time spent in MoodTools (Total Duration). The first PHQ-9 score recorded during users' first app session was included in analysis. PHQ-9 scores with a value of 0 were excluded from analysis because it was impossible to determine whether a value of 0 represented a valid score from a completed test versus other unrelated app-based events that had an arbitrary value of 0. The Test Score and Total Duration variables yielded mild skewness (-.284, .405) and kurtosis (-.697, -.496), respectively. For Total Duration, data was transformed with log10 and outliers beyond three standard deviations from the mean were

Winsorized to the nearest acceptable upper- and lower-bound value. Kolmogorov-Smirnov test of normality found that both variables were not normally distributed ($p < .001$). However, it is notable that the Kolmogorov-Smirnov test is sensitive to small deviations from normality for a large sample size such as $n = 88{,}023$ (Ghasemi & Zahediasl, 2012). Results found that there was no correlation between users' first PHQ-9 test score and log-transformed total amount of time spent in MoodTools, $r(88{,}021) = -.002$, $p = .592$.

5 DISCUSSION

This study aimed to evaluate the extent to which a self-help mHealth app for depression called MoodTools circumvents barriers to care in traditional psychotherapy and engages its users. First, MoodTools users and sessions were characterized to ascertain who used the app and how it was being used. Second, app use was used to examine the potential of the app to circumvent traditional barriers to psychotherapy. Finally, the relationship between app use and depression symptom severity was investigated as a measure of how well the app engages users. Results indicated that people used MoodTools an average of 4 minutes each time they opened the app and that the majority of users returned to the app at least once after initial download (52.36%). As expected, there was a moderate positive correlation between number of users who downloaded MoodTools and rate of unmet mental health need in the United States. Unexpectedly, there was no statistically significant difference in the use of MoodTools during business hours (9:00am-4:59pm) versus non-business, non-sleep hours (5:00pm-12:59am). In addition, there was no correlation between users' first PHQ-9 score from their first app session and total amount of time spent in the app.

Real-world mHealth app data allows for better understanding of how individuals utilize smartphone technology to improve mental health. Findings from this study indicated that a self-help app for individuals with depression, MoodTools, was downloaded across the globe in 198 countries. In the United States, users accessed MoodTools from both city and non-city areas. The data demonstrated that there was a global interest in a smartphone app that delivers self-help tools for individuals with depression.

5.1 Circumventing Barriers to Care

This is the first study to identify a positive correlation between app downloads and unmet mental health need in the United States. This finding supports the idea that mHealth interventions for mental health can help improve access to treatment, especially in areas where the rate of unmet need for treatment is high. It may also suggest that individuals who are facing barriers to traditional forms of treatment (i.e. in-person) may turn to alternative sources of help like mHealth apps.

There was no relationship between MoodTools use and time of day. Specifically, use of the app during business hours was not different from non-business, non-sleep hours. Despite the null finding, the high percentage of MoodTools sessions initiated outside of business hours (62%) suggests that MoodTools can provide mental health tools to users when they do not have access to in-person care during business hours. Daily app use peaked at 10:00pm, which is similar to findings from Baumel et al. (2019) that saw a daily peak in mental health app use at 8:00pm. These findings support the idea that mHealth interventions for mental health can circumvent structural barriers to traditional psychotherapy.

5.2 User Engagement and Retention

5.2.1 User engagement

Data on user engagement is critical to evaluate the utility of apps for improving mental health. One problem with the literature is that there is not an agreed-upon conceptualization for engagement with mental health apps. Perski and colleagues (2017) noted in a systematic review that some studies of digital behavioral health interventions conceptualize engagement as the extent of usage over time - a combination of breadth, depth, frequency, and duration of use which is described as “dosage” of an intervention. Engagement can also be differentiated into "active" and "passive" engagement, where active behaviors involve contribution to the intervention whereas passive behaviors involve listening, reading, or activities where initiative is not needed. Yet others conceptualize engagement as a subjective experience, such as an individual's state of "flow" (Csikszentmihalyi, 1990; Zhou, 2013) or "immersion" (Jennett et al., 2008). It is therefore not surprising that there is no standardized metric for reporting user engagement. Even when examining similar conceptualizations of engagement, the scale of measurement may vary. App use may be measured in frequency of logins and number of modules completed (Donkin et al., 2011) or time spent in the app (Owen et al., 2015).

Due to these problems and the fact that research on real-world engagement with mental health apps is in its infancy, there is little literature in which to put the current findings on user engagement into context. A "head-to-head" comparison of user engagement can be made between MoodTools and PTSD Coach. Over the span of 90 days, MoodTools users engaged with the app for an average of 12 minutes across 3 sessions, whereas PTSD Coach users engaged with the app for an average of 5 minutes across 6.3 sessions before discontinuing use. The median session duration for PTSD Coach was 47 seconds (Owen et al., 2015), compared to an average of 4 minutes for MoodTools. These differences may be a reflection of the target populations. PTSD Coach is designed for military veterans and civilians with PTSD symptoms, whereas MoodTools is designed for individuals with low mood or depressive symptoms. Given that MoodTools does not collect demographic or personally identifying information, conclusions cannot be made about demographic differences between users of both apps. App layout and design may play a role in how each app is used. Rodriguez-Paras & Sasangohar's (2017) usability study of PTSD Coach found that lack of clarity on how to use the symptom management tools negatively affected usability. This is in contrast with MoodTools' layout, which offers fewer activities but prominently displays all symptom management tools from a home page for an easier navigation experience. Likewise, participants of the usability study found the visual design and color scheme of PTSD Coach unfavorable and was also deemed to affect usability (Rodriguez-Paras & Sasangohar, 2017). There are no usability studies on MoodTools, so direct comparisons cannot be made. Altogether, target population, app layout, and app design differences between the two apps may explain differences in user engagement.

5.2.2 User retention

Measures of user retention are inconsistent across real-world studies of mHealth apps. In some cases, engagement may be defined as retention (Fleming et al., 2018), which further complicates the use of both constructs in the literature. For this study, retention was defined as continued use of the app as measured by session counts. Results from this study showed that just over half (52.36%) of users return to the app after their first session, which is comparable to IntelliCare (about 50%) and PTSD Coach (61.1%), although this study operationalized retention as any return to the app, whereas the other apps operationalized retention as return to the app more than one day after initial download (Lattie et al., 2016; Owen et al., 2015).

Undeniably, the realm of digital mental health is in a period of incredible growth. Fleming and colleagues (2018) conducted a systematic review of real-world uptake and engagement for self-help interventions. Seven publicly available digital self-help interventions for depression, low mood, and anxiety were identified as of their publication; the review included PTSD Coach (Owen et al., 2015) and IntelliCare (Lattie et al., 2016). Fleming et al. (2018) grouped engagement into three categories: minimal use equated to using the intervention at least once or completing at least one module or assessment; completed or sustained use equated to at least 6 weeks of use or completion of the intervention; and moderate use was any amount of use between minimal and sustained. Across studies, 21-88% of users used the self-help intervention at least once, 7-42% of users sustained use after 4 weeks, and sustained use after 6 weeks was 0.5-28.6% (Fleming et al., 2018). Regarding minimal use, 38.7% to 70.2% of IntelliCare users used their apps for at least one day (Lattie et al., 2016), while Happify saw the lowest initial use—21.2% of users completed one assessment after registering for the program (Carpenter et al., 2016). PTSD Coach yielded the highest sustained use at 28.6% after 3 months (Owen et al., 2015), while 0.5% of users of MoodGYM (an online cognitive-behavioral therapy program) completed a noncompulsory assessment in their last module (Christensen et al. 2004). This review highlighted the variability in use across self-help interventions for depression and anxiety and yet painted a similar picture of user retention patterns over time. In this context, MoodTools showed a relatively high initial retention rate of 52.36%.

Although it could be useful to identify similarities between user retention rates in studies of real-world user behavior and dropout rates from clinical trials of app-based interventions for depression, it is difficult to make direct comparisons due to measuring differences. For MoodTools users, retention dropped to around half after the first session alone. In a recent review, after accounting for publication bias, the pooled dropout rate from 18 RCTs of smartphone apps for depressive symptoms was 47.8% (Torous et al., 2020). Torous and colleagues (2020) defined dropout as incompletion of end-of-intervention assessments, which are generally collected outside of the smartphone app of interest. The act of initiating a new app session cannot be equated to participation in end-of-intervention assessments. Hence, clinical trial-related dropout is inherently different from engagement as measured by real-world user behavior. Future clinical trials should measure engagement-related dropout as well as assessment-related dropout to better understand the overlap between these constructs.

Alternatively, real-world mHealth apps might adopt a similar standardized assessment structure in order to mimic the data collection procedures in clinical trials. One important consideration is how to define the endpoint or end-of-intervention point of a mental health app. Such deductions cannot be made currently given limited knowledge on the dose-effect relationship of mental health apps and meaningful clinical improvement.

5.3 Symptom Severity and App Use

In in-person psychotherapy, attrition is predicted by poor mental health, such as depression and anxiety. Findings from this study were inconsistent with attrition research—there was no correlation between initial depressive symptom severity and amount of time spent in MoodTools. This is also inconsistent with a recent study on Deprexis, an iCBT program, which found that higher depressive symptoms were associated with greater use of the program (Fuhr et al., 2018). This may have been a reflection of several factors. First, app design or structure may have impacted app use. Deprexis has a sequential navigation model and consists of 10 modules. Deprexis can also be used with or without clinician guidance (Berger et al., 2011). Next, all PHQ-9 scores of 0 were removed from analysis of MoodTools due to data collection limitations, which may have skewed our results. Finally, time spent in MoodTools may be underreported for specific sections of the app. Across mental health apps with real-world usage, apps containing mindfulness/meditation techniques see significantly more daily use compared to apps using other techniques such as psychoeducation and mood tracking (Baumel et al., 2019). Although MoodTools features videos on mindfulness/meditation, time spent watching these videos do not count toward app use because these videos bring the user to YouTube instead.

5.4 App Design Considerations

Given the unstructured, open-navigation layout of MoodTools, users can use any or all six self-help tools at any time. In this regard, greater use of some tools over others may be a reflection of real-world interest or demand. Results from this study indicated that the Thought Diary (thought record) and Test (mood self-monitoring) tools were the most highly used. PTSD Coach is similar to MoodTools in its open-navigation layout. For non-first-time users of PTSD Coach, the most visited content areas were Self-Assessment (symptom tracking) and Manage Symptoms (Owen et al., 2015). The IntelliCare suite is different from MoodTools and PTSD Coach in that each of the 12 interactive apps serve a singular function, coordinated by a hub app. With IntelliCare, around one-third of users downloaded more than one app and the average number of app downloads per user was 1.94 (Lattie et al., 2016) of the 13 available self-help tools. Of the apps, the Thought Challenger (thought restructuring) and Worry Knot (worry management) apps were most downloaded. In summary, despite some variability in the layout of these self-help apps, across the three apps, users seem to have more interest in cognitive restructuring and symptom tracking tools. There is currently no study on real-world usage of mHealth apps for mental health that use a fixed length or sequential navigation structure; therefore, no comparisons can be made between open-navigation and fixed or sequential layouts. More research is needed to better understand whether the navigation structure or layout of an mHealth app affects user engagement.

5.5 Limitations

It is important to note that this study only included users from the Android platform of MoodTools. Whereas the app is available on iOS, the SDK for Google Analytics was not implemented into the iOS platform, and thus mobile analytics data were not obtained.

Consequently, caution should be used when generalizing Android user behaviors to iOS users, as user behavior may differ based on type of smartphone ownership. For example, user reviews of PTSD Coach differed by platform—Android users saw less distress reduction from the app's tools compared to iOS users (Owen et al., 2015). Demographic or market audience differences between Android and iOS devices may also influence user behavior. For example, iOS users are more likely to be female, more educated, in a higher income group, and have more technology knowledge (Pryss et al., 2018).

Around one-third of all MoodTools sessions lasted 10 seconds or fewer, indicating that some sessions were likely too short to be meaningful. The high frequency of these "touch-and-go" sessions denotes a limitation to the interpretability of user engagement as it is measured in this study. Specifically, it cannot be assumed that every session equates to meaningful use of MoodTools.

5.6 Future Directions

Findings from this study introduce new questions for investigation. With MoodTools, half of all users did not return to the app after their first session. Hence, there is urgency in needing to capture the user's attention and maintain engagement from the very first session. Identifying users who may be likely to disengage after one app session would allow for better retention and higher dosage of the intervention. The use of app-based reminders or notifications, as well as incentives structures like gamification, should be examined to see how these app features impact user engagement. More attention should be devoted to carefully defining and measuring the construct of engagement, making sure to distinguish between "active" and "passive" engagement. In this study, objective behavioral measures of engagement, such as app frequency and duration, indicated that MoodTools users engaged in the app around the world, at all times of the day, and over time. Future studies should investigate other approaches, such as subjective measures in the form of self-report questionnaires, or physiological measures like cardiac activity, or psychophysical measures like eye tracking (Perski et al., 2017).

Another area of interest is the relationship between longitudinal change in depression symptom severity and app use. For example, Wysa users in the high use group had significantly higher depressive symptom improvement compared with those in the low use group (Inkster et al., 2018), suggesting that engagement with the app may predict symptom reduction. Another study of a coach-assisted version of IntelliCare saw significant reduction in depression and anxiety symptoms over an 8-week period; however, this was a single-arm pilot study and not a real-world assessment of app engagement (Mohr et al., 2017). Examining real-world MoodTools use and symptom improvement over time may contribute to this nascent area of knowledge. Overall, understanding how initial symptom severity is associated with app use will provide critical information on predicting app engagement and how best to approach individuals with varying levels of distress.

It is important to determine how much app use is needed to provide meaningful improvement to an individual. Research indicates that there is a relationship between app use and clinically meaningful benefit (Mattila et al., 2016; Zhang et al., 2019), but a dose effect relationship has not been identified. In psychotherapy, half of patients are estimated to improve after 8 sessions and 75% of patients are improved after 26 sessions (Howard et al., 1986; McNeilly & Howard, 1991). Psychotherapy sessions are generally scheduled weekly for about 50 minutes each. In comparison, MoodTools users spend an average of 12 minutes over 90 days, or 12 weeks, in the app. Evaluating the effect of MoodTools and other smartphone apps' use on symptom improvement over time is a logical next step. Ultimately, understanding the dose-effect relationship between amount of mHealth app use and therapeutic benefit can be used to guide recommendations for how long mHealth apps should be used in clinical studies and for assigning mHealth apps as an adjunct to psychotherapy.

Given the limited understanding of individual user characteristics (e.g. gender, age, socioeconomic status), the ability to assess the impact of individual factors on attrition is also limited. It is important in a future study to identify the variables uncontrolled for in this current iteration, such as demographics, psychological comorbidities, individual interest, perceived app fit, and perceived app aesthetics. Self-report questionnaires, such as the user version of the Mobile Application Rating Scale (uMARS; Stoyanov et al., 2016), can provide subjective data on user perceptions of a mental health app. Understanding how a mental health app's content, approachability, and style affects user engagement is a critical next step.

Future research should also determine the efficacy of MoodTools in improving depressive symptoms in real-world users. A review of evidence-based apps for anxiety and depression showed that while 74% of apps were free to download, only 3% of apps had research to justify claims of effectiveness. Thirty percent of apps claimed to have expert development input and 20% had an affiliation with a government body, academic institution, or medical facility (Marshall, Dunstan, & Bartik, 2019). Efficacy studies remain rare in the ever-changing landscape of publicly available mHealth apps. Even so, it remains the gold standard for determining whether an mHealth app can be called evidence-based or research-supported. Global interest in mHealth remains strong as well. The UK's National Health Service and U.S. National Institute of Mental Health see mHealth apps as cost-effective and scalable solutions to addressing the mental health treatment gap (Chandrashekar, 2018). Therefore, the promise of affordable, accessible, and scalable digital mental health interventions for a global population is tied to our ability to assess the efficacy of these apps.

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APPENDICES

Appendix A

Patient Health Questionnaire (PHQ-9)

Over the last two weeks, how often have you been bothered by any of the following problems?

1. Little interest or pleasure in doing things
   - Not at all
   - Several days
   - More than half the days
   - Nearly every day

2. Feeling down, depressed, or hopeless
   - Not at all
   - Several days
   - More than half the days
   - Nearly every day

3. Trouble falling or staying asleep, or sleeping too much
   - Not at all
   - Several days
   - More than half the days
   - Nearly every day

4. Feeling tired or having little energy
   - Not at all
   - Several days
   - More than half the days
   - Nearly every day

5. Poor appetite or overeating
   - Not at all
   - Several days
   - More than half the days
   - Nearly every day

6. Feeling bad about yourself—or that you are a failure or have let yourself or your family down
   - Not at all
   - Several days
   - More than half the days
   - Nearly every day

7. Trouble concentrating on things, such as reading the newspaper or watching television

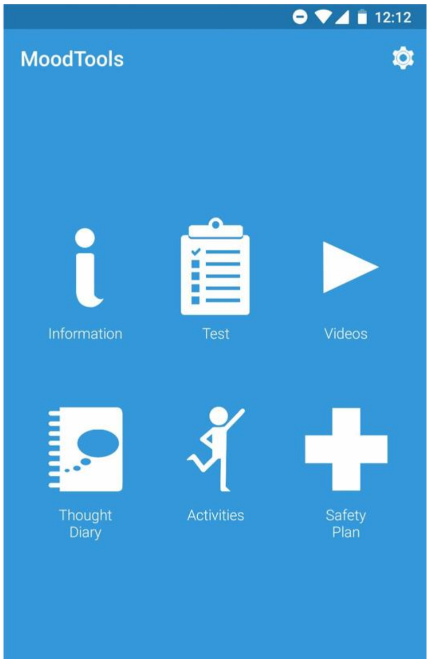
- Not at all
- Several days
- More than half the days
- Nearly every day

8. Moving or speaking so slowly that other people could have noticed. Or the opposite—being so fidgety or restless that you have been moving around a lot more than usual
    - Not at all
    - Several days
    - More than half the days
    - Nearly every day

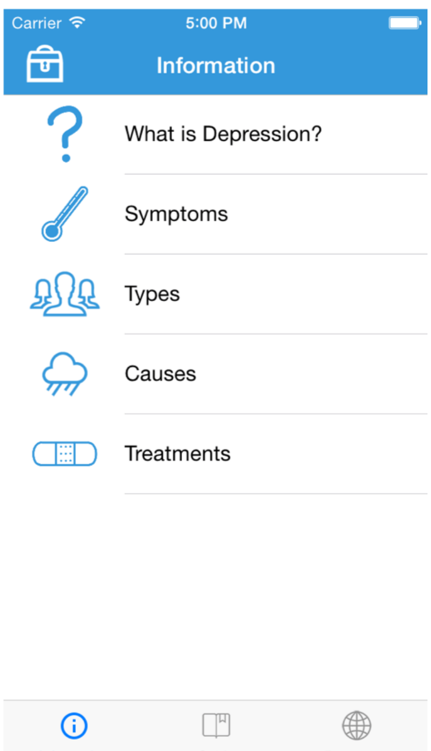
9. Thoughts that you would be better off dead, or of hurting yourself
    - Not at all
    - Several days
    - More than half the days
    - Nearly every day

Appendix B

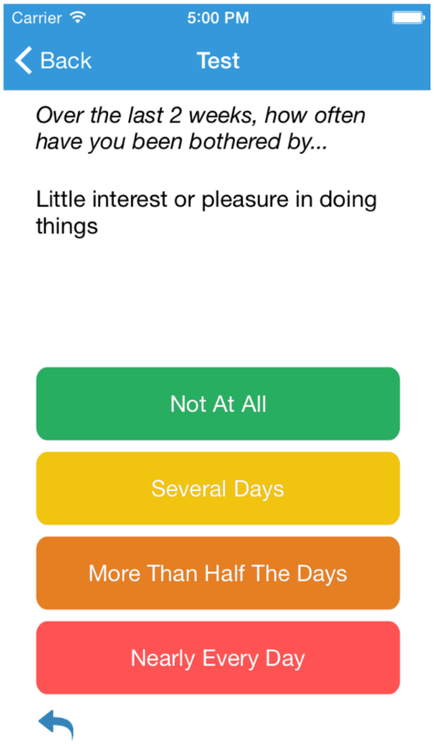
Screenshots of MoodTools



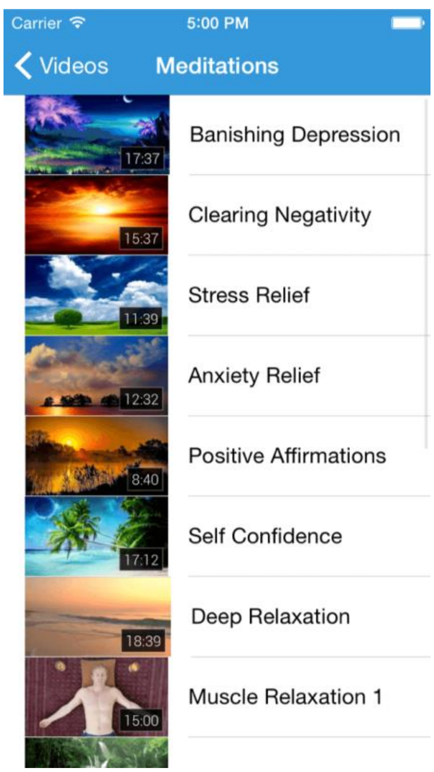
Main Page



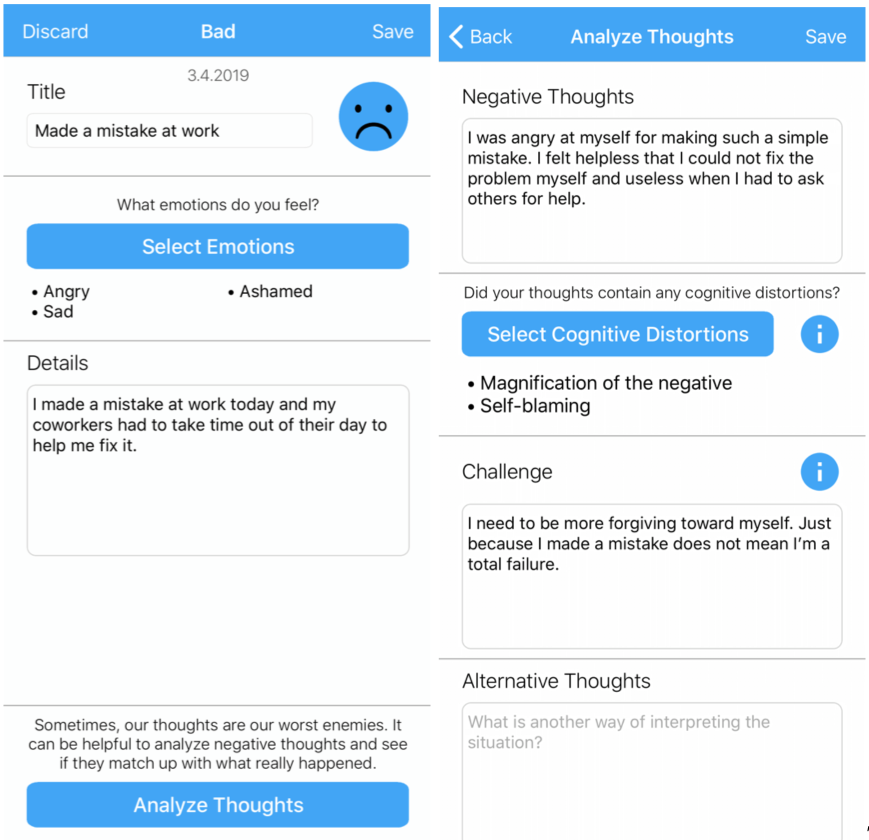
Information Tool



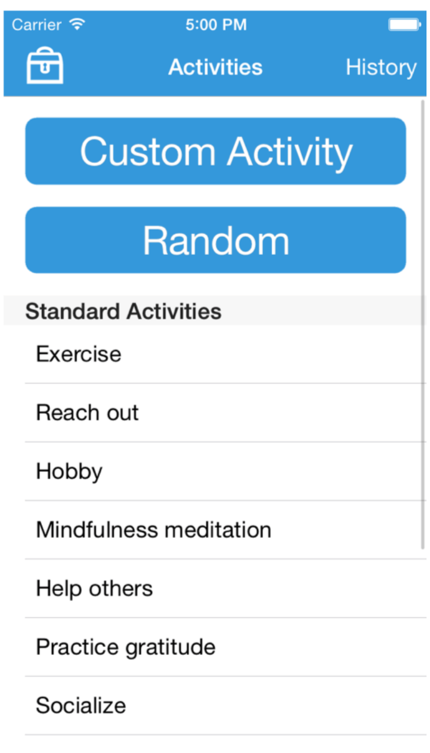
Test Tool



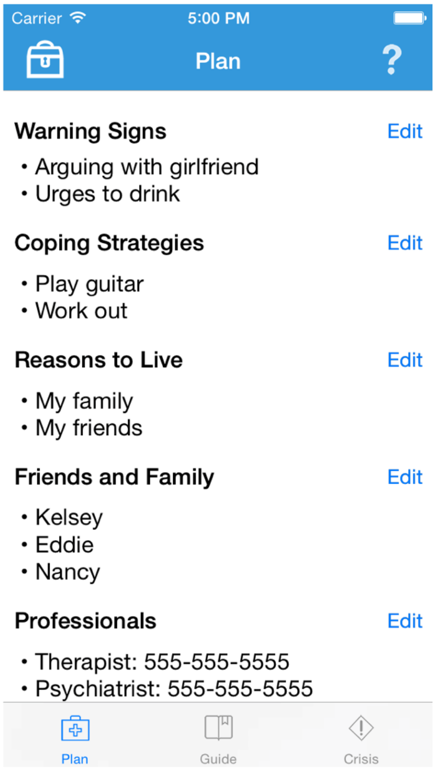
Videos Tool



Thought Diary Tool



Activities Tool



Safety Plan Tool

Appendix C

Appendix C.1 MoodTools users by continent

Continent	**Users (%)**
Americas	50.457
Europe	26.459
Asia	15.477
Oceania	4.823
Africa	2.608
Not Set	0.177

Appendix C.2 MoodTools users by subcontinent

Subcontinent	**Users (%)**
Northern America	46.537
Northern Europe	13.324
Southern Asia	9.709
Western Europe	7.169
Australasia	4.782
Southeast Asia	3.820
Southern Europe	3.370
Eastern Europe	2.760
South America	2.444
Western Asia	1.371
Southern Africa	1.123
Northern Africa	0.952
Central America	0.923
Eastern Asia	0.615
Caribbean	0.341
Eastern Africa	0.302
Western Africa	0.208
Central Asia	0.030
Middle Africa	0.016
Melanesia	0.015
Micronesian Region	0.012
Polynesia	0.002
Not Set	0.176

Appendix C.3 MoodTools users by country

Country	Users (%)
United States	40.8286
United Kingdom	10.6379
India	8.4695
Canada	5.5900
Australia	4.0220
Germany	3.8305
Philippines	1.8301
Brazil	1.1133
South Africa	1.0749
Netherlands	1.0166
Spain	0.9107
France	0.9101
New Zealand	0.7521
Mexico	0.7323
Poland	0.7143
Italy	0.7081
Ireland	0.7069
Indonesia	0.6771
Malaysia	0.6201
Sweden	0.5978
Pakistan	0.5941
Russia	0.5904
Romania	0.5520
Argentina	0.5291
Egypt	0.5148
Switzerland	0.4944
Austria	0.4702
Singapore	0.4622
Portugal	0.4306
Israel	0.4101
Greece	0.3946
Belgium	0.3847
Finland	0.3668
Norway	0.3333
Denmark	0.3240
Bangladesh	0.3017
Serbia	0.2887
United Arab Emirates	0.2652
Colombia	0.2546
Croatia	0.2497
Czechia	0.2478
Saudi Arabia	0.1970
Chile	0.1927
Morocco	0.1821
Hungary	0.1716
South Korea	0.1648
Slovenia	0.1642
Ukraine	0.1549
Japan	0.1499
Hong Kong	0.1425
Iran	0.1413
Kenya	0.1406
Slovakia	0.1351
Thailand	0.1351
Bulgaria	0.1332
Lithuania	0.1301
Peru	0.1301
Algeria	0.1202
Nigeria	0.1196
Tunisia	0.1189
China	0.1128
Estonia	0.1128
Nepal	0.1109
Lebanon	0.0966
Vietnam	0.0960
Trinidad & Tobago	0.0892
Bosnia & Herzegovina	0.0855
Sri Lanka	0.0799
Iceland	0.0787
Jamaica	0.0774
Jordan	0.0725
Ghana	0.0719
Latvia	0.0700
Puerto Rico	0.0694
Venezuela	0.0688

North Macedonia	0.0632
Costa Rica	0.0607
Ecuador	0.0595
Taiwan	0.0576
Mauritius	0.0496
Kuwait	0.0483
Dominican Republic	0.0477
Malta	0.0471
Cyprus	0.0458
Belarus	0.0446
Qatar	0.0434
Uruguay	0.0434
Turkey	0.0403
Guatemala	0.0353
Oman	0.0347
Bahrain	0.0335
Panama	0.0335
Albania	0.0328
Bolivia	0.0316
Iraq	0.0291
Namibia	0.0291
Luxembourg	0.0279
Tanzania	0.0279
Paraguay	0.0229
Cambodia	0.0204
Zimbabwe	0.0204
Botswana	0.0186
Moldova	0.0186
Uganda	0.0180
El Salvador	0.0173
Honduras	0.0167
Azerbaijan	0.0161
Kazakhstan	0.0161
Myanmar (Burma)	0.0155
Syria	0.0155
Bahamas	0.0149
Belize	0.0149
Yemen	0.0142
Zambia	0.0142

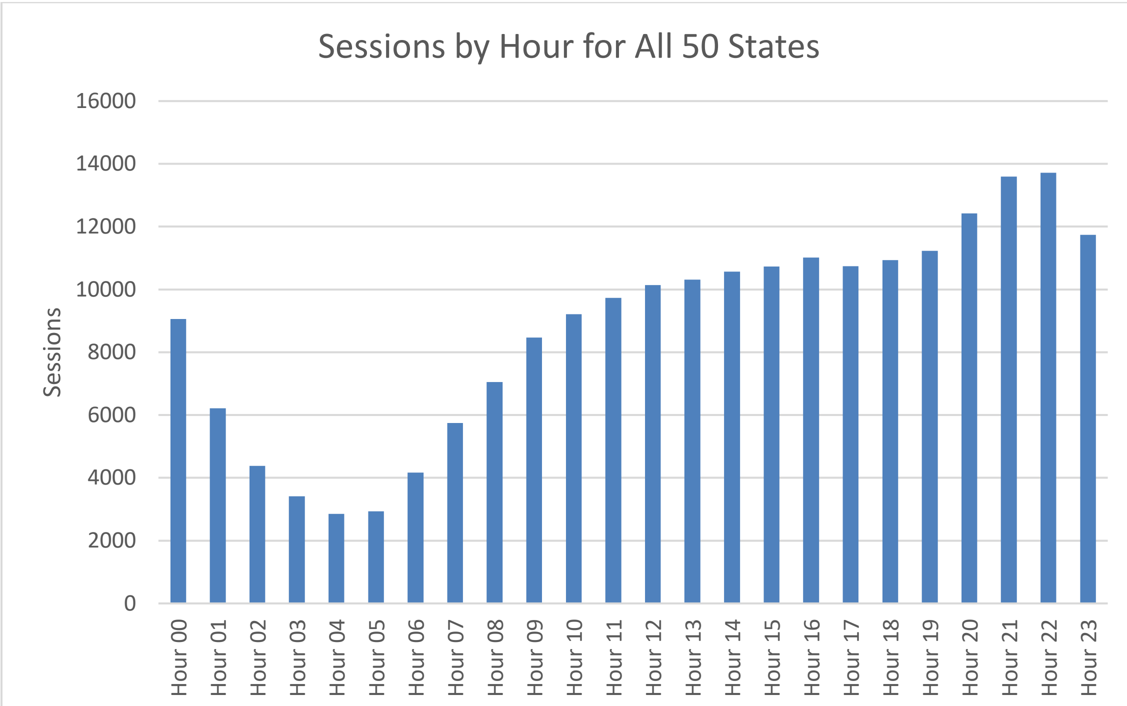
Ethiopia	0.0136
Kosovo	0.0124
Nicaragua	0.0112
Fiji	0.0105
Guam	0.0105
Maldives	0.0105
Cameroon	0.0099
Sudan	0.0099
Côte d'Ivoire	0.0093
Armenia	0.0087
Georgia	0.0081
Guernsey	0.0081
Aruba	0.0056
Jersey	0.0056
Kyrgyzstan	0.0050
Mozambique	0.0050
Palestine	0.0050
Rwanda	0.0050
Afghanistan	0.0043
Uzbekistan	0.0043
Antigua & Barbuda	0.0037
Barbados	0.0037
Brunei	0.0037
Cayman Islands	0.0037
Libya	0.0037
Montenegro	0.0037
Angola	0.0031
Bermuda	0.0031
Cuba	0.0031
Curaçao	0.0031
Haiti	0.0031
U.S. Virgin Islands	0.0031
St. Lucia	0.0025
Northern Mariana Islands	0.0025
Papua New Guinea	0.0025
Senegal	0.0025
Andorra	0.0019
Eritrea	0.0019
Gabon	0.0019

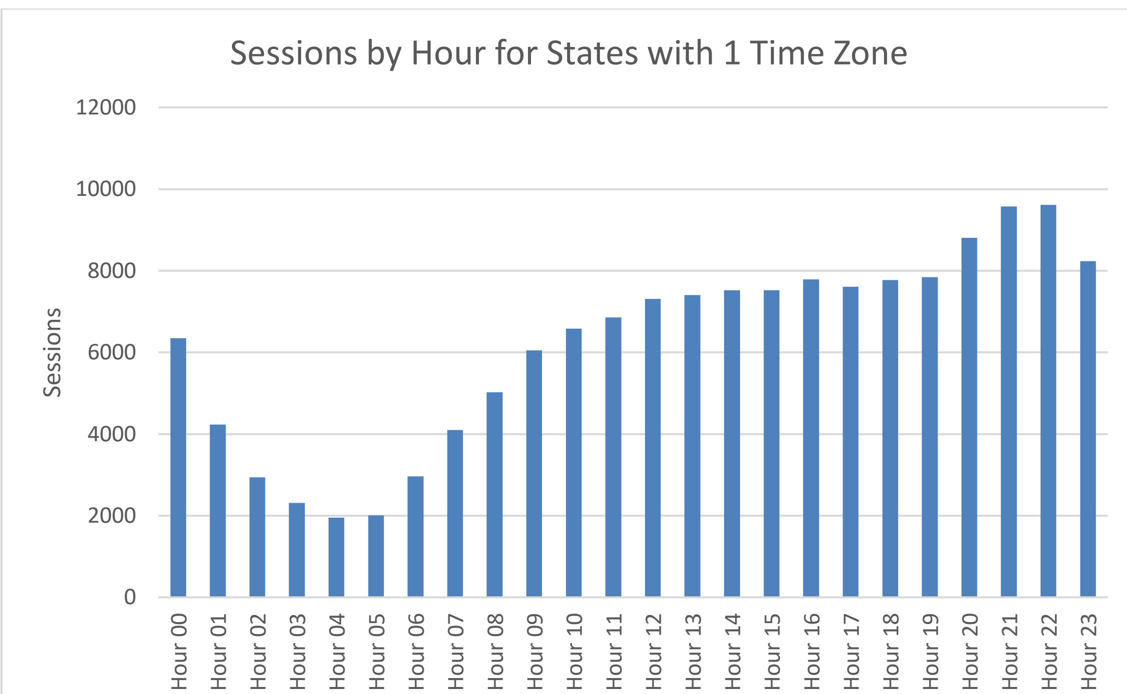
Guadeloupe	0.0019
Martinique	0.0019
Malawi	0.0019
Tajikistan	0.0019
Turkmenistan	0.0019
St. Vincent & Grenadines	0.0019
Vanuatu	0.0019
Burkina Faso	0.0012
Caribbean Netherlands	0.0012
Bhutan	0.0012
Dominica	0.0012
Faroe Islands	0.0012
Gibraltar	0.0012
Guyana	0.0012
St. Kitts & Nevis	0.0012
Laos	0.0012
Madagascar	0.0012
Mongolia	0.0012
Réunion	0.0012
Svalbard & Jan Mayen	0.0012
Somalia	0.0012
Suriname	0.0012
Mayotte	0.0012

Anguilla	<0.001
American Samoa	<0.001
Burundi	<0.001
Benin	<0.001
Congo - Kinshasa	<0.001
Cook Islands	<0.001
Cape Verde	<0.001
Djibouti	<0.001
French Guiana	<0.001
Greenland	<0.001
Gambia	<0.001
Guinea	<0.001
Liechtenstein	<0.001
Macao	<0.001
Montserrat	<0.001
Niger	<0.001
Seychelles	<0.001
South Sudan	<0.001
Sint Maarten	<0.001
Turks & Caicos Islands	<0.001
Tonga	<0.001
Samoa	<0.001
Not Set	0.1759

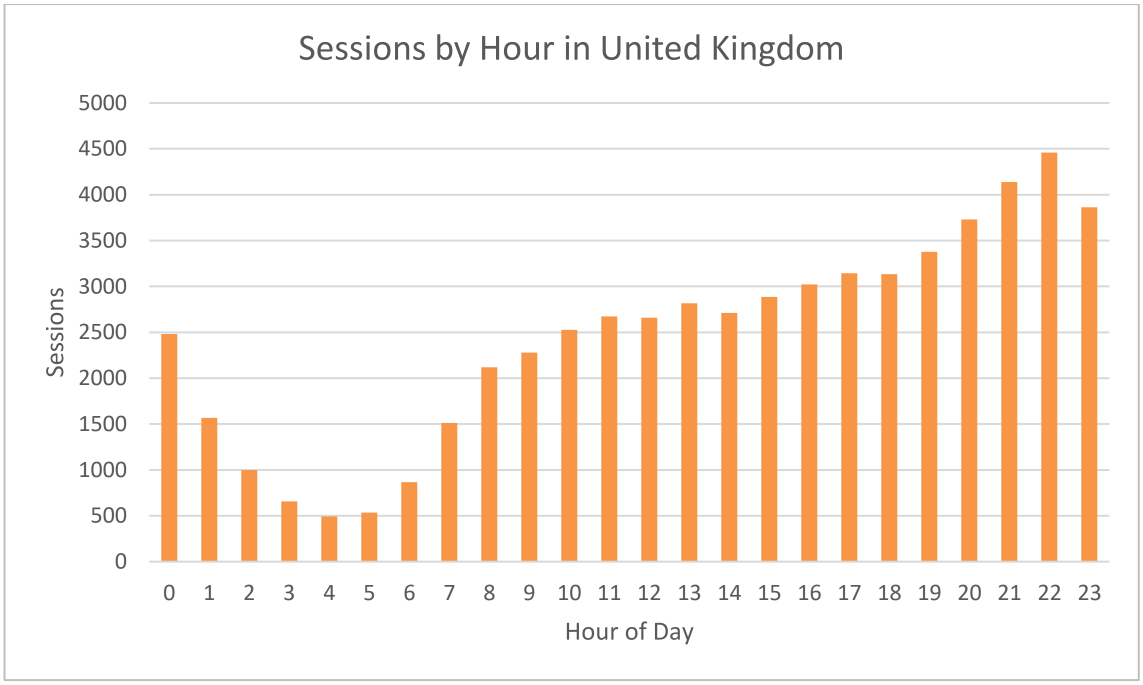
Appendix D

Appendix D.1 App Sessions by Hour-of-Day in United States

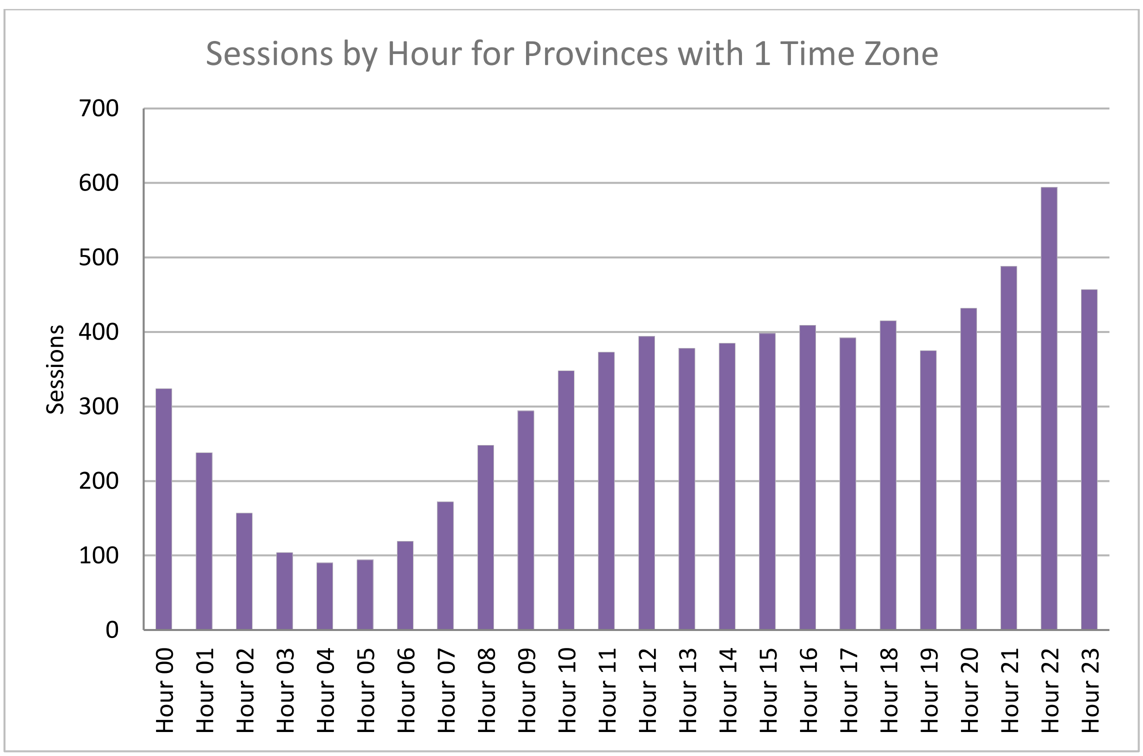


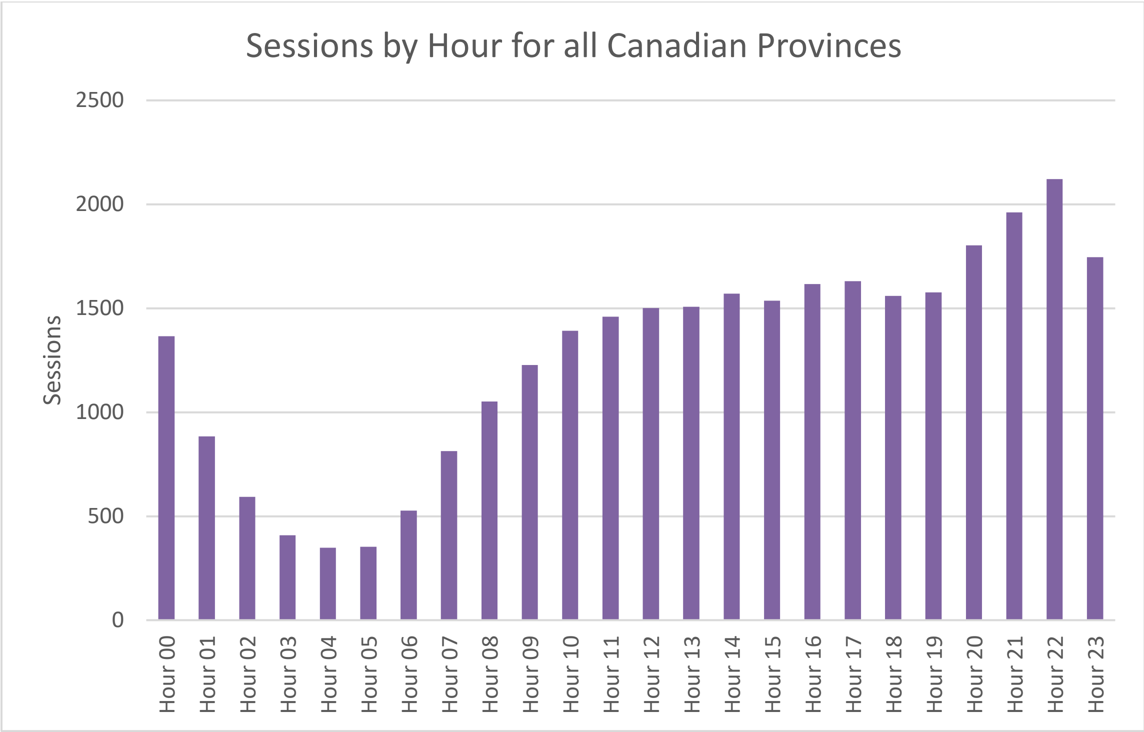


Appendix D.2 App Sessions by Hour-of-Day in United Kingdom

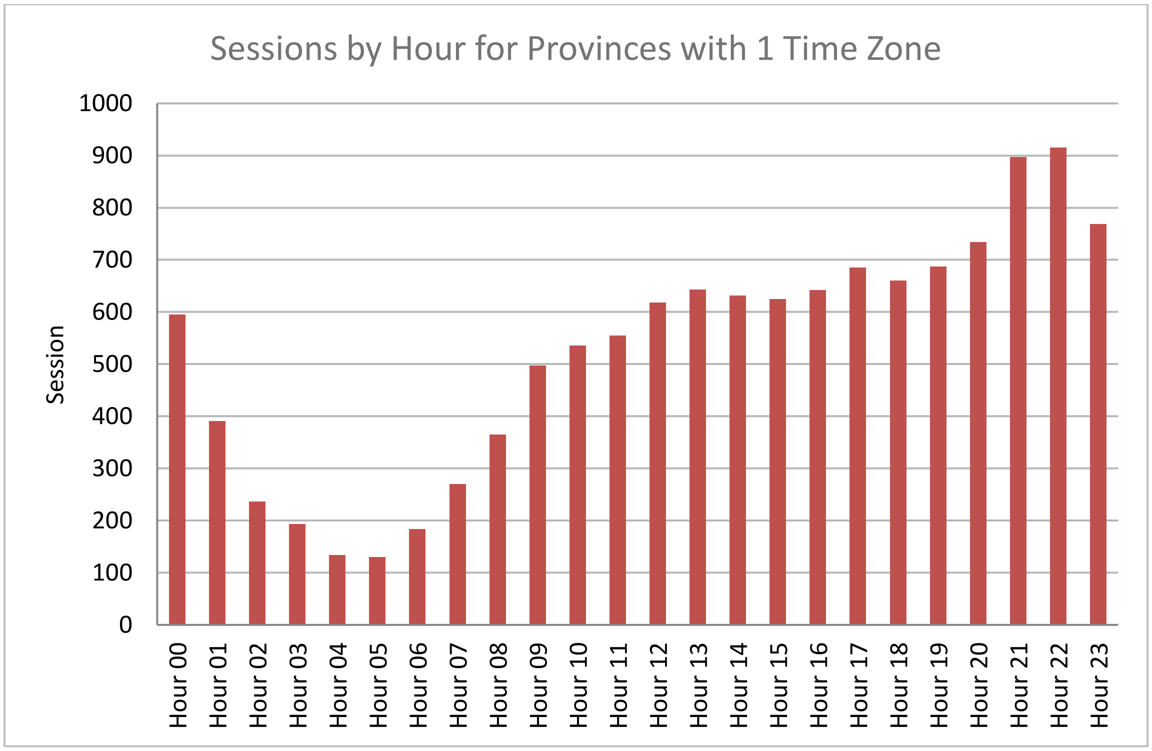


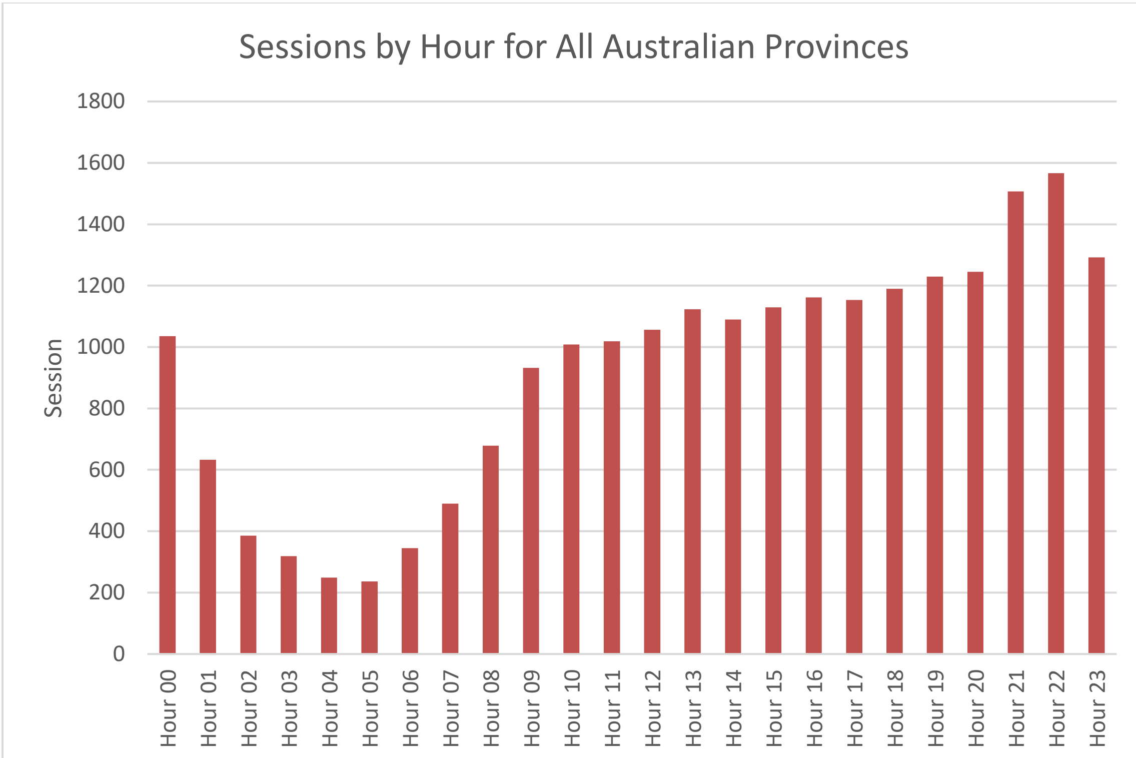
Appendix D.3 App Sessions by Hour-of-Day in Canada





Appendix D.4 App Sessions by Hour-of-Day in Australia




Sessions by Hour for All Australian Provinces
Session
1800
1600
1400
1200
1000
800
600
400
200
0
Hour 00
Hour 01
Hour 02
Hour 03
Hour 04
Hour 05
Hour 06
Hour 07
Hour 08
Hour 09
Hour 10
Hour 11
Hour 12
Hour 13
Hour 14
Hour 15
Hour 16
Hour 17
Hour 18
Hour 19
Hour 20
Hour 21
Hour 22
Hour 23