Using Individual Characteristics and Habit Measures to Predict Meditation App Use Behavior

by

Mariah Sullivan

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Graduate Supervisory Committee:

Chad Stecher, Chair
Jennifer Huberty
Matt Buman
Linda Larkey
Yunro Chung

ARIZONA STATE UNIVERSITY

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ABSTRACT

Meditation app usage is associated with decreases in stress, anxiety, and depression symptoms. Many meditation app subscribers, however, quickly abandon or reduce their app usage. This dissertation presents three manuscripts which 1) determined the behavioral, demographic, and socioeconomic factors associated with the abandonment of a meditation app, Calm, during the COVID-19 pandemic, 2) determined which participant characteristics predicted meditation app usage in the first eight weeks after subscribing, and 3) determined if changes in stress, anxiety, and depressive symptoms from baseline to Week 8 predicted meditation app usage from Weeks 8-16. In Manuscript 1, a survey was distributed to Calm subscribers in March 2020 that assessed meditation app behavior and meditation habit strength, and demographic information. Cox proportional hazards regression models were estimated to assess time to app abandonment. In Manuscript 2, new Calm subscribers completed a baseline survey on participants' demographic and baseline mental health information and app usage data were collected over 8 weeks. In Manuscript 3, new Calm subscribers completed a baseline and Week 8 survey on demographic and mental health information. App usage data were collected over 16 weeks. Regression models were used to assess app usage for Manuscripts 2 and 3. Findings from Manuscript 1 suggest meditating after an existing routine decreased risk of app abandonment for pre-pandemic subscribers and for pandemic subscribers. Additionally, meditating "whenever I can" decreased risk of abandonment among pandemic subscribers. No behavioral factors were significant predictors of app abandonment among the long-term subscribers. Findings from Manuscript 2 suggest men had more days of meditation than women. Mental health diagnosis increased average daily meditation minutes. Intrinsic motivation for meditation increased the likelihood of completing any meditation session, more days with

meditation sessions, and more average daily meditation minutes. Findings from Manuscript 3 suggest improvements in stress increased average daily meditation minutes. Improvements in depressive symptoms decreased daily meditation minutes. Evidence from this three-manuscript dissertation suggests meditation cue, time of day, motivation, symptom changes, and demographic and socioeconomic variables may be used to predict meditation app usage.

DEDICATION

To my mom for her support during the past four years. I truly would not have been able to finish this degree without you. And to my dad who was proud of me for all things big and small. Even though you're no longer here, I know you're still proud.

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TABLE OF CONTENTS

Page

LIST OF TABLES vii

LIST OF FIGURES viii

CHAPTER

1 INTRODUCTION 1

2 MANUSCRIPT 1 5

Introduction 6

Methods 9

Results 12

Discussion 31

Conclusion 35

3 MANUSCRIPT 2 36

Introduction 37

Methods 39

Results 45

Discussion 60

Conclusion 65

4 MANUSCRIPT 3 67

Introduction 68

Methods 71

Resutls 75

Discussion 85

Conclusion 88

DISCUSSION 90

CHAPTER Page

Future Directions 92

Conclusion 94

REFERENCES 95

APPENDIX

A SENSITIVITY CHECK 104

LIST OF TABLES

Table Page

1.1 Descriptive Statistics for Each Subscription Start Date Cohort ...………………..13

1.2 Determinants of App Abandonment Among Subscribers Who Started Just Before (<4 Months) the Pandemic …………………………………………………………16

1.3 Determinants of App Abandonment Among Subscribers Who Started At Least One Year Before the Pandemic …………………………………………………………22

1.4 Determinants of App Abandonment Among Subscribers Who Started During the Pandemic …………………………..……………………………………..……27

2.1 Descriptive Characteristics of the Sample ……………..…………………..…………46

2.2 App Usage over the First Eight Weeks Regressed on Individual Characteristics .48

2.3 App Usage Over the First Week Regressed on Individual Characteristics ……….52

2.4 App Usage Over the Last Week Regressed on Individual Characteristics 55

2.5 App Usage Over the Last Week Regressed on IMI Regression Results 59

3.1 Descriptive Statistics for the Sample...75

3.2 Changes in Mental Health Symptoms from Baseline to Week 8...........................76

3.3 Mean App Usage within the First and Last Eight Weeks......................................77

3.4 Changes in Usage from Weeks 0-8 To Weeks 8-16 by Symptom Improvements .79

3.5 Changes in Usage from Weeks 0-8 to Weeks 8-16 by Moods Lodded in First 8 Weeks ……….…………………..…………………………………………….. 82

LIST OF FIGURES

Figure Page

1. Log Transformed Average Daily Minutes of Meditation For All Sessions 45

2. Average Daily Minutes of Meditation by Intrinsic Motivation Inventory Median Split 59

CHAPTER 1

INTRODUCTION

Meditation is a conscious-oriented practice for resting the mind that encourages a heightened state of awareness and focused attention (Kabat-Zinn, 2009; West, 1979). Meditation originated thousands of years ago to deepen one's understanding of divine life forces but is now used by many as a tool for relaxation and stress reduction (Bergen-Cico et al., 2014b; Goyal et al., 2014b; Kabat-Zinn, 2009; West, 1979). One of the most popular types of meditation is mindfulness meditation (hereinafter meditation), which entails a heightened state of consciousness and nonjudgmental awareness (Brown & Ryan, 2003; Eberth & Sedlmeier, 2012; Gerritsen & Band, 2018; Kabat-Zinn, 2009). For example, a technique commonly used in meditation is to bring awareness to one's breathing pattern by continuously observing the inhales and exhales.

Meditation has been linked to several mental health benefits, including reduced stress, anxiety, and depressive symptoms, as well as improved sleep, concentration, and patience (Edenfield & Saeed, 2012; Goyal et al., 2014b; J. L. Huberty et al., 2021; Pascoe et al., 2017). These benefits have long been anecdotally reported and recently evaluated in randomized clinical trials in both clinical and non-clinical populations (e.g., Flett et al., 2019; Howells et al., 2016; J. L. Huberty et al., 2021). Meditation has also been shown to be effective for improving components of physical health, such as increased energy, management of chronic pain and high blood pressure, and general well-being (e.g., Adams et al., 2018; Champion et al., 2018; Flett et al., 2019; Howells et al., 2016).

Until recently, meditation was typically practiced in person by a trained meditation teacher. In 2012, the two leading meditation apps, Headspace and Calm, adapted this typically in-person practice and created mobile apps to make meditation more accessible. Since their creation, mobile meditation apps have dominated the wellness app market. In a 2020 report, the three most globally downloaded mental wellness apps were meditation apps: Calm (3.9 million), Headspace (1.5 million), and Meditopia (1.4 million) (Chapple, 2020). Researchers have begun to evaluate the benefits of meditation delivered via an app and have found comparable benefits to in-person meditation for both mental and physical health. For example, meditation app interventions have been effective in reducing stress (Bostock et al., 2019; J. Huberty, Green, et al., 2019), anxiety (Baumel et al., 2020; Flett et al., 2019; Rowland, Fitzgerald, Holme, Powell, & McGregor, 2020), and depressive symptoms (Baumel et al., 2020; Rowland, Fitzgerald, Holme, Powell, & McGregor, 2020), as well as improving sleep quality (J. L. Huberty et al., 2021) and general wellbeing (Bostock et al., 2019; Howells et al., 2016) in both clinical and non-clinical populations.

Although meditation apps have a high number of downloads and have been shown to effectively improve mental and physical health, only a small number of users continue using their apps. For example, one study on mental health apps, including meditation apps, reported a 3.9% median 15-day retention rate and 3.3% median 30-day retention rate (Baumel et al., 2019). Even beyond the first 30 days, app usage remains low. Another study reported that among active health app users, there is a 4% median daily usage rate (Kerst et al., 2020b). Meditation app intervention data show similar patterns with dropout rates typically between 21-77% (Flett et al., 2019; Forbes et al., 2018b; Howells et al., 2016; J. Huberty, Green, et al., 2019). Because of the numerous benefits of meditation, low meditation app usage rates are a major problem; those who do not actively use the apps likely do not experience the associated benefits. To solve this problem and promote meditation app usage, it is necessary to examine the potential determinants of meditation app use.

The ability to create and adhere to a habit is a well-established determinant of health behavior. Recent studies have found that the formation of a strong daily habit has been associated with meditation app usage, though the specific components of successful meditation habits need further investigation (Stecher, Sullivan, et al., 2021a; Wood & Neal, 2016a). Cues to action are one component of creating a strong habit in which a new behavior is anchored onto an existing behavior, or one might choose a new cue as a signal to complete the new behavior (Burner et al., 2014; Carden & Wood, 2018; Nilsen et al., 2012). For example, one might use their daily routine of reading before bed as a cue to meditate or set a new alarm as a cue to meditate. Time of day is also a key component of strong daily habits, though more exploration in meditation app subscribers is needed as well. One study reported that those who meditated in the morning were more likely to continue to meditate throughout the observation period (Stecher, Sullivan, et al., 2021a). On the other hand, another study found that the time of day was not a significant predictor of continued meditation but rather consistency in participants' chosen time of day to meditate was a strong predictor (Stecher, Berardi, et al., 2021). Because development and adherence to a strong habit is an important potential predictor of meditation app use, further exploration is needed.

Additionally, numerous studies on health app usage have identified user demographic and socioeconomic variables, as well as motivation, thoughts, and behaviors, as determinants of usage. For example, younger age was associated with those who used an app to reduce drinking (Garnett et al., 2017), and "motivation to be thin" predicted healthy eating app usage (Elavsky et al., 2017). A recent meditation app user characteristics study has linked gender and physical health diagnoses to app usage, which suggests user characteristic findings observed in other health app studies may be applicable to meditation app usage as well (J. Huberty, Vranceanu, et al., 2019).

However, further exploration of user characteristics and app usage, including objective observational data and a more comprehensive pool of predictors, is needed.

Finally, subscribers' symptom improvements may also be linked to meditation app usage. Researchers believe that those who engage in a behavior for a specific reason, such as reducing mental health symptoms, will be more likely to continue the behavior (Crane et al., 2010b; Valls-Serrano et al., 2016b). The most commonly reported reasons for meditating typically include improving symptoms of stress and anxiety, reducing pain, and managing depressive symptoms (Cramer et al., 2016b). One cross-sectional study reported longer self-reported app usage was associated with reported improvements in these symptoms (J. Huberty, Vranceanu, et al., 2019), however longitudinal, observational data is needed to verify these findings. Additionally, noticing these improvements, such as through tracking one's mood, may be an important element of the relationship between symptoms improvement and meditation app usage, though this has not yet been explored.

The purpose of this three-manuscript dissertation is to explore the determinants of meditation app use. Manuscript 1 aims to evaluate the behavioral, demographic, and socioeconomic factors associated with the abandonment of a meditation app, Calm, during the COVID-19 pandemic. Manuscript 2 aims to investigate which participant characteristics predicted meditation app usage in the first eight weeks after subscribing. Finally, Manuscript 3 aims to determine if changes in stress, anxiety, and depressive symptoms from baseline to week eight predicted meditation app usage from weeks eight through 16.

CHAPTER 2

MANUSCRIPT 1: Mindfulness Meditation App Abandonment During the COVID-19 Pandemic: An Observational Study

Abstract:

Objectives: Mindfulness meditation apps are used by millions of adults in the U.S. to improve mental health, however many new app subscribers quickly abandon their use. The purpose of this study was to determine the behavioral, demographic, and socioeconomic factors associated with the abandonment of a popular meditation app, Calm during the COVID-19 pandemic.

Methods: A survey was distributed to Calm subscribers at the start of the COVID-19 pandemic in March 2020 that assessed meditation app behavior and meditation habit strength, as well as demographic and socioeconomic information. Calm app usage data were also collected from the start of each participant's Calm subscription until May 2021. Participants were divided into three cohorts according to their subscription start date: 1) pre-pandemic subscribers (<4 months before pandemic start), 2) long-term subscribers (>1 year before pandemic start), and 3) pandemic subscribers (joined during the pandemic).

Results: Meditating after an existing routine was associated with a lower risk of app abandonment for pre-pandemic subscribers (hazard ratio = 0.607, 95% CI: 0.422,0.874; $P = 0.007$) and for pandemic subscribers (hazard ratio = 0.434, 95% CI: 0.285,0.66; $P < 0.001$). Additionally, meditating "whenever I can" was associated with lower risk of abandonment among pandemic subscribers (hazard ratio = 0.437, 95% CI: 0.271,0.706; $P < 0.001$), and no behavioral factors were significant predictors of app abandonment among the long-term subscribers.

Conclusion: These results show that combining mediation with an existing daily routine was a commonly utilized strategy for promoting persistent meditation app use during the COVID-19 pandemic for many Calm subscribers. This finding supports existing evidence that pairing new behaviors with an existing routine is an effective method for establishing new health habits.

Introduction

Mindfulness meditation is currently used by millions of adults in the U.S. to reduce psychological symptoms from stress, anxiety, and depression and to increase overall wellbeing (Bostock et al., 2019; Eberth & Sedlmeier, 2012; Edenfield & Saeed, 2012, 2012; Lacaille et al., 2018). The recent development of mindfulness meditation mobile phone apps has made meditation more accessible to the general population and contributed to the growing popularity and practice of meditation. Similar to other health-promoting daily behaviors though, the benefits of meditation are primarily experienced through persistent practice over time (Shen et al., 2020; Tang et al., 2012), and many new meditation app subscribers quickly stop (or "abandon") their use. To illustrate this point, dropout rates in meditation app interventions typically range from 21% to 54% (e.g., Goldberg et al., 2020; Huberty et al., 2019; Puzia et al., 2020), and in general, the daily use of health apps among paying subscribers is less than 4% (Kerst et al., 2020b). Thus, there is a need to better understand the determinants of mobile meditation app abandonment in order to design new behavioral tools and interventions that can promote more persistent use of meditation apps.

One important behavioral determinant of meditation app abandonment is the formation of a strong daily habit, which has been shown to underly persistent use of meditation apps and prevent app abandonment (Stecher, Sullivan, et al., 2021b; Wood & Neal, 2016b). Psychology research has defined habits as automatic or reflexive behavioral responses to environmental cues (Gollwitzer, 1999; Wood & Neal, 2007), where cues can be external, such as a visual reminder, or internal, such as physical sensations or the completion of the proceeding action in one's daily routine (V. L. Champion & Skinner, 2008a; McArthur et al., 2018). The use of environmental cues to trigger daily behaviors has been shown to support a wide range of healthy habits, such as hand washing, flossing, medication adherence, and meditation (e.g., Burner et al., 2014; Hussam et al., 2017; Judah et al., 2013; Lally & Gardner, 2013; Saghafi-Asl et al., 2020; Stecher, Mukasa, et al., 2021). In one recent study, meditation app subscribers who were instructed to use environmental cues to create a meditation routine were more likely to continue using the app over an eight-week follow-up period than those who did not use cues (Stecher, Sullivan, et al., 2021b). This behavioral intervention approach for establishing persistent meditation app use was not successful for many participants though, so the role of environmental cues in preventing meditation app abandonment is still unknown. It is also unclear what type of environmental cues are the most supportive of meditation app habits and thus the most protective against meditation app abandonment.

Another behavioral determinant of persistent health habits is the time of day of behavioral performance, which in turn may have an important influence on meditation app abandonment. It has been shown that some health behaviors are more persistently performed if completed in the morning (Kouchaki & Smith, 2014; Pignatiello et al., 2020; Stecher, Sullivan, et al., 2021b). In the recent study on meditation app habits by Stecher, et al. (2021), those who meditated in the morning were more likely to persistently meditate than those who meditated at other times of day. However, another recent study found that those who meditated at the same time each day were more likely to persistently meditate regardless of what time in the day they meditated (Stecher, Berardi, et al., 2021). Thus, it is unclear if and how the time of day of meditation app use is associated with meditation app abandonment.

An important additional determinant of meditation app abandonment was the COVID-19 pandemic, which significantly disrupted many individuals' and households' daily routines and health habits (Burner et al., 2014; Carden & Wood, 2018; Carroll et al., 2020; Lally & Gardner, 2013; Souza et al., 2021). Whether it was working from home, providing childcare, or taking care of sick family members, the disruption of daily routines due to the COVID-19 pandemic may have contributed to greater meditation app abandonment. Additionally, the impact of the pandemic on meditation app abandonment likely depends on how long subscribers had been using the app. For example, those who subscribed to Calm just before the pandemic may have begun to form a meditation app habit before the pandemic disrupted their routines, while those who began their subscriptions at least one year before the pandemic may have already had strong meditation habits and thus were less likely to abandon the app during the pandemic. Additionally, meditation app subscribers who began their subscriptions during the pandemic may have had a difficult time establishing a consistent daily routine but simultaneously were likely to have had a stronger initial motivation to use the app to reduce symptoms of stress and anxiety. Therefore, we will examine the impact of the pandemic on meditation app abandonment separately among these three cohorts of app subscribers. In addition to the COVID-19 pandemic and behavioral determinants of app abandonment, users' demographics and socioeconomic status may be associated with meditation app abandonment. To date, however, the role of demographics and socioeconomic status on meditation app abandonment during COVID-19 has not been studied in a real-world (i.e., non-intervention) setting.

Therefore, the purpose of this study is to determine the behavioral, demographic, and socioeconomic factors that were associated with the abandonment of the popular meditation app, Calm, among paying subscribers who responded to a survey assessing meditation app behaviors and mental health at the start of the COVID-19 pandemic. For this research, app subscribers were divided into three cohorts: 1) those who started their subscription just before the World Health Organization (WHO) declared COVID-19 a pandemic (March 11, 2020) (i.e., November 2019 – February 2020), 2) those who started their subscription at least one year before the pandemic (before March 2019), and 3) those who started their subscription during the pandemic (March-May 2020) in order to examine how the COVID-19 pandemic differentially impacted subscribers app abandonment based on their different levels of experience using the app.

Methods

Ethics Approval

The Institutional Review Board at Arizona State University (STUDY00011867) approved this study. All respondents consented via an electronic survey.

Study Design

Our study examines data collected as part of a larger longitudinal study assessing the mental health and health behaviors of a U.S.-based sample of Calm meditation app subscribers during the COVID-19 pandemic (Green et al., 2021). In the longitudinal study, a series of six surveys were distributed from April 2020 to May 2021, with the final survey administered 12 months from the baseline survey. Calm app usage data were collected for all survey respondents from the time of their subscription until the final 12-month survey. The data analyzed in this paper include all available Calm app usage data and survey data obtained from the baseline survey (administered in May

2020). The baseline survey occurred, on average, 5 months (SD = 11.14) after respondents first subscribed to the Calm app.

Procedures

All study procedures were conducted online. Calm subscribers were emailed an invitation to participate in the study, which was advertised as the "COVID-19 Health and Well-being Survey". The email contained information about the study timeline and a link to a 1-minute eligibility survey to be completed in Qualtrics (*Qualtrics*, 2020). The Calm data team sent this recruitment email to subscribers if they had opened an email from Calm at least once in the last 90 days and used Calm at least once in the last 90 days. Calm subscribers were then determined eligible to participate if they indicated they: 1) were at least 18 years old, 2) could read and understand English, and 3) lived in the U.S. If eligible, subscribers were directed to an electronic informed consent form, and consenting subscribers then completed the baseline survey.

The baseline survey contained investigator-developed questions that assessed meditation app behavior and habit strength, as well as demographic and socioeconomic information. Specifically, respondents were asked to identify what type of environmental cue they used to trigger their meditation (e.g., reminder, alarm, existing routine behavior) and what time of day they typically meditated using the app (i.e., morning, afternoon, or evening). Demographic and socioeconomic status information collected included gender, age, race/ethnicity, education level, income, and employment status.

Participants were divided into three cohorts, which were determined by their subscription start date: 1) pre-pandemic subscribers (i.e., subscription start date between November 2019 and February 2020), 2) long-term subscribers (i.e., subscription state date on or before March 2019), and 3) pandemic subscribers (i.e., subscription start date between March and May 2020). In the long-term subscriber cohort, subscription start dates ranged from July 2014 to February 2019. Since Calm only offers annual subscriptions, the long-term subscribers had all renewed their annual meditation app subscription at least once before the start of the data collection period. Conversely, the annual subscription renewal dates among the pandemic subscriber cohort occurred towards the end of our data collection period, so app abandonment among our three cohorts represents different levels of payment(s) and commitment to the meditation app. Calm app usage data were analyzed for all study participants from their start date until May 2021. All Calm usage data were obtained via the Calm data informatics team.

Statistical Analysis

Cox proportional hazards regression models were estimated to assess the relationships between app abandonment and 1) meditation practice environmental cues, 2) meditation practice time of day, and 3) demographic and socioeconomic variables. We estimated three regression specifications that increasingly incorporated each of these variables better understand the sensitivity of the main results, where the final model (Model 3) included all available behavioral, demographic, and socioeconomic predictors.

The date of app abandonment was defined as the last meditation session completed for each respondent, which was used to calculate the days until app abandonment. This measure was considered unobserved (or censored) if the date of app abandonment occurred on or after April 1, 2021, which was 30 days before the end of our data collection period. That is, even if participants did not record a meditation session after April 1, 2021, we did not consider them to have abandoned the app because they could have continued with their practice in June 2021 or later. Statistical significance was set at $P < .05$. All analyses were conducted in Stata and SPSS (*IBM SPSS Statistics for Macintosh*, 2020; *StataCorp*, 2021).

Results

A total of 8,386 respondents completed the baseline survey. After removing any cases with missing app usage data or those who never completed a meditation session with the app, 4,921 respondents were included in the analyses. Respondents' subscription start dates ranged from July 27, 2014, to May 21, 2021. A total of 1,468, 513, and 1,294 respondents were included in the pre-pandemic subscribers, long-term subscribers, and pandemic subscribers cohorts, respectively. Respondents with subscriptions that did not occur within the dates that comprised the three cohorts (i.e., April – October 2019) or with missing start date data were not included in the analysis (n=1,646).

Table 1.1 shows descriptive statistics for the total sample by subscriber cohort. Among the pre-pandemic subscribers, respondents were predominantly female (75.4%, 1,107/1,468), White (80%, 1,175/1,468), earned more than $100,000 (53.4%, 696/1,468), and were employed (67.6%, 928,1,468). There were few statistically significant differences in these observable characteristics between the three subscriber cohorts. Additionally, a total of 704 (47.9%), 273 (53.2%), and 464 (35.8%) participants abandoned the app within the pre-pandemic subscriber, long-term subscriber, and pandemic subscriber cohorts, respectively. The median time to app abandonment was 15.0 months (95% CI: 14.50, 15.49) for the pre-pandemic subscribers, 41.0 months (95% CI: 39.21, 42.79) for the long-term subscribers, and 10.2 months (95% CI: 9.48, 10.50) for the pandemic subscribers.

Table 1.1. Descriptive Statistics for Each Subscription Start Date Cohort.							
Subscription Start Date:	<4 months before COVID-19		>12 months before COVID-19		During COVID-19		
	Frequency	Percent	Frequency	Percent	Frequency	Percent	*P* value
Meditation cue							
Time of day	301	20.5	98	19.1	246	19.0	0.995
Alarm	8	0.5	4	0.8	4	0.3	0.403
Part of a daily routine	557	37.9	183	35.7	537	41.5	0.004
Specific emotions (e.g., boredom)	197	13.4	94	18.3	197	14.6	0.005
Specific physical sensations (e.g., fatigue)	129	8.8	49	9.6	129	7.7	0.410
Whenever I can	204	13.9	63	12.3	204	12.8	0.931
Reminder	72	4.9	22	4.3	72	4.2	0.868
Meditation time of day							
Morning (wake - 11 am)	564	38.6	191	37.4	541	42.0	0.009
Evening (4 pm - sleep)	721	49.3	246	48.1	583	45.2	0.560
Afternoon (11 am - 4 pm)	177	12.1	74	14.5	165	12.8	0.134
Gender							
Female	1107	75.4	391	81.3	987	76.3	0.642
Male	264	18.0	87	18.0	234	0.9	0.543
Other	8	0.5	3	0.6	73	22.9	0.502
Age							
Under 25	47	3.6	14	3.1	27	2.3	0.589
25-34	233	17.7	73	16.0	229	19.3	0.118
35-44	294	22.3	118	25.8	269	22.6	0.289
45-54	334	25.4	104	22.8	257	21.6	0.389
55-64	225	17.1	95	20.8	228	19.2	0.325
Over 65	183	13.9	53	11.6	179	15.1	0.110

Race/Ethnicity							
Native American/Alaska Native	6	0.4	2	0.4	4	0.3	0.564
Asian	36	2.5	16	3.1	22	1.7	0.175
Black or African American	36	2.5	12	2.3	33	2.6	0.674
Native Hawaiian or Pacific Islander	4	0.3	*none*	*none*	5	0.4	0.031
White Non-Hispanic	1175	80	408	79.5	1044	80.7	0.348
Hispanic/Latinx	88	6	23	4.5	82	6.3	0.683
Other	123	8.4	52	10.1	104	8.0	0.112
Education							
High school/GED or less	23	1.7	9	1.9	32	2.6	0.063
Some college	147	10.7	53	11.0	114	9.2	0.143
Two year college	514	37.3	160	33.2	478	38.8	0.056
Bachelors degree	69	5.0	32	6.6	60	4.9	0.269
Graduate degree	626	45.4	228	47.3	549	44.5	0.465
Income							
$20,000 or less	43	3.3	13	2.8	37	2.9	0.919
$21,000 - $40,000	77	5.9	34	7.3	57	4.4	0.182
$41,000 - $60,000	122	9.4	56	12.1	106	8.2	0.082
$61,000 - $80,000	152	11.7	70	15.1	156	12.1	0.159
$81,000 - $100,000	214	16.4	83	17.9	176	13.6	0.422
More than $100,000	696	53.4	207	44.7	636	49.1	0.002
Employment status							
Employed	928	67.6	337	70.6	853	65.9	0.253
Unemployed	92	6.7	43	9.0	77	6.3	0.028
Unable to work	46	3.4	15	3.1	35	2.7	0.592
Homemaker	66	4.8	10	2.1	55	4.5	0.108
Student	36	2.6	15	3.1	26	2.1	0.545

Retired	204	14.9	57	11.9	182	14.8	0.264
Observations	**1468**		**513**		**1294**		
Observed app abandonment	704	47.9	273	53.2	464	35.8	
Average time to abandonment	15.51 months		41.14 months		10.24 months		

Table 1.2 shows the results of Cox regression models estimated among the pre-pandemic subscribers who started <4 months before the pandemic. The final model (Model 3) included all available behavioral, demographic, and socioeconomic predictors. From Model 3 in Table 1.2, we can see that using an existing routine to cue daily meditation was associated with a lower risk of app abandonment (hazard ratio = 0.61 95% CI: 0.422,0.874; *P* = 0.007). Additionally, reporting homemaker as one's employment status was weakly associated with a lower risk of app abandonment (hazard ratio = 0.56, 95% CI: 0.607,1.043; *P* = .007) compared to those who were retired. Predictors of an increased risk of app abandonment included being younger in age: those under 25 (hazard ratio = 2.47, 95% CI: 1.419,4.304; *P* = .001), between 25-34 (hazard ratio = 1.86, 95% CI: 1.222,2.821; *P* = 0.004), and between 34-44 (hazard ratio = 1.723, 95% CI: 1.15,2.581; *P* = .008) had a significantly higher risk of abandonment compared to those over 65; and having completed less education: those who completed some college (hazard ratio = 1.62, 95% CI: 1.233,2.120; *P* = .001) had a significantly higher risk of abandonment compared to those with a graduate degree.

Table 1.2. Determinants of App Abandonment Among Subscribers Who Started Just Before (<4 Months) the Pandemic.

	Model 1		**Model 2**		**Model 3**	
	Hazard Ratio [95% CI]	*P* value	Hazard Ratio [95% CI]	*P* value	Hazard Ratio [95% CI]	*P* value
Meditation cue						
Time of day	0.705 [0.503,0.989]	0.043	0.684 [0.487,0.96]	0.028	0.797 [0.546,1.162]	0.238
Alarm	1.236 [0.527,2.901]	0.626	1.407 [0.598,3.311]	0.434	1.659 [0.566,4.862]	0.356
Part of a daily routine	0.538 [0.389,0.745]	<.001	0.535 [0.386,0.742]	<.001	0.607 [0.422,0.874]	0.007
Specific emotions	0.976 [0.689,1.381]	0.890	0.88 [0.62,1.249]	0.475	0.919 [0.619,1.363]	0.674
Whenever I can	0.819 [0.577,1.163]	0.265	0.777 [0.547,1.104]	0.159	0.965 [0.652,1.428]	0.858
Reminder	*reference*		*reference*		*reference*	
Meditation time of day						
Morning (wake - 11 am)			0.845 [0.652,1.095]	0.202	0.854 [0.642,1.138]	0.282
Evening (4 pm - sleep)			1.254 [0.99,1.59]	0.061	1.162 [0.896,1.507]	0.259
Afternoon (11 am - 4 pm)			*reference*		*reference*	

Gender			
Woman		1.196 [0.959,1.49]	0.112
Other		1.986 [0.767,5.147]	0.158
Man		*reference*	
Age			
Under 25		2.472 [1.419,4.304]	0.001
25-34		1.856 [1.222,2.821]	0.004
35-44		1.723 [1.15,2.581]	0.008
45-54		1.438 [0.964,2.145]	0.075
55-64		1.314 [0.895,1.929]	0.163
Over 65		*reference*	
Race/Ethnicity			
Native American/Alaska Native		0.768 [0.216,2.724]	0.682

Asian		0.708 [0.349,1.434]	0.337
Black or African American		0.997 [0.501,1.982]	0.993
Native Hawaiian or Pacific Islander		0.696 [0.158,3.063]	0.631
White		0.752 [0.451,1.252]	0.273
Hispanic/Latinx		0.746 [0.413,1.346]	0.330
Other		*reference*	
Education			
High school/GED or less		1.325 [0.706,2.486]	0.381
Some college		1.617 [1.233,2.12]	0.001
Bachelors degree		1.118 [0.928,1.347]	0.240
Two year degree		1.319 [0.909,1.914]	0.146
Graduate degree		*reference*	
Income			

$20,000 or less		1.149 [0.716,1.846]	0.565
$21,000 - $40,000		1.211 [0.844,1.737]	0.298
$41,000 - $60,000		0.778 [0.57,1.061]	0.113
$61,000 - $80,000		1.132 [0.873,1.468]	0.350
$81,000 - $100,000		1.045 [0.827,1.319]	0.713
More than $100,000		*reference*	
Employment status			
Employed		0.905 [0.63,1.3]	0.590
Unemployed		0.966 [0.611,1.527]	0.882
Unable to work		0.735 [0.422,1.28]	0.277
Homemaker		0.607 [0.353,1.043]	0.070
Student		0.648 [0.336,1.248]	0.194
Retired		*reference*	
Observations			

Total	1468	1462	1244
Percent who abandoned	48.0%	47.8%	47.7%

To assess the robustness of the findings in Model 3, Models 1 and 2 describe the association between app abandonment and meditation cues or meditation time of day without controlling for the demographic or socioeconomic variables. The results in Table 1.2 show that meditating as part of a daily routine remained significant in Model 1 (hazard ratio = 0.54, 95% CI: 0.389,0.745; $P < .001$) and Model 2 (hazard ratio = 0.54, 95% CI: 0.386,0.742; $P < .001$). Using time of day as a meditation cue was significantly associated with a lower risk of app abandonment in Model 1 (hazard ratio = 0.71, 95% CI: 0.503,0.989; $P = .043$) and Model 2 (hazard ratio = 0.68, 95% CI: 0.487,0.96; $P = .028$). However, this variable did not remain significant in Model 3.

Table 1.3 displays the results of Cox regression models estimated among study participants who subscribed at least one year before the pandemic. The only significant determinant of app abandonment was earning between $61,000 - $80,000 per year (hazard ratio = 0.62, 95% CI: 0.393,0.988; $P = .044$) compared to those who earned more than $100,000. There were no significant behavioral predictors in any of the models (Models 1 – 3).

Table 1.3. Determinants of App Abandonment Among Subscribers Who Started At Least One Year Before the Pandemic.

	Model 1		**Model 2**		**Model 3**	
	Hazard Ratio [95% CI]	*P* value	Hazard Ratio [95% CI]	*P* value	Hazard Ratio [95% CI]	*P* value
Meditation cue						
Time of day	1.052 [0.573,1.93]	0.871	1.012 [0.545,1.88]	0.969	1.203 [0.557,2.597]	0.638
Alarm	0.722 [0.163,3.202]	0.668	0.683 [0.153,3.049]	0.617	0.747 [0.152,3.675]	0.719
Part of a daily routine	1.007 [0.562,1.806]	0.981	0.996 [0.551,1.802]	0.991	1.415 [0.677,2.959]	0.356
Specific emotions	1.184 [0.643,2.183]	0.587	1.072 [0.579,1.984]	0.825	1.543 [0.718,3.317]	0.267
Specific physical sensations	1.385 [0.728,2.634]	0.321	1.171 [0.608,2.255]	0.637	1.384 [0.622,3.079]	0.425
Whenever I can	0.976 [0.512,1.861]	0.940	0.907 [0.475,1.734]	0.768	1.293 [0.578,2.893]	0.531
Reminder	*reference*		*reference*		*reference*	
Meditation time of day						
Morning (wake - 11 am)			0.833 [0.558,1.245]	0.373	0.747 [0.466,1.198]	0.226
Evening (4 pm - sleep)			1.327 [0.92,1.914]	0.131	1.411 [0.909,2.19]	0.125
Afternoon (11 am - 4 pm)			*reference*		*reference*	

Gender			
Woman		1.302 [0.872,1.944]	0.197
Other		2.045 [0.4,10.447]	0.390
Man		*reference*	
Age			
Under 25		1.212 [0.434,3.379]	0.714
25-34		1.058 [0.541,2.07]	0.869
35-44		0.816 [0.431,1.544]	0.531
45-54		0.85 [0.442,1.636]	0.627
55-64		1.289 [0.709,2.347]	0.405
Over 65		*reference*	
Race/Ethnicity			
Native American/Alaska Native		0 [0,2.508E+139]	0.947

Asian		1.003 [0.349,2.885]	0.996
Black or African American		2.339 [0.797,6.863]	0.122
Native Hawaiian or Pacific Islander		*none*	
White		0.921 [0.426,1.99]	0.834
Hispanic/Latinx		0.658 [0.243,1.78]	0.410
Other		*reference*	
Education			
High school/GED or less		1.168 [0.399,3.415]	0.777
Some college		0.677 [0.395,1.161]	0.156
Bachelors degree		0.909 [0.654,1.263]	0.570
Two year degree		1.383 [0.77,2.484]	0.278
Graduate degree		*reference*	
Income			
$20,000 or less		1.745 [0.803,3.79]	0.159

$21,000 - $40,000			0.724 [0.405,1.295]	0.276
$41,000 - $60,000			0.918 [0.573,1.47]	0.721
$61,000 - $80,000			0.624 [0.393,0.988]	0.044
$81,000 - $100,000			0.844 [0.564,1.262]	0.409
More than $100,000			*reference*	
Employment status				
Employed			0.817 [0.449,1.486]	0.508
Unemployed			0.654 [0.315,1.36]	0.256
Unable to work			0.746 [0.285,1.953]	0.550
Homemaker			0.903 [0.275,2.967]	0.867
Student			0.859 [0.347,2.129]	0.743
Retired			*reference*	
Observations				
Total	513	511	441	
Percent who abandoned	53.2%	53.2%	50.8%	

Finally, Table 1.4 shows the results of Cox regression models estimated among the subscribers who started during the pandemic. Two types of meditation cues were significantly associated with a lower risk of app abandonment: meditating after an existing routine (hazard ratio = 0.43, 95% CI: 0.285,0.66; $P < 0.001$) and meditating "whenever I can" (hazard ratio = 0.43, 95% CI: 0.271,0.706; $P < 0.001$) had significantly lower hazard ratios compared to meditating using reminders. Demographic and socioeconomic factors that were associated with a higher risk of app abandonment includes income: earning $61,000 - $80,000 per year (hazard ratio = 1.31, 95% CI: 0.969,1.759; $P = 0.080$) compared to more than $100,000; and employment status: being unemployed (hazard ratio = 1.733, 95% confidence interval: 1.839,3.111; $P = .023$) compared to those who were retired.

Table 1.4. Determinants of App Abandonment Among Subscribers Who Started During the Pandemic.						
	Model 1		**Model 2**		**Model 3**	
	Hazard Ratio [95% CI]	*P* value	Hazard Ratio [95% CI]	*P* value	Hazard Ratio [95% CI]	*P* value
Meditation cue						
Time of day	0.570 [0.383,0.85]	0.006	0.573 [0.380,0.863]	0.008	0.697 [0.445,1.091]	0.114
Alarm	0.143 [0.019,1.046]	0.055	0.16 [0.38,0.863]	0.072	0.453 [0.06,3.405]	0.442
Part of a daily routine	0.382 [0.262,0.555]	<0.001	0.393 [0.267,0.579]	<0.001	0.434 [0.285,0.66]	<0.001
Specific emotions	0.642 [0.429,0.961]	0.031	0.647 [0.431,0.971]	0.036	0.732 [0.468,1.145]	0.172
Specific physical sensations	0.668 [0.426,1.048]	0.079	0.646 [0.409,1.02]	0.061	0.743 [0.455,1.214]	0.236
Whenever I can	0.380 [0.244,0.592]	<0.001	0.373 [0.238,0.585]	<0.001	0.437 [0.271,0.706]	<0.001
Reminder	*reference*		*reference*		*reference*	
Meditation time of day						
Morning (wake - 11 am)			0.892 [0.661,1.205]	0.457	0.890 [0.644,1.23]	0.482
Evening (4 pm - sleep)			1.086 [0.818,1.443]	0.568	1.093 [0.804,1.485]	0.569
Afternoon (11 am - 4 pm)			*reference*		*reference*	
Gender						

Woman		1.109 [0.851,1.446]	0.444
Other		0.969 [0.296,3.174]	0.959
Man		*reference*	
Age			
Under 25		1.149 [0.522,2.529]	0.73
25-34		0.676 [0.434,1.051]	0.082
35-44		0.896 [0.59,1.362]	0.609
45-54		0.731 [0.483,1.106]	0.138
55-64		0.799 [0.532,1.198]	0.277
Over 65		*reference*	
Race/Ethnicity			
Native American/Alaska Native		0.72 [0.089,5.835]	0.758
Asian		1.154 [0.467,2.851]	0.756
Black or African American		1.835 [0.833,4.039]	0.132

Native Hawaiian or Pacific Islander		0 [0,9.62E+101]	0.937
White		1.092 [0.584,2.043]	0.783
Hispanic/Latinx		1.384 [0.685,2.798]	0.365
Other		*reference*	
Education			
High school/GED or less		0.854 [0.405,1.8]	0.677
Some college		1.261 [0.869,1.83]	0.222
Bachelors degree		1.124 [0.9,1.404]	0.303
Two year degree		1.219 [0.785,1.894]	0.378
Graduate degree		*reference*	
Income			
$20,000 or less		1.356 [0.775,2.375]	0.286
$21,000 - $40,000		1.251 [0.751,2.083]	0.389
$41,000 - $60,000		0.764 [0.52,1.124]	0.172

$61,000 - $80,000			1.305 [0.969,1.759]	0.080
$81,000 - $100,000			1.09 [0.824,1.443]	0.545
More than $100,000			*reference*	
Employment status				
Employed			1.366 [0.917,2.035]	0.125
Unemployed			1.839 [1.087,3.111]	0.023
Unable to work			1.845 [0.968,3.518]	0.063
Homemaker			1.382 [0.766,2.494]	0.283
Student			0.801 [0.328,1.954]	0.625
Retired			*reference*	
Observations				
Total	1294	1289	1120	
Percent who abandoned	35.9%	49.9%	36.8%	

To assess the robustness of the findings in Model 3 of Table 1.4, we found that meditating as part of a daily routine was also significant in Model 1 (hazard ratio = 0.38 95% CI: 0.262,0.555; $P < .001$) and Model 2 (hazard ratio = 0.54 95% CI: 0.393,0.579; $P < .001$) compared to using meditation reminders. Meditating "whenever I can" was also significantly associated with a lower risk of app abandonment in Model 1 (hazard ratio = 0.71, 95% CI: 0.380,0.592; $P < .001$) and Model 2 (hazard ratio = 0.68, 95% CI: 0.373,0.585; $P < .001$). Cueing meditation based on the time of day was also associated with lower risk of meditation app abandonment in Model 1 (hazard ratio = 0.71, 95% CI: 0.383,0.85; $P = .006$) and Model 2 (hazard ratio = 0.57, 95% CI: 0.38,0.863; $P = .008$) compared to using reminders; however, this variable did not remain significant in Model 3.

Discussion

The purpose of this study was to determine the behavioral, demographic, and socioeconomic factors that were associated with meditation app abandonment during the COVID-19 pandemic. Approximately 48%, 53%, and 36% of respondents abandoned the app in the pre-pandemic subscriber, long-term subscriber, and pandemic subscriber cohorts, respectively. The most robust predictor of persistent meditation app use, and thus lower app abandonment, was meditating as part of a daily routine. The use of an existing routine to cue meditation was significantly associated with a lower risk of abandonment among the pre-pandemic subscribers and pandemic subscribers, which suggests that anchoring meditation to an existing routine was a beneficial strategy for maintaining a meditation practice for many subscribers during the COVID-19 pandemic. This behavioral approach to establishing a persistent meditation practice was significantly more effective than using reminders or alarms, which helps to guide the design of future interventions that aim to maintain app engagement and prevent abandonment.

Additionally, meditating according to a specific time of day was weakly associated with a lower risk of meditation app abandonment for those in the pre-pandemic subscriber and pandemic subscriber cohorts. However, there were no significant differences in app abandonment between those who chose to meditate in the mornings versus the afternoons or evenings. This suggests that consistency in the time of day of meditation is an important determinant of persistent meditation app use, but that the optimal time of day for meditation varies between individuals. Future meditation app interventions should ask participants to identify a time of day for meditation that would be most appropriate for their schedules, and then encourage them to consistently meditate at their chosen time of day. Our findings suggest that this strategy may be more effective for preventing app abandonment than requiring all participants to meditate at the same time of day.

A few demographic and socioeconomic variables were also significantly associated with meditation app abandonment, which help us to identify the app users most in need of additional meditation supports. In the pre-pandemic subscriber cohort, those who were younger and had completed less formal education were associated with a higher risk of app abandonment. In the long-term subscriber and pandemic subscriber cohorts, having a lower income was associated with a higher risk of app abandonment, and in the pandemic subscriber cohort, being unemployed was associated with a higher risk of app abandonment. Taken together, these findings suggest that a lower socioeconomic status was associated with faster app abandonment during the COVID-19 pandemic. Thus, future meditation interventions should consider targeting these groups for additional behavioral supports to help establish more persistent meditation habits that can help mitigate the burden of the COVID-19 pandemic or other potential adverse events.

Cohort specific findings

There were several important differences in our findings between subscriber cohorts that provide a deeper understanding of the value of meditation routines and using environmental meditation cues. For the pre-pandemic subscribers, meditating as part of an existing daily routine was associated with a lower risk of app abandonment. Since this cohort began using the app a few months before the pandemic, our findings suggest that using an existing routine to trigger meditation may have enabled many of these subscribers to establish a meditation habit that was more resilient to lifestyle or personal impacts of pandemic. For those who subscribed to the app during the pandemic, the rate of app abandonment was the smallest among the three subscriber cohorts and we found that both meditating “whenever I can” as well as meditating with an existing routine were associated with a lower risk of app abandonment. Thus, the pandemic subscribers likely had a higher level of initial motivation for using the meditation app, and both using a routine or allowing for some flexibility in their meditation practice appears to have supported persistent meditation among these more motivated users. Finally, we found that none of the behavioral factors were significantly associated with app abandonment among the long-term app subscribers. These long-term subscribers were also the most likely to abandon the app during the pandemic, which suggests that meditation cues and the time of day were significant determinants of meditation habits among this cohort. Thus, future research is needed to better understand the strategies used by the individuals who maintain their engagement with the app over many years, which appear to be different strategies than those used to maintain meditation over shorter periods of time.

Prior Work

The results from this study build on several findings from the existing literature such as the importance of a daily routine for establishing persistent health habits. Specifically, daily routines have been identified as a strong determinant of persistent health behaviors such as taking medication and daily exercise (e.g., Argent, 2018; Phillips et al., 2016; Thorneloe et al., 2018). Additionally, anchoring (or pairing) a new habit to an existing routine has been shown to be an effective intervention for promoting physical activity (Prestwich et al., 2003), dieting (Achtziger et al., 2008), and smoking cessation (Armitage & Arden, 2008). These findings support the conclusion that incorporating meditation into one's existing routine can be a successful way to build a persistent meditation practice and prevent abandonment. Future research is still needed to investigate the types of routines that are most supportive of a new meditation app habit.

Meditating at a consistent time of day was also associated with a lower risk of abandoning the app, which is supported by literature on the temporal consistency of healthy habits. For example, two recent studies found that temporal consistency was a strong predictor of persistent physical activity (Kaushal et al., 2017; Kaushal & Rhodes, 2015), and prior research has hypothesized that temporal consistency can help to create a protected time in the day for the targeted behavior (Rhodes & De Bruijn, 2010). Another recent study also found that meditating at roughly the same time each day was associated with greater meditation app persistence than those who meditated at different times in the day (Stecher, Berardi, et al., 2021). Future research should investigate the mechanisms the underlie the role of temporal consistency on habit formation, and additional research is needed to identify the causal effect of temporal consistency on behavioral persistence.

Limitations

Our study used a large sample of meditation app users to investigate the determinants of app abandonment during the COVID-19 pandemic, however, these findings should be considered in light of the following limitations. First, we used app usage data collected during the COVID-19 pandemic, so our results have unknown generalizability to app abandonment patterns either pre- or post-pandemic. The generalizability of our findings may also be limited by the relatively homogenous sample demographics. Specifically, participants of this study were mostly White, educated women who earned over $100,000 per year. While this is generally representative of current meditation app users, our results may not apply to the app abandonment of other health apps or to the meditation app abandonment among specific clinical study populations, e.g. meditation app use among cancer patients. Additionally, our app abandonment measure was censored and thus unobserved for some of our participants. Future studies should attempt to observe meditation app users' behavior over longer durations in order to more accurately capture and characterize the timing of app abandonment.

Conclusion

This study examined the behavioral, demographic, and socioeconomic variables that were associated with meditation app abandonment among a real-world sample of mediation app users, and found that meditating as part of an existing daily routine was associated with a lower risk of app abandonment. This suggests that combining mediation with an existing daily routine is a promising strategy for promoting persistent meditation app habits. Given the significant mental health benefits that are associated with persistent long-term meditation, these findings demonstrate how meditating as part of a daily routine can be used to improve mental health outcomes.

CHAPTER 3

MANUSCRIPT 2: Predicting meditation app use among new app subscribers: An observational study

Abstract:

Objective*:* The purpose of this study was to determine which individual characteristics predict app usage during the first eight weeks after newly subscribing to a mindfulness meditation app.

Methods*:* New subscribers to the Calm meditation app completed a baseline survey and objective app usage data were collected over eight weeks from the time of first subscribing. Survey data included demographic and socioeconomic information, level of mindfulness, personality traits, intrinsic motivation for meditation, meditation barriers, and symptoms of stress, anxiety, and depression. Regression models were used to assess the relationship between these self-reported variables and five app usage measures: 1) days with any app session, 2) average daily minutes including all app session types, 3) an indicator for completing any meditation session, 4) days with a meditation session, and 5) average daily minutes of meditation.

Results*:* Across the five app usage outcomes, a few consistent trends emerged. First, men had more days of meditation (2.13 IRR, 95% CI 1.555,2.928; $P < 0.01$) than women during both the first week after subscribing and over the first eight weeks. Second, reporting a mental health diagnosis was associated with 0.409 more average daily meditation minutes (95% CI 0.055,0.764; $P = 0.038$) over the first eight weeks after subscribing. Finally, intrinsic motivation for meditation was the strongest predictor of meditation behavior across all usage measures, where intrinsic motivation was associated with 4.085 greater odds of completing any meditation session (95% CI 0.813,2.001; $P < 0.01$), more days with meditation sessions (1.754 IRR, 95% CI

1.456,2.112; $P < 0.01$), and 0.315 more average daily meditation minutes (95% CI 0.135,0.494; $P < 0.01$). When examining the individual components of the intrinsic motivation inventory during the last week of the observation period, feeling pressure was most strongly associated with fewer days with any session (.794 IRR, 95% CI -0.402,-0.061; $P < 0.01$), 210 fewer average daily minutes (95% CI -0.410,-0.010; $P < 0.01$), fewer days with any meditation session (.687 IRR, 95% CI 0.522,0.880; $P < 0.01$), and -0.188 fewer average daily meditation minutes (95% CI -0.324,-0.053; $P < 0.01$).

Conclusions*:* The gender, mental health status, and intrinsic motivation of new meditation app subscribers were the strongest predictors of app usage over the first eight weeks after newly subscribing. Additionally, feeling pressure to meditate was the strongest predictor of app usage over this initial period after subscribing. These user characteristics should be targeted for meditation app behavioral adherence strategies. These findings help both health apps and researchers better design interventions that can increase app use among new subscribers, which will enable more users to attain the health benefits from these mobile health tools.

Introduction

Mobile meditation apps have millions of users in the U.S. and have been shown to improve mental and physical health (e.g., Baumel et al., 2020; Bostock et al., 2019; Howells et al., 2016; Rowland et al., 2020). Mindfulness meditation (hereinafter meditation) is a behavioral health practice centered around a heightened state of consciousness and focused attention with nonjudgmental awareness (Miller et al., 1995). Mobile meditation apps have adopted this practice from traditional, in-person settings and early research has shown app delivery to have comparable benefits to in-person meditation studies. For example, studies exploring the daily use of meditation apps have reported improvements in participants' levels of stress (Bostock et al., 2019; Green et al., 2021; Huberty, Green, et al., 2019), anxiety (Baumel et al., 2020; Flett et al., 2019; Rowland et al., 2020), and depressive symptoms (Baumel et al., 2020; Rowland et al., 2020). Meditation apps have also been shown to improve sleep quality (Howells et al., 2016) and reported general well-being (Howells et al., 2016). However, like many health behaviors, continued practice is necessary to attain the full health benefits associated with meditation (Shen et al., 2020; Tang et al., 2012).

While the meditation app study findings show meditation delivered via an app is beneficial for mental and physical health, only a small number of individuals continue to use meditation apps after subscribing. Findings from meditation app interventions suggest the rate of participants who abandon (i.e., do not continue) app use during the study timeframe to be between 21-77% (Flett et al., 2019; Forbes et al., 2018; Howells et al., 2016; Huberty, Green, et al., 2019). One study that evaluated the use of mental health apps, including meditation, reported in clinical studies. Rates of those who continued using the app throughout the observation period ranged from 44-99%, compared to real-world settings which ranged from 1-28% (Fleming et al., 2018). The significantly lower mediation app usage rates in real-world settings compared to research studies warrants additional research that can help to better understand determinants of real-world meditation app behaviors.

Studies using real-world data show that for most health apps, although the number of daily subscription purchases is relatively high, the number of subscribers who continue to use these apps is low. For example, one study reported mental health apps to have a median 15-day retention rate of 3.9% and a 30-day retention rate of 3.3% (Baumel et al., 2019). App usage also appears to remain low beyond the first 30 days of subscription. Cross-sectional data show that among active health app users, there is a median daily usage rate of 4% (Kerst et al., 2020). Identifying the characteristics of those who do maintain their use of mobile meditation apps after subscribing can provide important insights into the design of new app features and behavioral interventions for helping more subscribers maintain app usage and attain the full benefits of meditation.

Few studies have investigated the relationships between subscriber characteristics and meditation app usage. In one recent study, it was observed that men were more likely to meditate using an app than women, and subscribers with a physical health diagnosis meditated more frequently than those without a diagnosis (Huberty, Vranceanu, et al., 2019). Another study reported that those who were intrinsically motivated to use health apps were more likely to use meditation apps, specifically, than both other types of apps and when compared to those with extrinsic or a-motivation (Alqahtani et al., 2022). A limitation to this nascent literature is the reliance on cross-sectional surveys and self-reported app usage measures. Objective app usage data are needed to deepen our understanding of the subscriber characteristics that are associated with app use over time.

Given the evidence that meditation apps can provide important of mental and physical health benefits, there is a need to examine the app subscriber characteristics associated with successfully maintaining meditation app use after subscribing. Therefore, the purpose of this study is to determine which user characteristics predict meditation app usage in the first eight weeks after subscribing. To objectively measure meditation app usage, we will examine the number of days with any session, average daily minutes of any session, if users recorded any meditation session, the number of days with a meditation session, and average daily minutes of meditation.

Methods

Ethics Approval

The Institutional Review Board at Arizona State University (STUDY00014199) approved this study. All respondents consented via an electronic survey.

Study Design

This was an observational study in which we examined usage data from new subscribers to the Calm meditation app over eight weeks and administered a survey at baseline. Calm users completed a baseline survey within one week of purchasing a subscription to the Calm app. Calm app usage data were collected for all users from the time of their subscription purchase through the eighth week of their subscription.

Procedures

Eligibility

Calm users were eligible to participate in the study if they were at least 18 years of age, lived in the U.S., were able to read and understand English, had not previously used Calm or another meditation app, and did not have a meditation practice without an app in the past six months. Calm users must have answered “yes” to the question, “Do you want to reduce symptoms of stress, anxiety, and/or depression?” and have elevated stress levels, measured by the four-item Perceived Stress Scale (PSS-4) and using the criteria of a score of 6 or higher (mean score=6.11, SD=3.14 in the general population)(Cohen, 2020).

Recruitment

To recruit for this study, a member of the Calm team emailed those who had purchased a one-year subscription to the app within the past week and provided information about the study. If interested, Calm users clicked on a link to an eligibility survey. If eligible, the users were provided an informed consent form and asked to sign electronically. Recruitment occurred from July 2021 through November 2021.

A baseline survey followed the electronically signed informed consent via Qualtrics. Calm users in this study were not given instructions regarding Calm app use but were informed that we would be collecting their app usage data for eight weeks. As compensation for time completing the surveys, users were entered into a drawing to win one of ten $100 Amazon gift cards.

Baseline Questionnaire

The baseline questionnaire took approximately 10-15 minutes to complete, and Calm users were informed that they could skip any question or stop completing the survey at any time. The baseline questionnaire contained the following modules:

Demographic and socioeconomic information. Demographic and socioeconomic information collected included age, gender, ethnicity, race, geographic location, education level, chronic conditions, height, and weight.

Health behaviors. Calm users in this study were asked a series of investigator-developed questions related to their behaviors including smoking, alcohol consumption, and exercise. For each behavior, users were asked about their frequency (e.g., days of exercise per week) and amount (e.g., minutes per exercise bout).

Mindfulness. Mindfulness at baseline was measured using the Mindfulness Attention Awareness Scale (MAAS). The MAAS is a 15-item scale that measures the extent to which respondents can maintain awareness of present-moment experiences. The survey uses a 6-point Likert scale ranging from almost always to almost never. This survey is a valid and reliable measure with good internal consistency (Cronbach's α=.80-.87) (Brown & Ryan, 2003).

Personality traits. Personality traits were evaluated via the Big Five Inventory (BFI) (John & Srivastava, 1999). The BFI is a 44-item measure of personality traits, specifically on the five main dimensions of personality: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness. Each item uses a 5-point Likert scale ranging from disagree strongly to agree strongly. The subscales have satisfactory internal consistency (Cronbach's α= .80) (Hongyan et al., 2015).

Intrinsic motivation for meditation. Calm users in this study were asked about their motivation to begin meditating using the Calm app using a 9-item version of the Intrinsic Motivation Inventory (IMI)(Reynolds, 2006). This version contains the subscales of interest/enjoyment, effort/importance, and pressure/tension. Respondents react to statements about their motivations for meditation using a 7-point Likert scale from 1 (not at all true) to 7 (very true). The subscales are scored by taking the average of each item (Reynolds, 2006).

Barriers. Perceived barriers to meditation app usage were measured using the Determinants of Meditation Practice Inventory (DMPI). The DMPI is a 17-item scale that is designed to measure perceived barriers in naïve meditators. The scale uses a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) and items are summed to yield a total score with a possible range of 17-85. High scores indicate more perceived barriers. This scale has demonstrated good internal consistency (Cronbach's α=.87) (Williams et al., 2011).

Stress. Stress was measured using the Perceived Stress Scale (PSS). The PSS is a 10-item questionnaire that assesses one's self-appraised stress within the past month. Scores range from 0-40 with higher scores indicating higher levels of perceived stress (Cohen, 2020; Lee, 2012). This 10-item scale has demonstrated good internal consistency across various populations (Cronbach's α=.74-.92) (Lee, 2012).

Anxiety. The State-Trait Anxiety Inventory (STAI) was used to measure symptoms of anxiety. This scale has two forms, state anxiety and trait anxiety, which each include 20 items assessed using a 4-point Likert scale. Form Y-1 (state) asks respondents to select the response for how they feel currently, whereas form Y-2 (trait) asks respondents to select the response for how they generally feel. Scores range from 20-80, with higher scores indicating higher anxiety (Sydeman, 2018). This scale demonstrates good reliability and validity (Cronbach's α=.86-.95) (Spielberger, 1983).

Depressive symptoms. The Center for Epidemiological Studies-Depression (CES-D) scale was used to measure depressive symptoms. The CES-D is a 20-item scale with a 4-point Likert scale ranging from 0-3. Scores range from 0-60 with higher scores indicating more depressive symptoms (Radloff, 1997). Cronbach's alpha of .90 has been recently reported for general population adults (Cosco et al., 2017).

Usage Data

App usage data was provided by the Calm data analytics team. This data included Calm subscribers' frequency of use, duration per session, and type of session (e.g., meditation, sleep stories, etc.). The data were coded into three different definitions of app use: 1) if users recorded a session, 2) the number of days with any recorded session, and 3) average daily minutes. These variables were created for both meditation-specific app use and all app use.

Statistical Analysis

An a-priori statistical power analysis was conducted based on a recent study of an app-based meditation intervention (N=169) that included 10 predictor variables on adherence to the intervention (Forbes et al., 2018). The effect size in this study was .171. Using a more conservative estimation of .15, an alpha=.05, and power=.80, the targeted sample size for this study was approximately N=274. The power analysis was conducted using G*power (Erdfelder et al., 2009; Faul et al., 2007).

App usage data were analyzed by regression models that varied in functional form for each outcome. Meditation app use was described by the following five outcomes: 1) days with any session, 2) average daily minutes including all sessions, 3) any meditation, 4) days with a meditation session, and 5) average daily minutes of meditation. Negative binomial regression models were estimated to assess the relationship between user characteristics and the count of days with any recorded session for both meditation sessions and all app use sessions. A logistic regression was estimated to assess the relationship between user characteristics and whether users recorded any meditation session. Finally, ordinary least squares linear regression models were estimated to assess the relationship between user characteristics and the average daily minutes for both meditation and all app use minutes. To further explore how user characteristics impact app usage over the duration of the observation period, the five regression models above were re-estimated using only app use data for each user's first (Week 1) and last (Week 8) week in the observation period.

All outcome variables were checked for normality and the measures of average daily minutes were log-transformed to satisfy the normality assumption (see Figure 1). Additionally, only sessions that were >90% complete were considered in these analyses. For example, if a meditation session was 10 minutes in duration, users who listened to at least nine minutes were considered to have completed the session. Finally, only users who completed at least one session of any kind after subscribing to the app were included in the analyses to remove people with duplicate accounts or those who unintendedly subscribed. Only usage data from the date of users' subscription purchases through the following eight weeks were included in the analysis. Statistical significance was set at $P < .05$. All analyses were conducted in Stata (*StataCorp*, 2021).

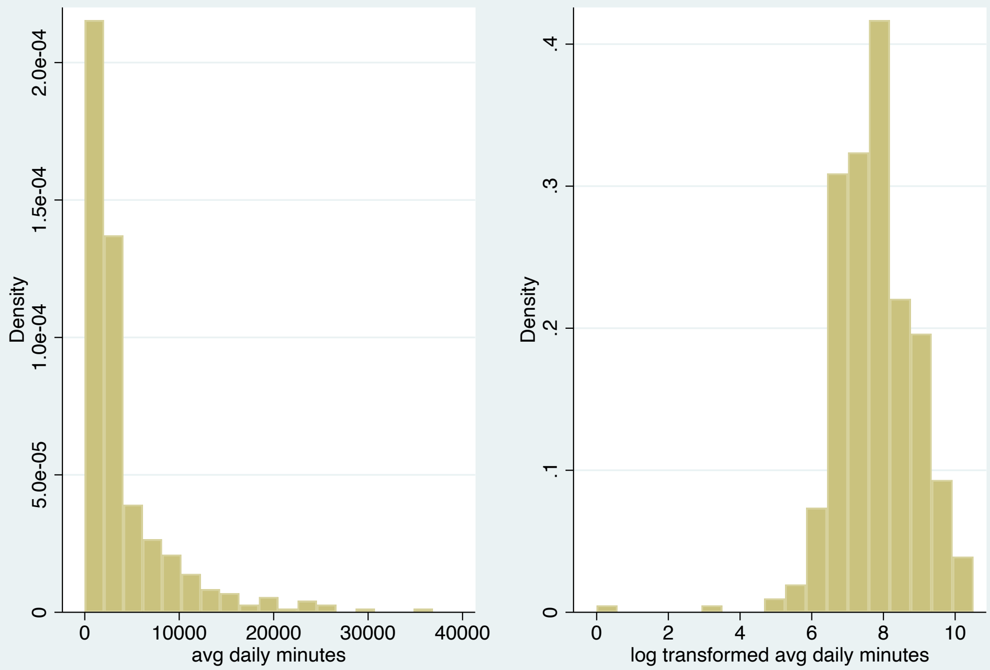

Figure 1. Log transformed average daily minutes for all sessions.

Results

A total of 632 new Calm app subscribers completed the baseline survey. After removing cases with missing app usage data, 304 were included in the analyses. Calm users' subscription start dates ranged from July 15, 2021, to November 15, 2021.

Table 2.1 shows the descriptive statistics of the sample. Users were mostly female (79%, 240/304), White (82%, 248/304), and had either a bachelor's degree (31%, 94/304) or graduate degree (39%, 119/304). The most common chronic conditions were mental health diagnoses, with 77% (234/304) reporting at least one of the following: depression (65%, 186/304), anxiety (61%, 179/304), and PTSD (33%, 98/304). Most users did not smoke (92%, 279/304), 55% of users reported drinking fewer than seven drinks per week, and users reported exercising either three times or more per week (44%, 133/304) or between one and three times (34%, 104/304).

Table 2.1. Descriptive Characteristics of the Sample.

	Frequency	Percent
Age		
Under 25	12	4%
25 to 34	72	24%
35 to 44	87	29%
45 to 54	59	19%
55 to 64	41	13%
Over 65	31	10%
Gender		
Woman	240	79%
Man	60	20%
Other gender	4	1%
Race/ethnicity		
White	248	82%
Asian	14	5%
Black	9	3%
Hispanic	20	7%
Other race	13	4%
Region		
West	79	26%
Southwest	35	12%
Midwest	65	21%
Southeast	67	22%
Northeast	52	17%
Education		
High school diploma	10	3%
Some college	48	16%
Associate's degree	33	11%
Bachelors degree	94	31%
Graduate degree	119	39%
Chronic conditions		
Mental health diagnosis	234	77%
Health behaviors		
Heavy smoker (≥6 packs per day)	17	6%
Light smoker (<6 packs per day	8	3%
Non-smoker	279	92%
Heavy drinker (≥7 drinks per week)	24	8%

Light drinker (<7 drinks per week)	166	55%
Non-drinker	114	38%
Heavy exerciser (≥3 times per week)	133	44%
Light exerciser (<3 times per week)	104	34%
Non-exerciser	67	22%
	Mean	**SD**
Number of physical health conditions	0.63	0.98
BMI	28.28	7.22
Mindfulness level (MAAS)	3.65	0.87
Intrinsic motivation for meditation (IMI)	4.42	0.95
Perceived barriers to meditation (DMPI)	2.31	0.57
Personality		
Extraversion	20.58	6.39
Agreeableness	33.48	5.78
Conscientiousness	32.57	5.89
Neuroticism	29.50	5.27
Openness	36.75	6.29
Mental health symptoms		
Perceived stress (PSS)	26.83	5.24
State anxiety (STAIY1)	2.47	0.59
Trait anxiety (STAIY2)	2.63	0.53
Depressive symptoms (CESD)	24.91	11.45
Chronic conditions	**Frequency**	**Percent**
Depression	186	63%
Anxiety	179	61%
Post-Traumatic Stress Disorder	98	33%
High blood pressure	49	17%
High cholesterol	39	13%
Diabetes	10	3%
Asthma	31	11%
Emphysema	2	1%
Other	1	0%
Heart	13	4%
Arthritis	34	12%
Cancer	11	4%
Other	61	21%

None	59	20%

Table 2.2 shows the results from the regression models estimated from the app usage data throughout the duration of the eight-week observation period. Men had approximately 2.13 times more days of meditation (95% CI 1.555,2.928; *P* < 0.01) compared to women. Having a mental health diagnosis was associated with 0.409 more average daily meditation minutes (95% CI 0.055,0.764; *P* = 0.038). Those with higher BMIs were less likely to complete any meditation session (.509 OR, 95% CI -1.297,-0.054; *P* = 0.033), had 0.807 times fewer days with meditation sessions on average (95% CI 0.690,0.945; < 0.01) for each one-unit increase in BMI. Level of intrinsic motivation for meditation was associated with a 4.085 odds ratio of completing any meditation session (95% CI 0.813,2.001; *P* < 0.01), 1.754 times more days with meditation sessions (95% CI 1.456,2.112; *P* < 0.01), and 0.315 more average daily meditation minutes for each unit increase on the Intrinsic Motivation Inventory (IMI) (95% CI 0.135,0.494; *P* < 0.01). As a sensitivity check, these models were repeated with anxiety and depressive symptoms removed (see Appendix A).

Table 2. App usage over the first eight weeks regressed on individual characteristics.

	All session usage		Meditation-specific usage		
	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Any meditation (coef in OR)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)
Under 25	*reference*				
25 to 34	1.06	0.301	1.281	0.982	0.347
	[0.640,1.754]	[-0.398,1.001]	[0.125,13.178]	[0.515,1.873]	[-0.398,1.092]
35 to 44	1.045	0.421	1.065	0.911	0.346
	[0.630,1.736]	[-0.279,1.122]	[0.083,13.682]	[0.475,1.745]	[-0.417,1.108]
45 to 54	1.620*	0.453	0.445	1.736	0.528
	[0.968,2.713]	[-0.273,1.178]	[0.042,4.709]	[0.873,3.450]	[-0.243,1.300]
55 to 64	1.268	0.476	6.908	1.438	0.659*

	[0.738,2.179]	[-0.339,1.292]	[0.171,278.41]	[0.695,2.975]	[-0.116,1.435]
over 65	1.521	0.768*	0.275	1.59	0.508
	[0.869,2.662]	[-0.049,1.585]	[0.022,3.499]	[0.765,3.304]	[-0.283,1.300]
Woman	*reference*				
Man	1.282*	-0.119	2.408	2.133***	0.246
	[0.996,1.652]	[-0.424,0.186]	[0.639,9.077]	[1.555,2.928]	[-0.083,0.575]
Other gender	1.759	0.433	0.051**	1.803	-0.203
	[0.637,4.858]	[-0.438,1.305]	[0.003,0.840]	[0.386,8.421]	[-1.694,1.288]
White	0.817	-0.337	3.22	0.997	-0.015
	[0.512,1.303]	[-0.964,0.289]	[0.371,27.979]	[0.502,1.979]	[-0.858,0.828]
Asian	0.708	-0.823**	1.001	1.155	0.466
	[0.371,1.351]	[-1.58,-0.063]	[1.000,1.000]	[0.470,2.836]	[-0.533,1.465]
Black	0.584	-0.51	3.246	0.602	0.241
	[0.301,1.134]	[-1.314,0.294]	[0.117,89.863]	[0.228,1.590]	[-0.850,1.332]
Hispanic	0.813	-0.136	2.5	0.998	0.108
	[0.480,1.379]	[-0.924,0.653]	[0.156,39.958]	[0.466,2.138]	[-0.813,1.030]
Other race/ethnicity	*reference*				
West	1.360**	0.103	0.69	1.854***	-0.028
	[1.001,1.848]	[-0.260,0.466]	[0.167,2.857]	[1.212,2.838]	[-0.390,0.334]
Southeast	1.246	0.01	1.001	1.371	-0.038
	[0.886,1.754]	[-0.427,0.447]	[1.000,1.000]	[0.906,2.074]	[-0.463,0.387]
Midwest	1.328*	0.207	0.349	1.378	-0.015
	[0.954,1.850]	[-0.151,0.566]	[0.082,1.491]	[0.917,2.069]	[-0.440,0.410]
Southeast	0.929	0.047	0.240**	0.715*	-0.313
	[0.680,1.269]	[-0.299,0.393]	[0.063,0.913]	[0.488,1.046]	[-0.698,0.071]
Northeast	*reference*				
High school diploma	0.685	-0.207	0.763	0.420**	-0.109
	[0.386,1.216]	[-0.934,0.521]	[0.088,6.635]	[0.184,0.958]	[-0.842,0.623]
Some college	0.843	0.118	0.384	0.774	-0.145
	[0.610,1.166]	[-0.299,0.535]	[0.096,1.535]	[0.510,1.174]	[-0.601,0.312]
Associates degree	0.660**	-0.247	1.028	0.549***	-0.118
	[0.439,0.991]	[-0.777,0.283]	[0.194,5.453]	[0.353,0.855]	[-0.563,0.328]
Bachelors gegree	0.986	0.066	2.382	1.057	0.229
	[0.783,1.242]	[-0.223,0.356]	[0.610,9.299]	[0.780,1.432]	[-0.080,0.538]
Graduate degree	*reference*				

Number of physcial health conditions	0.929	-0.093	1.643	1.044	0.001
	[0.829,1.040]	[-0.249,0.063]	[0.754,3.579]	[0.912,1.196]	[-0.137,0.139]
Mental health diagnosis	1.207	0.114	1.667	1.154	0.409**
	[0.941,1.547]	[-0.211,0.440]	[0.415,6.693]	[0.813,1.639]	[0.055,0.764]
No chronic conditions	*reference*				
BMI	0.928	0.059	0.509**	0.807***	-0.153*
	[0.824,1.046]	[-0.096,0.213]	[0.273,0.948]	[0.690,0.945]	[-0.313,0.006]
Heavy smoker (≥6 packs per day)	0.954	0.275	0.5	1.128	0.141
	[0.642,1.419]	[-0.225,0.776]	[0.080,3.134]	[0.616,2.067]	[-0.334,0.616]
Light smoker (<6 packs per day	1.254	0.37	0.134*	1.5	0.225
	[0.752,2.090]	[-0.093,0.833]	[0.018,1.018]	[0.693,3.245]	[-0.555,1.005]
Non-smoker	*reference*				
Heavy drinker (≥7 drinks per week)	0.664*	-0.238	0.951	0.734	-0.407
	[0.439,1.003]	[-0.755,0.278]	[0.171,5.298]	[0.426,1.265]	[-1.004,0.189]
Light drinker (<7 drinks per week)	0.928	-0.117	2.054	0.902	0.068
	[0.752,1.146]	[-0.383,0.150]	[0.601,7.022]	[0.686,1.186]	[-0.223,0.358]
Non-drinker	*reference*				
Heavy exerciser (≥3 times per week)	1.085	0.08	1.251	1.342	0.137
	[0.802,1.467]	[-0.288,0.448]	[0.286,5.469]	[0.942,1.911]	[-0.264,0.537]
Light exerciser (<3 times per week)	0.848	-0.131	0.896	0.993	-0.066
	[0.624,1.153]	[-0.508,0.246]	[0.231,3.475]	[0.671,1.470]	[-0.468,0.336]
Non-exerciser	*reference*				
Mindfulness level (MAAS)	1.041	0.12	1.418	0.834	-0.034
	[0.704,1.540]	[-0.367,0.608]	[0.114,17.591]	[0.525,1.323]	[-0.575,0.506]
Extraversion	0.877**	-0.125*	1.57	0.935	0.046
	[0.782,0.983]	[-0.262,0.012]	[0.847,2.911]	[0.800,1.092]	[-0.106,0.197]
Agreeableness	0.919	-0.015	0.997	0.994	-0.017
	[0.823,1.026]	[-0.154,0.125]	[0.569,1.749]	[0.866,1.141]	[-0.155,0.121]
Conscientiousness	1.05	-0.062	0.783	0.942	0.005
	[0.938,1.175]	[-0.207,0.083]	[0.445,1.376]	[0.826,1.075]	[-0.131,0.142]

Neuroticism	1.026	-0.05	2.250*	1.101	0.036
	[0.904,1.164]	[-0.214,0.113]	[0.983,5.149]	[0.919,1.320]	[-0.152,0.223]
Openness	1.009	0.017	0.998	0.938	-0.045
	[0.909,1.119]	[-0.116,0.150]	[0.553,1.799]	[0.814,1.080]	[-0.179,0.089]
Intrinsic motivation for meditation (IMI)	1.054	-0.082	4.085***	1.754***	0.315***
	[0.928,1.197]	[-0.265,0.101]	[2.256,7.399]	[1.456,2.112]	[0.135,0.494]
Perceived barriers to meditation (DMPI)	0.996	0	0.74	0.948	-0.083
	[0.880,1.127]	[-0.149,0.149]	[0.470,1.163]	[0.823,1.091]	[-0.228,0.062]
Perceived stress (PSS)	0.936	-0.023	1.034	0.96	0.069
	[0.810,1.082]	[-0.207,0.160]	[0.512,2.089]	[0.784,1.176]	[-0.108,0.246]
State anxiety (STAIY1)	0.973	-0.015	1.08	0.963	-0.091
	[0.832,1.138]	[-0.190,0.159]	[0.499,2.337]	[0.769,1.207]	[-0.304,0.121]
Trait anxiety (STAIY2)	1.068	0.125	0.622	1.125	-0.017
	[0.883,1.293]	[-0.119,0.370]	[0.223,1.739]	[0.888,1.426]	[-0.256,0.221]
Depressive symptoms (CESD)	0.985	-0.018	1.018	0.978	0.005
	[0.962,1.008]	[-0.044,0.008]	[0.910,1.139]	[0.950,1.007]	[-0.025,0.036]
N	304	304	304	304	304

Table 2.3 shows the results from the regression models estimated from the app usage data during the first week of the observation period to examine if predictors are different for immediate app use after purchasing a subscription. Older age was associated with more days with any sessions (age 45-54: 1.700 IRR; 95% CI 1.092,2.645; *P* = 0.019; age over 65: 1.645 IRR; 95% CI 1.010,2.681; *P* = 0.046) and days with meditation sessions (age 45-54: 2.638 IRR; 95% CI 1.223,5.688; *P* = 0.013; age over 65: 2.335 IRR; 95% CI 1.036,5.267; *P* = 0.041) compared to those under 25. Men had 1.686 times more days with meditation sessions (95% CI 1.239,2.295; *P* < 0.01) compared to women. Each unit increase in BMI reduced the odds of completing any meditation session by 0.684 (95% CI -0.683,-0.075; *P* = 0.015). Intrinsic motivation for meditation was associated with a 1.977 odds ratio of completing a meditation session

(95% CI 0.309,1.054; *P* < 0.01), 1.431 times more days with meditation sessions (95% CI 1.225,1.671; *P* < 0.01), and 0.381 more average daily meditation minutes (95% CI 0.184,0.577; *P* < 0.01).

Table 2.3. App Usage Over the First Week Regressed on Individual Characteristics.

	All session usage		Meditation-specific usage		
	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Any meditation (coef in OR)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)
Under 25	*reference*				
25 to 34	1.241	0.225	2.108	1.708	0.569
	[0.795,1.938]	[-0.688,1.139]	[0.492,9.026]	[0.796,3.663]	[-0.152,1.290]
35 to 44	1.364	0.429	2.418	1.674	0.484
	[0.876,2.123]	[-0.479,1.337]	[0.568,10.282]	[0.775,3.613]	[-0.247,1.215]
45 to 54	1.700**	0.546	3.542	2.638**	0.792**
	[1.092,2.645]	[-0.378,1.470]	[0.781,16.056]	[1.223,5.688]	[0.043,1.541]
55 to 64	1.299	0.034	4.197*	2.078*	0.569
	[0.801,2.106]	[-0.998,1.066]	[0.828,21.265]	[0.922,4.684]	[-0.235,1.372]
over 65	1.645**	0.218	2.333	2.335**	0.628
	[1.010,2.681]	[-0.849,1.285]	[0.478,11.395]	[1.036,5.267]	[-0.188,1.444]
Woman	*reference*				
Man	1.081	0.127	2.054*	1.686***	0.519**
	[0.874,1.338]	[-0.355,0.610]	[0.987,4.274]	[1.239,2.295]	[0.069,0.969]
Other gender	0.92	0.127	0.762	0.746	-0.697
	[0.376,2.255]	[-1.586,1.840]	[0.084,6.917]	[0.199,2.789]	[-2.226,0.833]
White	1.373	1.449**	2.63	1.324	0.777*
	[0.721,2.616]	[0.330,2.568]	[0.598,11.574]	[0.526,3.335]	[-0.133,1.686]
Asian	1.04	0.795	7.113**	1.299	0.86
	[0.499,2.169]	[-0.410,2.000]	[1.193,42.413]	[0.435,3.878]	[-0.216,1.935]
Black	1.244	1.271*	1.407	0.588	0.068
	[0.553,2.798]	[-0.227,2.769]	[0.149,13.289]	[0.160,2.160]	[-1.161,1.298]
Hispanic	1.344	1.551**	11.125**	1.41	0.91
	[0.677,2.666]	[0.292,2.810]	[1.648,75.085]	[0.541,3.679]	[-0.181,2.000]
Other race/ethnicity	*reference*				
West	1.133	0.246	2.211*	1.297	0.11
	[0.880,1.458]	[-0.333,0.825]	[0.873,5.598]	[0.903,1.863]	[-0.392,0.611]
Southeast	0.976	-0.054	0.871	1.009	-0.226
	[0.720,1.323]	[-0.733,0.624]	[0.300,2.530]	[0.653,1.560]	[-0.841,0.390]
Midwest	1.152	0.408	1.001	1.18	-0.131
	[0.879,1.510]	[-0.187,1.004]	[0.410,2.439]	[0.815,1.708]	[-0.655,0.393]
Southeast	0.944	-0.082	0.726	0.701*	-0.408
	[0.723,1.232]	[-0.699,0.534]	[0.308,1.713]	[0.481,1.021]	[-0.913,0.098]
Northeast	*reference*				

High school diploma	0.92	-0.138	1.369	0.903	0.173
	[0.575,1.470]	[-1.242,0.966]	[0.232,8.089]	[0.441,1.848]	[-0.803,1.149]
Some college	0.952	0.355	1.505	1.003	0.244
	[0.743,1.220]	[-0.279,0.988]	[0.601,3.768]	[0.680,1.481]	[-0.308,0.797]
Associates degree	0.735*	-0.663	0.964	0.928	0.088
	[0.518,1.043]	[-1.469,0.142]	[0.363,2.560]	[0.608,1.415]	[-0.503,0.679]
Bachelors degree	0.951	-0.168	1.872*	1.344**	0.345*
	[0.782,1.157]	[-0.624,0.288]	[0.943,3.717]	[1.011,1.788]	[-0.046,0.737]
Graduate degree	*reference*				
Number of physical health conditions	0.929	-0.032	1.248	0.965	0.055
	[0.845,1.021]	[-0.253,0.190]	[0.910,1.711]	[0.846,1.100]	[-0.121,0.232]
Mental health diagnosis	0.955	0.052	1.752	1.119	0.089
	[0.767,1.189]	[-0.489,0.594]	[0.807,3.804]	[0.794,1.577]	[-0.385,0.563]
No chronic conditions	*reference*				
BMI	0.945	-0.065	0.684**	0.889*	-0.099
	[0.857,1.042]	[-0.298,0.169]	[0.505,0.928]	[0.773,1.022]	[-0.296,0.098]
Heavy smoker (≥6 packs per day)	1.138	0.699*	0.767	1.026	0.406
	[0.835,1.552]	[-0.061,1.459]	[0.209,2.806]	[0.568,1.854]	[-0.431,1.242]
Light smoker (<6 packs per day	1.453	0.755	1.649	1.349	0.537
	[0.910,2.321]	[-0.210,1.720]	[0.211,12.890]	[0.611,2.979]	[-0.310,1.384]
Non-smoker	*reference*				
Heavy drinker (≥7 drinks per week)	0.82	-0.115	1.258	1.023	-0.101
	[0.571,1.179]	[-0.984,0.754]	[0.389,4.069]	[0.594,1.762]	[-0.845,0.644]
Light drinker (<7 drinks per week)	1.006	0.043	1.258	1.169	0.227
	[0.844,1.198]	[-0.369,0.454]	[0.673,2.351]	[0.890,1.536]	[-0.122,0.575]
Non-drinker	*reference*				
Heavy exerciser (≥3 times per week)	0.875	-0.367	1.095	0.922	-0.081
	[0.689,1.110]	[-0.923,0.188]	[0.527,2.273]	[0.630,1.350]	[-0.556,0.393]
Light exerciser (<3 times per week)	0.814	-0.371	0.649	0.853	-0.281
	[0.636,1.042]	[-0.949,0.207]	[0.297,1.418]	[0.578,1.258]	[-0.772,0.209]
Non-exerciser	*reference*				
Mindfulness level (MAAS)	1.084	0.072	0.69	1.105	0.092
	[0.801,1.467]	[-0.643,0.787]	[0.239,1.995]	[0.719,1.698]	[-0.530,0.714]
Extraversion	0.933	-0.162	0.848	0.957	-0.064
	[0.846,1.029]	[-0.383,0.058]	[0.622,1.157]	[0.831,1.102]	[-0.248,0.121]
Agreeableness	0.999	0.053	1.078	1.075	0.086

	[0.906,1.101]	[-0.167,0.273]	[0.796,1.459]	[0.944,1.226]	[-0.097,0.269]
Conscientiousness	0.992	0.005	0.969	0.953	-0.014
	[0.904,1.089]	[-0.212,0.222]	[0.707,1.327]	[0.831,1.094]	[-0.199,0.171]
Neuroticism	1.003	-0.115	1.195	1.061	0.035
	[0.893,1.126]	[-0.404,0.173]	[0.797,1.790]	[0.894,1.260]	[-0.204,0.273]
Openness	1.033	0.084	0.839	0.993	0.067
	[0.944,1.129]	[-0.130,0.298]	[0.610,1.156]	[0.863,1.143]	[-0.109,0.242]
Intrinsic motivation for meditation (IMI)	1.043	0.074	1.977***	1.431***	0.381***
	[0.932,1.166]	[-0.185,0.333]	[1.362,2.869]	[1.225,1.671]	[0.184,0.577]
Perceived barriers to meditation (DMPI)	0.967	-0.042	1.007	0.998	-0.027
	[0.879,1.065]	[-0.248,0.164]	[0.731,1.386]	[0.868,1.148]	[-0.207,0.154]
Perceived stress (PSS)	0.938	-0.017	0.806	0.922	0.013
	[0.825,1.066]	[-0.310,0.277]	[0.531,1.222]	[0.755,1.126]	[-0.250,0.275]
State anxiety (STAIY1)	1.028	0.207	1.231	1.007	0.018
	[0.907,1.165]	[-0.085,0.499]	[0.807,1.878]	[0.834,1.216]	[-0.223,0.259]
Trait anxiety (STAIY2)	1.066	0.085	1.14	1.112	0.049
	[0.915,1.243]	[-0.293,0.464]	[0.671,1.935]	[0.877,1.409]	[-0.271,0.370]
Depressive symptoms (CESD)	0.995	-0.017	0.964	0.991	-0.002
	[0.978,1.012]	[-0.055,0.021]	[0.910,1.021]	[0.966,1.016]	[-0.037,0.032]
N	304	304	304	304	304

Table 2.4 shows the results from the regression models estimated from the app usage data during the last week of the observation period to examine if predictors are different for app use after having subscribed to the app for eight weeks. Men were 2.559 times more likely to complete a meditation session (95% CI 0.216,1.664; *P* = 0.011) and had 1.876 times more days with meditation sessions (95% CI 1.138,3.093; *P* = 0.014) compared to women. Mental health diagnoses were associated with 1.738 times more days with any session (95% CI 1.215,2.486; *P* < 0.01) and .514 more average daily minutes for all sessions (95% CI 0.057,0.971; *P* = 0.039). Users' number of physical health conditions was positively associated with completing a meditation session (1.419 OR; 95% CI 0.056,0.643; *P* = 0.020). Those with higher levels of intrinsic motivation for

meditation were 1.548 times more likely to complete a meditation session (95% CI 0.025,0.849; P = 0.038), had 1.612 more days with meditation sessions (95% CI 1.222,2.127; P < 0.01) for each unit of increase on the IMI.

Table 2.4. App Usage Over the Last Week Regressed on Individual Characteristics.

	All session usage		Meditation-specific usage		
	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Any meditation (coef in OR)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)
Under 25	*reference*				
25 to 34	0.615	-0.518	0.554	0.533	-0.47
	[0.338,1.119]	[-1.423,0.386]	[0.148,2.077]	[0.217,1.309]	[-1.169,0.230]
35 to 44	0.662	-0.303	0.834	0.642	-0.301
	[0.370,1.184]	[-1.211,0.606]	[0.218,3.186]	[0.268,1.540]	[-1.023,0.421]
45 to 54	1.272	0.161	0.858	1.125	-0.322
	[0.682,2.373]	[-0.842,1.165]	[0.211,3.493]	[0.438,2.890]	[-1.069,0.424]
55 to 64	0.977	0	1.889	1.231	-0.133
	[0.505,1.890]	[-1.047,1.047]	[0.445,8.009]	[0.473,3.206]	[-0.894,0.628]
over 65	0.955	-0.44	1.265	1.288	-0.212
	[0.485,1.879]	[-1.408,0.527]	[0.293,5.467]	[0.508,3.268]	[-0.978,0.555]
Woman	*reference*				
Man	1.252	0.251	2.559**	1.876**	0.274*
	[0.882,1.777]	[-0.162,0.664]	[1.241,5.279]	[1.138,3.093]	[-0.023,0.571]
Other gender	2.011	0.686	2.089	3.27	0.598
	[0.503,8.032]	[-1.289,2.661]	[0.134,32.603]	[0.458,23.331]	[-1.394,2.590]
White	0.787	0.054	0.537	0.943	0.106
	[0.376,1.649]	[-0.832,0.940]	[0.147,1.962]	[0.352,2.527]	[-0.385,0.596]
Asian	0.685	0.022	0.832	1.048	0.036
	[0.260,1.800]	[-1.204,1.248]	[0.141,4.900]	[0.279,3.939]	[-0.682,0.754]
Black	0.51	0.043	0.784	1.015	0.471
	[0.171,1.525]	[-1.327,1.413]	[0.068,9.066]	[0.111,9.257]	[-0.666,1.608]
Hispanic	0.948	-0.044	0.969	1.438	0.048
	[0.405,2.217]	[-1.044,0.956]	[0.214,4.391]	[0.443,4.673]	[-0.523,0.618]
Other race/ethnicity	*reference*				

West	1.487*	0.294	1.418	1.830*	0.2
	[0.981,2.256]	[-0.226,0.815]	[0.614,3.275]	[0.979,3.421]	[-0.148,0.549]
Southeast	1.443*	0.409	1.62	1.724*	0.152
	[0.937,2.223]	[-0.272,1.090]	[0.604,4.348]	[0.934,3.184]	[-0.303,0.607]
Midwest	1.416	0.235	1.451	1.829**	0.177
	[0.900,2.227]	[-0.343,0.813]	[0.569,3.699]	[1.016,3.292]	[-0.212,0.567]
Southeast	0.683*	-0.27	0.432*	0.624	-0.193
	[0.441,1.060]	[-0.763,0.222]	[0.176,1.060]	[0.331,1.175]	[-0.525,0.139]
Northeast	*reference*				
High school diploma	0.566	-0.278	0.159*	0.379	-0.33
	[0.235,1.359]	[-1.684,1.128]	[0.020,1.267]	[0.091,1.578]	[-1.285,0.624]
Some college	0.69	-0.422	0.585	0.594	-0.14
	[0.422,1.127]	[-1.031,0.187]	[0.213,1.607]	[0.291,1.209]	[-0.522,0.242]
Associates degree	0.478**	-0.710**	0.326*	0.459*	-0.416*
	[0.265,0.862]	[-1.374,-0.046]	[0.091,1.163]	[0.192,1.094]	[-0.836,0.005]
Bachelors degree	1.011	0.12	1.653	1.277	0.248*
	[0.728,1.405]	[-0.301,0.542]	[0.852,3.208]	[0.791,2.064]	[-0.037,0.532]
Graduate degree	*reference*				
Number of physical health conditions	0.944	-0.069	1.419**	1.175	0.084
	[0.799,1.115]	[-0.255,0.117]	[1.057,1.903]	[0.952,1.452]	[-0.046,0.214]
Mental health diagnosis	1.738***	0.514**	1.416	1.266	0.045
	[1.215,2.486]	[0.057,0.971]	[0.622,3.225]	[0.744,2.154]	[-0.245,0.335]
No chronic conditions	*reference*				
BMI	0.922	-0.042	0.838	0.87	-0.03
	[0.784,1.084]	[-0.210,0.126]	[0.613,1.145]	[0.684,1.107]	[-0.144,0.085]
Heavy smoker (≥6 packs per day)	1.521	0.487	3.146*	2.791**	0.39
	[0.812,2.848]	[-0.555,1.529]	[0.821,12.048]	[1.106,7.042]	[-0.326,1.105]
Light smoker (<6 packs per day	0.723	-0.265	0.667	0.856	-0.114
	[0.334,1.564]	[-1.089,0.558]	[0.117,3.814]	[0.162,4.533]	[-0.662,0.434]
Non-smoker	*reference*				
Heavy drinker (≥7 drinks per week)	0.554**	-0.231	1.503	0.875	0.003

	[0.325,0.947]	[-0.878,0.416]	[0.502,4.505]	[0.407,1.881]	[-0.428,0.434]
Light drinker (<7 drinks per week)	0.907	-0.124	0.803	0.806	-0.107
	[0.672,1.225]	[-0.533,0.285]	[0.439,1.468]	[0.525,1.239]	[-0.372,0.158]
Non-drinker	*reference*				
Heavy exerciser (≥3 times per week)	1.165	0.176	2.952**	1.648*	0.306*
	[0.759,1.786]	[-0.390,0.743]	[1.260,6.919]	[0.949,2.862]	[-0.022,0.634]
Light exerciser (<3 times per week)	0.871	0.098	1.041	0.774	-0.011
	[0.574,1.322]	[-0.452,0.649]	[0.427,2.536]	[0.424,1.413]	[-0.326,0.304]
Non-exerciser	*reference*				
Mindfulness level (MAAS)	0.901	-0.102	0.526	0.722	-0.221
	[0.542,1.497]	[-0.690,0.487]	[0.180,1.539]	[0.351,1.486]	[-0.665,0.224]
Extraversion	0.833**	-0.170*	0.89	0.913	-0.036
	[0.708,0.980]	[-0.366,0.025]	[0.655,1.208]	[0.721,1.156]	[-0.151,0.080]
Agreeableness	0.946	-0.003	1.069	1.02	-0.009
	[0.808,1.108]	[-0.204,0.198]	[0.774,1.475]	[0.818,1.272]	[-0.119,0.101]
Conscientiousness	1.147*	0.166	1.048	1.038	0.064
	[0.988,1.333]	[-0.032,0.364]	[0.748,1.468]	[0.833,1.294]	[-0.064,0.192]
Neuroticism	1.09	0.047	1.281	1.411**	0.066
	[0.885,1.342]	[-0.258,0.352]	[0.851,1.930]	[1.047,1.901]	[-0.110,0.243]
Openness	1.004	-0.098	0.798	0.863	-0.083
	[0.862,1.168]	[-0.292,0.096]	[0.578,1.101]	[0.685,1.087]	[-0.194,0.028]
Intrinsic motivation for meditation (IMI)	1.098	-0.016	1.548**	1.612***	0.123*
	[0.915,1.317]	[-0.266,0.234]	[1.025,2.337]	[1.222,2.127]	[-0.017,0.263]
Perceived barriers to meditation (DMPI)	1.044	-0.008	0.98	1.02	-0.056
	[0.856,1.272]	[-0.237,0.222]	[0.669,1.434]	[0.784,1.326]	[-0.207,0.095]
Perceived stress (PSS)	0.975	0.056	1.01	0.88	0.008
	[0.792,1.201]	[-0.208,0.320]	[0.684,1.492]	[0.652,1.186]	[-0.145,0.161]
State anxiety (STAIY1)	1.08	0.095	1.056	0.98	-0.026
	[0.849,1.373]	[-0.197,0.386]	[0.690,1.617]	[0.680,1.412]	[-0.213,0.161]
Trait anxiety (STAIY2)	0.843	-0.225	0.895	0.813	-0.106
	[0.648,1.097]	[-0.554,0.104]	[0.516,1.553]	[0.551,1.200]	[-0.332,0.121]

Depressive symptoms (CESD)	0.98	-0.009	0.975	0.993	0.009
	[0.945,1.017]	[-0.051,0.034]	[0.909,1.045]	[0.939,1.050]	[-0.019,0.037]
N	304	304	304	304	304

To visualize how intrinsic motivation for meditation impacted app usage, Figure 2 displays the average daily minutes of meditation over the eight weeks of the study. Users were split by IMI median score (4.42, SD = .95). While average daily minutes of meditation declined for all users over the course of the study, those with higher intrinsic motivation for meditation show higher daily minutes of meditation. To further explore intrinsic motivation, questions from the IMI used for this study were added into the regression models to estimate the app usage data throughout the duration of the eight-week study, in addition to all variables included in Tables 2.2-2.4. Table 2.5 shows each question from the IMI that was added to the models. Notably, the question, "I feel pressure to continue my meditation practice," was associated with .794 times fewer days with any session (95% CI -0.402,-0.061; $P < 0.01$), .210 fewer average daily minutes (95% CI -0.410,-0.010; $P < 0.01$), .616 decreased odds of recording any meditation session (95% CI -0.852,-0.118; $P < 0.01$), .687 times fewer days with meditation sessions (95% CI 0.522,0.880; $P < 0.01$), and -.188 fewer average daily meditation minutes (95% CI -0.324,-0.053; $P < 0.01$).

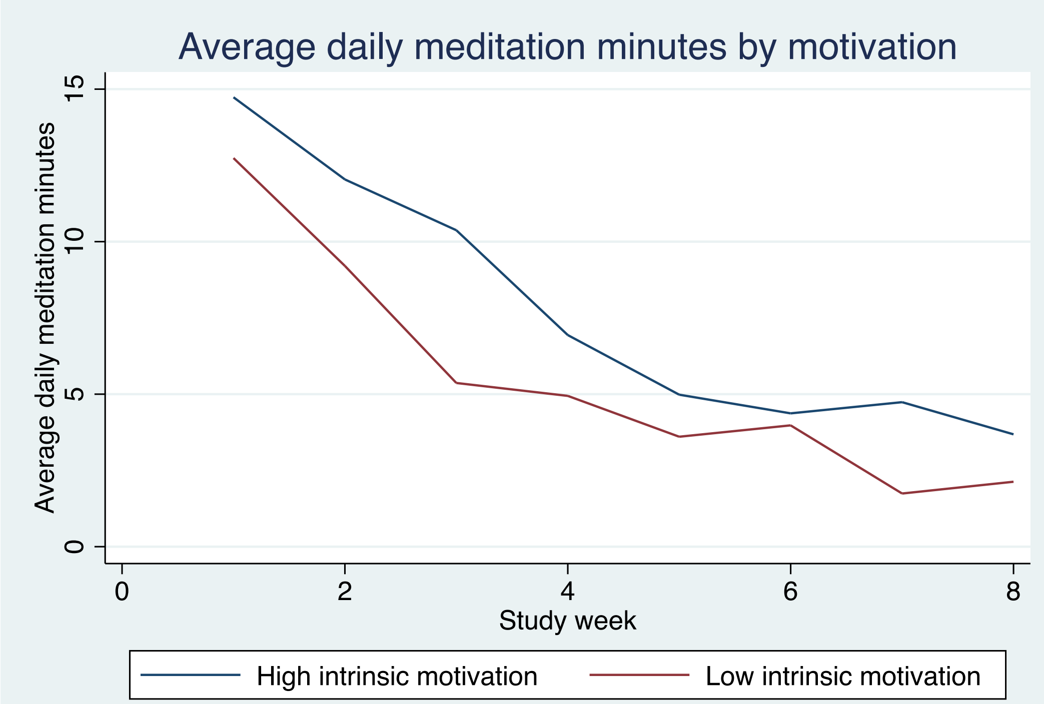

Figure 2. Average daily minutes of meditation by Intrinsic Motivation Inventory median split.

Table 2.5. App Usage Over the Last Week Regressed on IMI Regression Results.

	All session usage		Meditation-specific usage		
	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Any meditation (coef in OR)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)
I enjoy meditation very much (**interest/enjoyment)**	1.314*	0.086	1.667*	1.527**	0.117
	[0.998,1.731]	[-0.239,0.41]	[0.927,2.996]	[1.031,2.263]	[-0.094,0.33]
I put a lot of effort into my meditation practice **(effort/importance)**	0.853	-0.134	1.099	1.1	0.022
	[0.669,1.087]	[-0.43,0.165]	[0.640,1.888]	[0.769,1.572]	[-0.188,0.23]
I get anxious when I'm meditating (**pressure/tension)**	1.002	0.008	1.38	1.278*	0.094
	[0.848,1.183]	[-0.224,0.24]	[0.915,2.081]	[0.999,1.635]	[-0.039,0.23]
It is important to me to continue my meditation practice (**effort/importance)**	1.172	0.131	1.17	1.447**	0.107
	[0.920,1.493]	[-0.150,0.41]	[0.765,1.790]	[1.041,2.011]	[-0.046,0.26]
While meditating, I sometimes think about how	0.903	0.084	1.008	1.026	0.01

much I enjoy it **(interest/enjoyment)**					
	[0.730,1.116]	[-0.179,0.35]	[0.642,1.582]	[0.767,1.373]	[-0.162,0.18]
I feel pressure to continue my meditation practice (**pressure/tension)**	0.794***	-0.210**	0.616***	0.678***	-0.188***
	[0.669,0.941]	[-0.410,-0.01]	[0.426,0.889]	[0.522,0.880]	[-0.324,-0.05]
I try very hard to maintain my meditation practice **(effort/importance)**	1.192	0.085	1.368	1.172	0.079
	[0.947,1.500]	[-0.193,0.36]	[0.877,2.136]	[0.881,1.560]	[-0.08,0.239]
I think meditation is boring **(interest/enjoyment)**	0.948	-0.024	1.168	1.072	0.001
	[0.761,1.181]	[-0.16,0.258]	[0.723,1.887]	[0.776,1.480]	[-0.174,0.17]
I am very relaxed when engaging in meditation **(pressure/tension)**	0.889	-0.226*	0.983	0.961	-0.049
	[0.736,1.075]	[-0.471,0.02]	[0.612,1.579]	[0.747,1.237]	[-0.210,0.11]
N	301	301	301	301	301

Discussion

The purpose of this study was to determine which user characteristics predict meditation app usage in the first eight weeks after subscribing. Compared to younger adults, middle-age and older age were associated with more days of app usage during the first week of the study, but not during the last week or the entire study duration. This may indicate that middle-aged and older adults have higher levels of initial interest, leading to more app use during the first week after subscribing, but not persistence. It may be that meditation habits are more difficult to form for middle-aged and older adults or that their interest in meditation decreases after subscribing. Middle-age and older adults may need more support within meditation apps to promote persistent use after first subscribing, such as content specific to this demographic to keep them engaged and strategies to help them develop meditation habits.

Men reported more days with meditation in all models and were more likely to record a meditation session during the last week of the study compared to women. This suggests more overall app use as well as more persistent usage among men. These findings are consistent with other studies in which men reported using the meditation app more frequently than women (e.g., Huberty, Vranceanu, et al., 2019). It is possible that women tend to be more interested in meditation apps than men but the relatively small number of men who subscribe to meditation apps are more dedicated to their meditation practice. It is also possible that women, on average, find it more difficult to make meditation a habit. One key aspect of this difference between men and women is that men recorded more meditation-specific app usage, but not any type of app usage. It may be that women tend to find other app features, such as sleep stories or music, more useful whereas men gravitate toward meditation, specifically. This gender difference could also be reflective of more systemic disparities between men and women, such as roles within the home that allow for more time to meditate consistently. In either case, it would be of interest for meditation app developers to include more habitual supports within the app specifically geared toward women.

Users' number of chronic conditions was associated with meditating at least once during the last week of the study. A more consistent pattern emerged with mental health diagnoses, which were associated with more minutes of daily meditation over the duration of the study. Mental health diagnoses were also associated with more days with any session and more average daily minutes in the last week. However, there were no significant associations in the first week after subscription purchase. This pattern may suggest that improvements in mental and physical health symptoms are associated with continued app use, specifically. That is, if subscribers experience the benefit of symptom improvement through meditation app use, they may be more likely to continue using the app to keep reaping these benefits. These findings may offer insight into meditation app usage among those in interventions aimed at improving mental and physical health symptoms. For example, it may be possible that those who do not experience mental or physical health benefits drop out of the intervention and therefore the interventions' effects may be overestimated.

Finally, users with higher levels of intrinsic motivation for meditation were more likely to meditate and had higher average daily minutes of meditation than those with lower levels of intrinsic motivation. When the specific questions of the Intrinsic Motivation Inventory were added to the analysis, feeling pressure to continue meditation was negatively associated with app use throughout the duration of the study when controlling for all other variables. This could be because feeling pressure to perform a certain behavior indicates that an individual does not actually want to do so and thereby is less likely to perform the behavior (Ryan & Deci, 2000). For example, users may have had external influence to subscribe to the app, such as a family member urging them to meditate or subscribing because of a feeling that they ought to meditate. Meditation apps should focus on finding ways to make meditation more interesting and enjoyable for subscribers as well as focusing on ways to alleviate pressure to continue to meditate to promote persistent meditation practice. These results are also informative for adherence to future research interventions by identifying users who feel pressure to continue meditating as those who may need more support in their meditation habit formation.

Prior work

The results from this study build on several findings from the existing literature. In previous meditation app studies, most users were of the same demographic, specifically White, female, well educated, and middle to older in age (e.g, Bostock et al., 2019; Flett et al., 2019; Forbes et al., 2018; Green et al., 2021). However, it was unclear if and how these variables were associated with meditation app use beyond initial interest. This study suggests that gender is associated with meditation app use over the first eight weeks after subscribing to the app. Additionally, previous studies have found middle-aged and older adults were highly adherent to meditation interventions (e.g., Ribeiro et al., 2018). These findings are from intervention-based studies rather than real-world studies, which is an important distinction when considering how to promote meditation app usage in real-world settings. The current study only observed middle-aged and older adults having significantly more usage during the first week. Taken together, these findings may suggest that middle-aged and older adults are more active during the initial stages of meditation, such as a short intervention, but not active over time. Meditation app developers and researchers conducting longer interventions should target this demographic with supports to continue their meditation behavior over time.

In previous studies, data suggested chronic conditions may be associated with meditation app usage. Survey data have shown that those who meditate were more likely to have at least one chronic condition (Cramer et al., 2016). In a recent meditation app study, those who reported a physical health diagnosis, either alone or in addition to a mental health diagnosis, reported using the app more frequently than those who reported no diagnoses (Huberty, Vranceanu, et al., 2019). In the current study, chronic conditions were positively associated with meditation app use. Contrary to Huberty et al., findings from this study suggested that mental health diagnoses are more strongly associated with meditation app use than physical health, although both were significant. These findings suggest those with mental health conditions are more engaged with meditation apps than those with physical health conditions, though the reasons why this may be remain unclear.

Results from this study are also contradictory to other previous findings which suggested mindfulness, personality, and perceived barriers may predict meditation app use. In a study that examined adherence to an online meditation intervention, mindfulness at baseline was the strongest predictor of adherence (Forbes et al., 2018). However, mindfulness level at baseline was not a significant predictor in this study. Additionally, because prior studies have found mindfulness to be associated with different aspects of personality, personality traits were hypothesized to predict meditation app usage. For instance, mindfulness has been shown to be inversely associated with Neuroticism (Giluk, 2009; Hanley, 2016) and positively associated with Extraversion, Openness, Agreeableness, and Conscientiousness (Forbes et al., 2018; Giluk, 2009). While some personality trait variables were significant or approached significance in this study, no clear pattern emerged, suggesting that personality traits may be associated with mindfulness but not necessarily meditation app usage. Interestingly, perceived barriers to meditation were not associated with meditation app usage. To our knowledge, the only other study to examine barriers to meditation app participation was on college students, and the frequency and severity of a variety of barriers, such as feeling too distracted or anxious, were not associated with participants' adherence to the intervention.

Intrinsic motivation for meditation was a robust predictor of meditation app use. Motivation is generally hypothesized to predict engagement with any health behavior, especially intrinsic motivation, which is associated with interest, enjoyment, and importance (Ryan & Deci, 2000). Therefore, it was expected that higher levels of intrinsic motivation for meditation would be associated with more app use over the first eight weeks after subscribing. In previous work, pressure has been associated with initiating other health behaviors, such as healthy dietary choices (e.g., Ntoumanis et al., 2021; Sogari et al., 2018). The current study found that feeling pressure was strongly associated with reduced maintenance of app use over the observation period. It may be that feeling pressure to meditate was a reason some subscribers purchased a meditation app subscription, but this study suggests that to maintain meditation app use, feeling pressure is counterproductive. Other strategies, such as increasing enjoyment or forming a meditation habit, should be used for those who feel pressure to meditate. Future research should continue to explore individuals' intrinsic motivation for meditation over time, such as if a change in intrinsic motivation leads to a change in meditation app usage.

Limitations

This was the first study to predict meditation app use based on new subscribers' characteristics; however, there were limitations that should be considered. First, similar to previous meditation app studies, this sample was fairly homogeneous. Although this sample is representative of the population of subscribers to this meditation app, it would be beneficial to purposively sample a more diverse user demographic to increase generalizability. This would ultimately help researchers and app companies increase meditation app usage among more diverse users. Second, to combat survey fatigue, the number of user characteristics included in this study was limited. There are likely more variables related to meditation app usage that were not explored in this study. Finally, this study only used one timepoint of survey data collection and did not account for potential changes in user characteristics, such as changes in mental health symptoms or motivation. This is an important next step for determining predictors of meditation app usage over time.

Conclusion

This study determined which user characteristics predicted meditation app usage in the first eight weeks after subscribing. Results indicated that men and those with chronic conditions had more meditation app usage during the observation period. Higher levels of intrinsic motivation were also associated with more meditation app usage, and the specific construct of feeling pressure to meditate was negatively associated with meditation app usage. These findings suggest that user characteristics and motivation can be used to predict meditation app usage in new subscribers. Future meditation app research should consider including support strategies based on key user characteristics, such as age and gender, as well as finding ways of combatting users' feelings of pressure to meditate.

CHAPTER 4

MANUSCRIPT 3: Do improvements in symptoms of stress, anxiety, or depression after newly subscribing to meditation app predict continued meditation app use? Evidence from a random sample of new Calm app subscribers

Abstract:

Objective: The purpose of this study was to determine if perceived changes in mental health symptoms after newly subscribing to a meditation app predict continued app use.

Methods: New subscribers to the Calm meditation app completed two surveys: one within the first week of subscribing and another eight weeks later. The surveys included measures of stress, anxiety, and depressive symptoms as well as demographic and socioeconomic information. App usage data were collected over the first 16 weeks after subscribing, which included all types of app sessions (e.g. meditation, sleep stories, etc.) and the use of a mood tracking feature. Regression models were used to assess the relationships between changes in mental health symptoms over the first eight weeks after subscribing to the app and four outcomes measuring future app use over weeks eight through 16 after subscribing: 1) the number of days with any session, 2) the average daily minutes of app use including all sessions, 3) the number of days with a meditation session, and 4) the average daily minutes of meditation.

Results: Improvements in perceived stress and depressive symptoms significantly predicted users' future average daily minutes of meditation, but the effects were in the opposite direction. Improvements in stress were associated with 2.74 more average daily minutes of meditation (95% CI 0.056,5.543; P = .048), while improvements in depressive symptoms were associated with 5.94 fewer daily minutes of meditation (CI -9.616,-2.258; P < .001). There were no significant associations between using the mood tracking feature and any of the future meditation outcomes, but reporting specific types

of mood were predictive of future behavior. Specifically, reporting more days feeling angry was associated with 26.85 more average daily minutes of all types of app sessions (95% CI 1.995,51.699; P = .035) and reporting feeling content on more days was associated with a fewer number of days with any session (.259 IRR, 95% CI 0.083,0.813; P = .021) and a fewer number of days with meditation sessions (.176 IRR, 95% CI 0.065,0.473; P < .001).

Conclusion: Improvements in symptoms of stress and reporting the feeling angry were associated with higher levels of future meditation app use, while improvements in depressive symptoms and reporting the feeling of contentment were associated with lower future use. These findings suggest that experiencing changes in mental health symptoms can lead to greater future meditation app usage, but mood tracking may only have a shorter-term impact on meditation behavior. Future research should explore the effect of improvements in different mental health symptoms and continue to investigate how the mood tracking feature impacts meditation app usage.

Introduction

Over 70% of adults in the United States report regularly experiencing debilitating mental health symptoms such as stress, anxiety, and depressive symptoms (American Psychological Association, 2017). Meditation via a mobile app has been shown to be effective at reducing these negative mental health symptoms in both non-clinical and clinical populations. Specifically, meditation app interventions in the general population have been effective for reducing stress (Huberty et al., 2019; Bostock et al., 2016), anxiety (Baumel et al., 2020; Flett et al., 2019; Rowland et al., 2020), and depressive symptoms (Baumel et al., 2020; Rowland et al., 2020). Additionally, meditation app users have reported improvements in general wellbeing, energy, and concentration (Bergen-Cico et al., 2014; Gard et al., 2014; Goyal et al., 2014; Rowland et al., 2020).

Clinical studies exploring the benefits of meditation apps have shown small to large effect sizes in clinically measured outcomes, such as anxiety disorders (Boettcher et al., 2014; Flett et al., 2019; Krusche et al., 2013).

Although meditation apps have been shown to be effective for improving mental health, many app subscribers do maintain their app use over time. In one study, despite significant decreases in both stress and anxiety in participants who completed the meditation intervention, only 43% of participants successfully completed the two-week intervention (Forbes et al., 2018). Other meditation app intervention studies have observed dropout rates as high as 77% (e.g., Howells et al., 2016). Observational app-based data show similar user drop-off patterns but with even lower app usage rates over time. One observational study found a median 15-day retention day in health apps to be 3.9% (Baumel et al., 2019). Another study found that for those who used mental health apps, including meditation apps, the daily median rate of usage was 4% (Kerst et al., 2020). Thus, strategies to help users better maintain meditation app use, and thus attain the corresponding mental health symptoms, are needed.

Research suggests that those who engage in a behavior for a specific reason, such as reducing mental health symptoms, will be more likely to continue the behavior (Crane et al., 2010; Valls-Serrano et al., 2016). In a survey on why practitioners meditated, the most common reasons for doing so were feeling anxious, nervous, or worried (29.2%), experiencing frequent stress (21.6%), depression (17.8%), or back pain (12.0%) (Cramer et al., 2016). Participants reported meditation helped alleviate their goal symptoms either by “a great deal” (63.6%) or to some extent (30.4%) (Cramer et al., 2016). While these descriptive findings are informative, the authors did not explore how these perceived changes in mental health impacted subsequent meditation behavior. In app-specific meditation research, a recent survey found that the most common reasons for using the app included improving sleep (62.9%), reducing symptoms of stress (62.1%), reducing symptoms of depression or anxiety (54.5%), and improving overall health (40.1%) (Huberty et al., 2019). Maintained mediation app use was associated with reported improvements in general mental and physical health as well as symptoms of stress and sleep (J. Huberty et al., 2019). Although this study did not directly examine stress, anxiety, and depressive symptoms, it is plausible that these symptom improvements may be associated with meditation app usage.

An additional consideration when evaluating the relationship between symptom improvement and meditation app usage is the subscribers' awareness of improvement. The Health Belief Model (HBM) suggests a meditation app user's perception of the benefits of using the app is likely to dictate his or her use (Champion & Skinner, 2008). Similarly, the Expectation construct of the Social Cognitive Theory (SCT) suggests that people anticipate the outcomes of using the meditation app prior to doing so and this anticipation leads to engaging in app use (Bandura, 2004; Lin & Chang, 2018). The SCT also posits that expectations are derived from previous experience, meaning that if one has meditated the previous day and is now deciding whether to meditate, the previous day's experience may influence his or her decision to meditate. In both of these theoretical frameworks, noticing changes in symptoms is hypothesized to influence the maintenance of meditation app use. Tracking one's mood after meditating is one strategy that may help app subscribers better remember their experiences and therefore be more likely to mediate the following day. This theoretical application has recently been tested in a clinical setting and among other consumer-based app subscribers. Broadly, self-monitoring features were associated with lower rates of app abandonment and increased app usage (e.g., Huberty et al., 2021; Lee et al., 2018). However, several questions remain unexamined, such as how symptom change among new users affects subsequent app usage, and how these relationships differ based on reporting specific types of moods or mental health benefits.

The purpose of this study is to determine if changes in mental health symptoms (i.e., stress, anxiety, and depressive symptoms) from baseline to week eight predict meditation app usage from weeks eight through 16. To examine these relationships, we will first determine if changes in stress, anxiety, and depressive symptoms predict subsequent meditation app use. Second, we will examine subscribers' use of the mood tracking feature to determine if 1) using the mood tracking feature from baseline to week eight predicts future meditation app usage from weeks eight through 16, and 2) examine if specific types of moods experienced from baseline to week eight predict meditation app use from week eight through 16.

Methods

Ethics Approval

The Institutional Review Boast at Arizona State University (STUDY00014199) approved this study. All respondents consented via an electronic survey.

Study Design

In this observational study, usage data from new subscribers to the Calm app were collected over 16 weeks and surveys were administered at two time points. Calm users completed a baseline survey within one week of purchasing a subscription to the Calm app and a follow-up survey during the eighth week of their observation period. Calm app usage data were collected for all participants from the time of their subscription purchase through the 16th week of their subscription.

Procedures

Eligibility

Subscribers were eligible to participate in this study if they had purchased a subscription to the Calm app within one week of recruitment, were at least 18 years of age, lived in the U.S., were able to read and understand English, and had not used the Calm, another meditation app, or had a consistent meditation practice without an app within the past six months. Additionally, subscribers must have had elevated stress levels as measured by the four-item Perceived Stress Scale (PSS-4) and using the criteria of a score of 6 or higher (mean score=6.11, SD=3.14 in the general population) (Cohen, 2020). Subscribers must have also reported wanting to reduce symptoms of either stress, anxiety, or depressive symptoms.

Recruitment

A member of the Calm team emailed those who had purchased a year-long subscription to the app within the past week. The email included information about the study and a link to an eligibility survey. If eligible, Calm users were provided an informed consent form to electronically sign. Recruitment occurred from July 2021 through November 2021.

Surveys

Following the informed consent, Calm users were asked to complete a baseline questionnaire. This questionnaire took approximately 10-15 minutes to complete, and respondents were informed they could skip any question or stop completing the survey at any time. At the 8-week time point, users were given an almost identical questionnaire that included all questions from the baseline questionnaire except for the demographic variables.

Demographic and socioeconomic information. Demographic and socioeconomic information collected included age, gender, ethnicity, race, geographic location, education level, chronic conditions, height, and weight.

Stress. Stress was measured using the Perceived Stress Scale (PSS). The PSS is a 10-item questionnaire that assesses one's self-appraised stress within the past month. Scores range from 0-40 with higher scores indicating higher levels of perceived stress (Cohen, 2020; Lee, 2012). This 10-item scale has demonstrated good internal consistency across various populations (Cronbach's α=.74-.92) (Lee, 2012).

Anxiety. The State-Trait Anxiety Inventory (STAI) was used to measure symptoms of anxiety. This scale has two forms, state anxiety and trait anxiety, which each include 20 items assessed using a 4-point Likert scale. Form Y-1 (state) asks respondents to select the response for how they feel currently, whereas form Y-2 (trait) asks respondents to select the response for how they generally feel. Scores range from 20-80, with higher scores indicating higher anxiety (Sydeman, 2018). This scale demonstrates good reliability and validity (Cronbach's α=.86-.95) (Spielberger, 1983).

Depressive symptoms. The Center for Epidemiological Studies-Depression (CES-D) scale was used to measure depressive symptoms. The CES-D is a 20-item scale with a 4-point Likert scale ranging from 0-3. Scores range from 0-60 with higher scores indicating more depressive symptoms (Radloff, 1997). Cronbach's alpha of .90 has been recently reported for general population adults (Cosco et al., 2017).

Usage Data

App usage data was provided by the Calm data analytics team. This data included the day and time of every app session, the duration per session, and type of session (e.g., meditation, sleep stories, etc.). The data were coded into two different definitions of app use: 1) the number of days with any recorded session and 2) the average daily minutes of app use. These variables were created for both meditation-specific app use and all types of app use. This data also records participants' use of the mood tracking feature, and when used, what specific mood was reported after each session.

Statistical Analysis

An a-priori statistical power analysis was conducted based on a recent study of an app-based meditation intervention (N=169) that included 10 predictor variables on intervention adherence (Forbes et al., 2018). The effect size in this study was .171, which is considered to be moderate (Kelley & Preacher, 2012). Using a more conservative estimation of .15, an alpha=.05, and power=.80, the determined sample size for this project is approximately N=123. The power analysis was conducted using G*power (Erdfelder et al., 2009; Faul et al., 2007).

App usage data were analyzed by ordinary least squares linear regression models which estimated participant-level random effects and predictors for changes in app usage. Change in app usage was defined as changes in app use, on average, between the first eight weeks and the last eight weeks of observation. The four constructs of app use included 1) days with any recorded session, 2) average daily minutes including all session types, 3) days with a meditation session, and 4) average daily meditation minutes. For the outcomes that measured days with sessions, a threshold of completing (>90% complete) a session was used to assign binary variables for each day, meaning that participants must have listened to at least nine out of ten minutes in a 10-minute session, for example. The number of days with at least one complete session was totaled for the first eight weeks and for the last eight weeks. For the outcomes that measured average daily minutes, the number of minutes per day was averaged for the first eight weeks and for the last eight weeks.

Z-scores were used to standardize changes in stress, anxiety, and depression. Mood tracking data were analyzed by the total number of times participants used the mood tracking feature during the first and last eight weeks, and as a binary variable that indicated if they used the mood tracking feature at least once. Participants were included in the analysis only if they had completed at least one app session after subscribing to the app. Statistical significance was set at $P < .05$. All analyses were conducted in Stata (*StataCorp*, 2021).

Results

A total of 632 participants completed the baseline survey and 278 completed the week eight survey. After removing participants with missing usage data, 138 participants were included in the models. Participants' subscription start dates ranged from July 15, 2021, to November 15, 2021.

Table 3.1 shows descriptive statistics for the sample. Participants were predominantly women (79%, n=110/138), White (83%, n=114/138), and had a bachelors (34%, n=47/138) or graduate (43%, n=60/138) degree. A total of 27% (n=37/138) of participants were 25 to 34 years old, 25% (n=35/138) were 35 to 44 years old, and 21% (n=29/138) were 45 to 54 years old.

Table 3.1. Descriptive Statistics for the Sample.

	Frequency	Percent
Age		
Under 25	7	5%
25 to 34	37	27%
35 to 44	35	25%
45 to 54	29	21%
55 to 64	14	10%
Over 65	16	12%
Gender		
Woman	110	80%
Man	27	20%
Other gender	1	1%
Race/ethnicity		
White	114	83%
Asian	6	4%
Black	6	4%

Hispanic	8	6%
Other race	4	3%
Region		
West	33	24%
Southwest	17	12%
Midwest	30	22%
Southeast	30	22%
Northeast	24	17%
Education		
High school diploma	2	1%
Some college	17	12%
Associate's degree	12	9%
Bachelors degree	47	34%
Graduate degree	60	43%
Symptom goal		
Stress	37	27%
Anxiety	85	62%
Depressive symptoms	16	12%
Used mood tracking		
First 8 weeks: Yes	90	65%
First 8 weeks: No	48	35%
Last 8 weeks: Yes	49	36%
Last 8 weeks: No	89	64%

Table 3.2 shows participants' mental health symptoms over the course of the study. Participants reported a mean score of 26.91 (SD=5.16) for stress (PSS) at baseline and 20.22 (SD=6.18) at week eight. Participants reported a mean score of 2.41 (SD=0.55) for anxiety (STAI) at baseline and 2.14 (SD=.60) at week eight. Participants reported a mean score of 23.43 (SD=11.42) for depressive symptoms (CES-D) at baseline and 18.25 (SD=11.43) at week eight.

Table 3.2. Changes in Mental Health Symptoms from Baseline to Week 8.

		N	Mean	SD	Min	Max
All participants						
Stress						
	Baseline	138	26.91	5.16	15	44
	Week 8	138	20.22	6.18	6	36
	Change	138	6.69	6.00	-8	23

Anxiety						
	Baseline	138	2.41	0.55	1.25	3.95
	Week 8	138	2.14	0.60	1	3.85
	Change	138	0.27	0.55	-1.2	1.75
Depressive symptoms						
	Baseline	138	23.43	11.42	4	52

Table 3.3 shows participants' average app usage during the first and last eight weeks. Participants completed an average of 25.93 (SD=16.51) days with any app session over the first eight weeks and 18.08 (SD=17.99) days over the subsequent eight weeks. Participants averaged 71.75 (SD=84.21) daily minutes of all app usage over the first eight weeks and 66.22 (SD=200.41) days over the subsequent eight weeks. Participants averaged 20.13 (SD=15.20) daily minutes of meditation over the first eight weeks and 12.95 (SD=14.47) minutes over the subsequent eight weeks.

Table 3.3. Mean App Usage within the First and Last Eight Weeks.

	Mean	SD
Days with session		
First 8	25.93	16.51
Last 8	18.08	17.99
Change	-7.85	11.40
Average daily minutes		
First 8	71.75	84.21
Last 8	66.22	200.41
Change	-5.53	191.46
Days with meditation		
First 8	16.09	15.97
Last 8	10.37	15.07
Change	-5.72	11.00
Average daily meditation minutes		
First 8	20.13	15.20
Last 8	12.95	14.47
Change	-7.19	14.36

Table 3.4 shows results from the regression models estimating app usage from changes in symptoms of stress, anxiety, and depressive symptoms. Improvements in symptoms of stress were associated with 2.74 more average daily minutes of meditation (95% CI 0.056,5.543; *P* = .048), but this relationship did not remain significant when controlling for demographic variables. Improvements in depressive symptoms were associated with 5.937 fewer daily minutes of meditation (CI -9.616,-2.258; *P* < .001). This relationship remained significant when control variables were added to the model (-5.992 minutes, 95% CI -9.889,-2.095; *P* < .001).

Table 3.4. Changes In Usage from Weeks 0-8 To Weeks 8-16 by Symptom Improvements.

	All session usage		Meditation-specific usage		All session usage		Meditation-specific usage	
	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)
Symptom improvement								
Stress	1.209	15.594	0.519	2.744^{**}	1.898	14.892	1.043	2.712^{*}
	[0.07,20.53]	[-34.32,65.51]	[0.039,6.947]	[0.056,5.543]	[0.110,32.722]	[-36.149,65.93]	[0.086,12.607]	[-0.188,5.612]
Anxiety	6.449	-16.5	8.049^{*}	1.776	6.843	-15.809	7.503	2.043
	[0.674,61.65]	[-59.72,26.72]	[0.90,71.858]	[-0.705,4.257]	[0.634,73.835]	[-64.13,32.51]	[0.660,85.308]	[-0.448,4.534]
Depressive symptoms	0.31	-11.442	0.136	-5.937^{***}	0.258	-13.005	0.116	-5.992^{***}
	[0.013,7.21]	[-41.72,18.83]	[0.005,3.874]	[-9.616,-2.26]	[0.010,6.821]	[-47.39,21.38]	[0.004,3.392]	[-9.889,-2.095]
Under 25					*reference*			
25 to 34					0.215	56.71	0.554	3.62
					[0.00,12725.8]	[-74.34,187.7]	[0.0,395242.7]	[-8.802,16.04]
35 to 44					34.838	-10.432	17.465	2.873
					[0.001,14789]	[-47.01,26.14]	[0.00,965494]	[-8.994,14.74]
45 to 54					6.625	-27.784	4.462	-3.553
					[0.000,63883]	[-78.75,23.17]	[0.000,64791]	[-15.65,8.54]
55 to 64					0.067	-6.992	0.16	4.596
					[0.000,15499]	[-76.18,62.19]	[0.000,91962]	[-7.671,16.86]
over 65					20.357	-35.96	516.738	3.105
					[0.000,33055]	[-106.72,34.8]	[0.000,7.738]	[-9.257,15.46]
Woman					*reference*			

Man					0.026	78.853	0.001***	-1.171
					[0.000,3.682]	[-83.37,241.1]	[0.000,0.128]	[-8.548,6.206]
White					27.486	14.663	5.437	-0.629
					[0.004,18642]	[-24.81,54.14]	[0.002,16059]	[-8.693,7.435]
Black					77.665	55.739	11.307	-2.273
					[0.000,2.111]	[-13.72,125.2]	[0.000,51258]	[-15.08,10.53]
Hispanic					16.928	15.075	1262.797	3.849
					[0.000,16668]	[-43.69,73.85]	[0.189,84265]	[-4.129,11.82]
Other race/ethnicity					*reference*			
N	138	138	138	138	138	138	138	138

To explore mood tracking data, Table 3.5 shows results from the regression models estimating app usage from the number of times each mood was logged during the first eight weeks. There were no significant associations between using the mood tracking feature and any of the meditation outcomes. Among those who used the mood tracking feature, reporting being angry on more days in the first eight weeks was associated with 26.85 more average daily minutes of all types of sessions (95% CI 1.995,51.699; $P = .035$) over the subsequent eight weeks. This association remained significant when control variables were added to the models (28.84, 95% CI 2.412,55.258; $P = .033$). Reporting feeling content on more days during the first eight weeks was associated with fewer days with any session (.259 IRR, 95% CI 0.083,0.813; $P = .021$) and fewer days with meditation sessions (.176 IRR, 95% CI 0.065,0.473; $P < .001$).

Table 3.5. Changes in Usage from Weeks 0-8 To Weeks 8-16 by Moods Logged in First 8 Weeks.

	All session usage		Meditation-specific usage		All session usage		Meditation-specific usage	
	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)
angry	0.377	26.847**	0.024	4.425*	0.583	28.835**	0.045	4.016
	[0.00,27.38]	[1.995,51.699]	[0.000,2.420]	[-0.855,9.704]	[0.007,49.831]	[2.412,55.258]	[0.000,5.883]	[-1.740,9.772]
anxious	0.29	-8.051	0.145*	-0.097	0.31	-7.243	0.167*	0.638
	[0.027,3.138]	[-27.5,11.4]	[0.016,1.321]	[-3.319,3.125]	[0.029,3.339]	[-27.21,12.72]	[0.021,1.305]	[-2.639,3.916]
bored	0.012	-0.916	0.081	-1.253	0.062	-10.823	0.843	-2.312
	[0.000,5.066]	[-27.84,26.01]	[0.001,8.739]	[-9.605,7.098]	[0.000,217.15]	[-45.44,23.80]	[0.001,524.96]	[-12.121,7.49]
content	0.259**	1.815	0.176***	-0.71	0.322*	1.795	0.270**	-0.833
	[0.083,0.813]	[-5.292,8.923]	[0.065,0.473]	[-1.831,0.411]	[0.083,1.246]	[-6.75,10.34]	[0.083,0.879]	[-2.038,0.372]
excited	1.456	-8.296	12.677	-2.002	4.086	-8.881	64.864*	-1.667
	[0.05,41.87]	[-23.46,6.87]	[0.209,770.30]	[-6.960,2.957]	[0.083,200.88]	[-25.201,7.44]	[0.956,4400.0]	[-7.408,4.074]
grateful	3.616	2.522	12.672*	2.016	2.716	3.673	9.281	1.424
	[0.324,40.36]	[-9.687,14.73]	[0.640,250.90]	[-0.584,4.617]	[0.189,38.999]	[-8.916,16.26]	[0.327,263.63]	[-1.492,4.341]
happy	1.254	-6.735	1.57	1.508	0.972	-10.563	0.955	1.601
	[0.064,24.70]	[-18.35,4.88]	[0.098,25.25]	[-1.668,4.684]	[0.031,30.374]	[-27.091,5.96]	[0.043,21.204]	[-2.136,5.339]
relaxed	1.572	5.136	1.243	0.078	1.612	7.344	1.039	0.101
	[0.20,12.29]	[-4.28,14.55]	[0.181,8.560]	[-2.464,2.621]	[0.155,16.742]	[-7.081,21.77]	[0.142,7.598]	[-3.117,3.319]
sad	1.53	-3.686	1.124	-0.884	1.956	-2.613	1.584	-0.746
	[0.23,10.037]	[-15.69,8.32]	[0.184,6.876]	[-3.009,1.241]	[0.278,13.759]	[-14.269,9.04]	[0.310,8.102]	[-2.843,1.352]
stressed	2.06	-7.888	4.439	2.364	1.782	-8.294	3.212	2.652*
	[0.208,20.39]	[-25.89,10.12]	[0.46,42.85]	[-0.520,5.247]	[0.143,22.262]	[-28.21,11.62]	[0.315,32.718]	[-0.462,5.766]
tired	1.23	-2.811	2.198	-0.827	0.914	-2.79	1.321	-0.803
	[0.195,7.756]	[-15.99,10.37]	[0.425,11.38]	[-3.364,1.709]	[0.123,6.764]	[-17.87,12.29]	[0.256,6.814]	[-3.517,1.912]

unsure	1.095	7.66	1.293	0.151	1.102	7.775	1.477	0.033
	[0.156,7.697]	[-7.77,23.09]	[0.186,8.995]	[-2.727,3.029]	[0.138,8.786]	[-8.92,24.47]	[0.227,9.599]	[-3.035,3.101]
Under 25					*reference*			
25 to 34					0.744	-18.628	1.64	0.346
					[0.000,28885]	[-51.93,14.67]	[0.000,176192]	[-17.221,17.91]
35 to 44					45.927	-16.949	36.166	-0.757
					[0.000,1.37]	[-52.34,18.44]	[0.000,2.167]	[-18.053,16.54]
45 to 54					96.023	-41.623*	1124.303	-5.389
					[0.000,3.487]	[-89.73,6.49]	[0.000,1.224]	[-23.642,12.86]
55 to 64					5.758	-46.958	8.159	2.315
					[0.000,76749]	[-141.48,47.5]	[0.000,2.431]	[-15.742,20.37]
over 65					11.15	-5.655	62.504	-0.181
					[0.000,1.412]	[-34.84,23.53]	[0.000,4.076]	[-16.933,16.57]
Woman					*reference*			
Man					0.002	-9.475	0.000***	-3.394
					[0.000,8.621]	[-65.05,46.10]	[0.000,0.012]	[-12.674,5.885]
White					20.151	31.134	1.292	-6.446
					[0.000,36758]	[-38.84,101.1]	[0.011,154.84]	[-14.560,1.668]
Black					57.955	69.962	5.298	-5.96
					[0.000,3.001]	[-16.92,156.8]	[0.000,116975]	[-25.169,13.24]
Hispanic					162.891	54.388	11020.501*	0.323
					[0.000,1.852]	[-37.5,146.35]	[0.872,1.393]	[-10.411,11.05]

Other race/ethnicity					*reference*			
N	90	90	90	90	90	90	90	90

Discussion

The purpose of this study was to determine if changes in mental health symptoms (i.e., stress, anxiety, and depressive symptoms) from baseline to week eight predicted the maintenance of meditation app use from week eight through 16. After eight weeks, the average user reported improvements in symptoms of stress, anxiety, and depressive symptoms. Although this was not an experiment and causality cannot be implied, this finding is consistent with other experimental studies which show that meditation apps are effective for reducing these mental health symptoms (e.g., Bostock et al., 2019; Flett et al., 2019; Goldberg et al., 2020). Also consistent with previous studies, meditation app use declined throughout the observation period (e.g., Flett et al., 2019; Stecher et al., 2021).

Improvements in stress from baseline to week eight were associated with more average daily minutes of meditation during the last eight weeks of the observation period. That is, subscribers who experienced reductions in their stress levels recorded more minutes of meditation per day during the last eight weeks of the study. This pattern may be explained by the reinforcements and expectations constructs of Social Cognitive Theory, which posit that subscribers are more likely to use the app if they experience reductions in stress (Bandura, 2004). Specifically, using the app may be reinforced by feeling less stressed and subscribers anticipate this feeling when choosing whether to use the app. Inversely, those who experienced higher levels of stress recorded fewer minutes of meditation per day. It is possible that subscribers experienced stress-related barriers to meditation app use, which prevented them from using the app. For example, subscribers who feel stressed may also feel as though they do not have the time or energy to use their meditation app. Meditation app developers should consider promoting subscribers' awareness of the benefits of app use for their stress management.

Improvements in depressive symptoms over the first eight weeks were associated with fewer average daily minutes of mediation during the last eight weeks, and this association remained significant when control variables were added to the model. This finding may suggest that subscribers who experienced improvements in depressive symptoms became less reliant on meditation as a symptom management strategy. This finding may also suggest that those who were experiencing more depressive symptoms recorded more minutes of meditation as a coping strategy for their depressive symptoms. Because meditation offers additional benefits besides alleviating depressive symptoms, behavior retention strategies are needed so that subscribers reap these additional benefits. For example, benefits reported in the meditation app literature including improving sleep quality, social connection, and overall health and wellbeing (e.g., Goldberg et al., 2020; Howells et al., 2016; J. L. Huberty et al., 2021; Stecher et al., 2021) may not be achieved if subscribers do not continue their meditation practices. To encourage continued meditation app use, app developers should consider focusing users' attention to their stress and the use of apps as a stress management tool. The maintenance of meditation app use that followed improvements in stress may result from users experiencing more chronic sources of stress, which serve as continual reminders of the benefits of meditation and may help users maintain their meditation practice.

Using the mood tracking feature during the first eight weeks was not associated with meditation app use during the last eight weeks. This may be because tracking one's mood has a more immediate impact on app usage behavior rather than a long-term effect. When specific moods were examined, the number of times subscribers reported feeling angry was associated with more average daily minutes of overall app usage whereas reporting feeling content was associated with fewer days with any session and days with meditation sessions. These findings suggest that users who are not experiencing negative emotions are more likely to abandon to reduce their meditation app use. Conversely, feeling angry may result in an increase in meditation as a way to help resolve or combat these negative emotions.

Prior work

The findings from this study build on several key findings from the existing literature. While previous findings have established that subscribers use meditation apps to alleviate mental health symptoms, this study is the first to assess if changes in mental health symptoms are associated with subsequent meditation app use. One previous study found that participants' self-reported improvements in mental and physical health were associated with self-reported meditation app usage (J. Huberty et al., 2019). The current study explored this association more rigorously, using validated mental health symptom measures and objective app use data. The current study found that there were associations between symptom change and app use. However, contrary to the previous results, there was an inverse relationship between depressive symptoms and app use, and no significant association for anxiety. The current study also examined specific components of meditation app use to further explore how mental health symptom changes may be impacting each specific component.

Contrary to previous findings, the total number of moods logged and using the mood tracking feature as a binary variable were not significant (J. Huberty et al., 2021; Lee et al., 2018). One previous study found that using the mood tracking feature was positively associated with the likelihood of meditating the following week (J. Huberty et al., 2021). It is possible that using the mood tracking feature has a more immediate effect that was not sustained over the eight-week period in the current study. The mood tracking feature is typically used after an app session, as is thought to increase subscribers' awareness of the immediate benefits of the session. For example, if a subscriber reports that they are feeling happy, they may be more likely to notice that feeling than if they had not recorded it on the app. However, awareness of benefits may only have an immediate impact, such as promoting app use the following day, rather than a long-term or cumulative impact (Bandura, 2004; Lin & Chang, 2018).

Limitations

While this study was the first to rigorously examine the associations between changes in mental health symptoms and meditation, there were some limitations that should be considered. First, this study only examined three of the most common mental health symptoms to avoid survey fatigue among respondents. Future research should continue to explore changes in other meditation-relation outcomes, such as sleep and concentration. Second, while this study divided meditation app usage into four components which were each assessed individually, it did not examine types of app sessions beyond meditation and general app use. Therefore, results are not specific to app sessions such as the Breathe Bubble, Soundscapes, and Music. Finally, because this study was observational, subscribers were not asked to use the mood tracking feature. The mood-specific data was therefore limited to those who used the mood tracking feature. This study was also powered on the first analyses which examined the associations between symptom changes and app use. Future research should include a more robust examination of specific moods and app usage.

Conclusion

This study examined the association between changes in mental health symptoms and meditation app usage. Results indicated that improvements in stress from baseline to week eight were associated with more average daily minutes of meditation, and improvements in depressive symptoms were associated with fewer average daily minutes of meditation. Using the mood tracking feature during the first eight weeks was not associated with meditation app usage in the last eight weeks, though reporting more days of specific moods were significant predictors. These findings suggest that changes in mental health symptoms are associated with meditation app usage, and mood tracking may only have an immediate impact on meditation app usage. Future research should explore different symptoms and continue to investigate how the mood tracking feature impacts meditation app usage.

CHAPTER 5

DISCUSSION

The purpose of this three-manuscript dissertation was to investigate determinants of meditation app usage. This dissertation was designed to rigorously examine potential person-specific variables associated with various aspects of meditation app usage and abandonment. The purpose of Manuscript 1 was to determine the behavioral, demographic, and socioeconomic factors that were associated with meditation app abandonment during the COVID-19 pandemic. The purpose of Manuscript 2 was to determine which participant characteristics predict meditation app usage in the first eight weeks after subscribing. The purpose of Manuscript 3 was to determine if changes in mental health symptoms (i.e., stress, anxiety, and depressive symptoms) from baseline to Week 8 predict meditation app usage from Weeks 8 through 16. Consistent with previous literature, each manuscript reported, on average, a significant decline in app usage among all users (Stecher, Berardi, et al., 2021; Stecher, Sullivan, et al., 2021a). Findings from each manuscript, however, suggest strategies to combat this decline in app usage in both intervention and real-world settings.

Findings from Manuscript 1 suggest that the most robust predictor of meditation app abandonment was meditating as part of a daily routine. Specifically, meditating as part of a daily routine was associated with a lower risk of meditation app abandonment among those who subscribed to the app just before the COVID-19 pandemic and during the pandemic. These findings suggest that subscribers who were able to anchor their meditation practice to an existing routine may have combated the disruption of routine that many subscribers likely experienced during the pandemic. Meditating at a consistent time each day was also associated with a lower risk of app abandonment regardless of the specific time. These findings suggest that the optimal time of day to meditate may depend on the individual, and the most important consideration is the consistency of time.

Taken together, these findings suggest that to promote long-term meditation app usage, researchers and app developers should consider strategically utilizing routine and time of day. For example, researchers that aim to evaluate the efficacy of a meditation app intervention and therefore must eliminate the number of dropouts might consider suggesting these strategies to participants prior to beginning the intervention. This may include asking participants to identify a routine to which they can anchor their meditation practice or a time of day at which they are able to consistently meditate.

Findings from Manuscript 2 suggest that specific demographic and socioeconomic variables are associated with meditation app usage over the first eight weeks after subscribing. Specifically, middle- and older-age adults, men, those with physical and mental health conditions, and those with higher levels of intrinsic motivation for meditation were associated with at least one component of meditation app usage. Exploring different components of meditation app usage allowed for a more in-depth evaluation of usage patterns among these groups, which may help researchers target each groups' specific needs. For example, findings suggest that middle- and older-aged adults were more likely to record more days of app usage during the first week of the study, but not during the last week or the entire study duration. These findings suggest this demographic has high levels of initial usage but may need more support in maintaining their meditation app usage.

These findings also illustrate those who may be more likely to adhere to a meditation intervention. On average, men showed higher app usage rates than to women, and those with physical and mental health diagnoses also has higher app usage rates than those without. These demographics may be most successful in adhering to future meditation interventions than their counterparts, making them ideal participants for efficacy testing. On the other hand, women and those without chronic conditions may need more strategies to increase their meditation app usage. Taken together, these findings offer insight for both researchers and meditation app developers regarding those who continue to use the app and those who might be considered at-risk for decreased usage or abandonment.

Finally, findings from Manuscript 3 suggest that stress and depressive symptoms were both associated with meditation app usage, but in opposite directions. Improvements in stress during the first eight weeks were associated with more average daily minutes of meditation during the last eight weeks of the observation period. Alternatively, improvements in depressive symptoms were associated with fewer average daily minutes of mediation during the last eight weeks. These findings may be specific to the nature of the symptoms and how meditation is used by subscribers to alleviate their symptoms. Those who experience lower levels of stress may be more inclined to meditate because these reductions in stress act as a reward, encouraging the behavior (Bandura, 2004; Lin & Chang, 2018). Inversely, situations that contribute to stress, or stress itself, may act as barriers to meditating. Those with depressive symptoms may use meditation as a coping mechanism and thereby meditate longer if experiencing more symptoms. On the other hand, they may not rely as heavily on meditation as their symptoms improve. Although these findings are an important step for determining how symptom changes impact meditation app usage, reasons why this pattern emerged require additional research.

Future directions

This dissertation explored various determinants of meditation app usage, which generated new areas for future research. Consistent with studies that explored user-specific determinants of app usage in other health apps, each manuscript suggested that user characteristics are predictive of meditation app usage. However, this dissertation did not exhaustively evaluate potential determinants and therefore more research is needed that includes other predictor variables. The demographic was also consistent with previous meditation app studies in which the sample was relatively homogeneous. For example, most participants in meditation app studies are White, highly educated, and female (Bostock et al., 2019; Flett et al., 2019; J. Huberty, Vranceanu, et al., 2019; Stecher, Sullivan, et al., 2021a). Therefore, to gain a deeper understanding of meditation app use determinants generalizable to other demographics, a more purposively diverse sample is needed.

Second, this dissertation established which variables predicted meditation app usage, however it did not evaluate mechanisms or mediators in these relationships. For example, it is unclear why improvements in stress were associated with more daily minutes of meditation. It is possible that meditation was a repeated behavior due to the reward of symptoms reduction (Bandura, 2004) or that stressors acted as barriers to meditating (A. Williams et al., 2011), but more exploration is needed to test the mechanisms of this relationship. Third, this dissertation did not evaluate interactions between variables or assess predictors by demographic group. For example, meditating at a specific time of day may be more impactful for a specific age group or gender. Research in other health apps suggests these specific relationships may be significant (e.g., Elavsky et al., 2017; Garnett et al., 2017), therefore future research should investigate the interactions between variables in this dissertation.

Finally, intrinsic motivation for meditation was a robust significant predictor for meditation app usage, though more specific construct investigation is needed. For example, feeling pressure to meditate was a negative predictor of average daily minutes of meditation, though it is unclear why this was the only robust significant predictor. Interest and enjoyments, and other components of intrinsic motivation, should be further explored. This dissertation also did not evaluate change in intrinsic motivation for meditation, which may also predict meditation app usage (Forbes et al., 2018b).

Conclusion

This three-manuscript dissertation provided important insight for understanding and guidance in improving meditation app usage. The evidence presented suggests meditation cue, time of day, motivation, symptom changes, and demographic and socioeconomic variables may be used to predict meditation app usage. Given the significant health benefits associated with meditation app usage over time, targeting or considering these variables to promote meditation app usage may ultimately improve health outcomes. Future research is encouraged to continue to explore additional predictor variables that may be associated with meditation app usage and to examine variables from this dissertation more closely.

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APPENDIX A

APP USAGE OVER THE FIRST EIGHT WEEKS REGRESSED ON INDIVIDUAL CHARACTERISTICS WITH ANXIETY AND DEPRESSIVE SYMPTOMS REMOVED

	All session usage		Meditation-specific usage		
	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)	Any meditation (coef in OR)	Days with session (coef in IRR)	Avg. daily minutes (coef in minutes)
Under 25	*reference*				
25 to 34	1.05	0.246	1.747	1.025	0.337
	[0.643,1.714]	[-0.460,0.952]	[0.164,18.627]	[0.551,1.908]	[-0.380,1.054]
35 to 44	1.013	0.323	1.359	0.947	0.316
	[0.620,1.656]	[-0.380,1.025]	[0.108,17.138]	[0.513,1.750]	[-0.422,1.055]
45 to 54	1.546*	0.356	0.745	1.829*	0.55
	[0.938,2.549]	[-0.371,1.083]	[0.070,7.965]	[0.956,3.499]	[-0.198,1.298]
55 to 64	1.216	0.413	11.328	1.534	0.681*
	[0.717,2.065]	[-0.401,1.228]	[0.294,436.142]	[0.769,3.059]	[-0.057,1.420]
over 65	1.418	0.681	0.386	1.552	0.483
	[0.825,2.439]	[-0.143,1.506]	[0.035,4.292]	[0.778,3.097]	[-0.275,1.241]
Woman	*reference*				
Man	1.235*	-0.119	2.518	2.114***	0.242
	[0.978,1.560]	[-0.417,0.179]	[0.709,8.948]	[1.560,2.865]	[-0.066,0.550]
Other gender	1.495	0.333	0.057**	1.763	-0.186
	[0.549,4.074]	[-0.462,1.128]	[0.004,0.722]	[0.362,8.579]	[-1.672,1.301]
White	0.888	-0.282	2.677	1.086	-0.062

	[0.571,1.382]	[-0.895,0.332]	[0.356,20.159]	[0.570,2.070]	[-0.902,0.778]
Asian	0.785	-0.774**	1.001	1.242	0.45
	[0.411,1.501]	[-1.534,-0.014]	[1.000,1.000]	[0.516,2.991]	[-0.536,1.435]
Black	0.611	-0.514	2.278	0.629	0.165
	[0.316,1.179]	[-1.328,0.300]	[0.088,58.893]	[0.249,1.589]	[-0.909,1.239]
Hispanic	0.87	-0.151	2.431	1.14	0.083
	[0.522,1.451]	[-0.919,0.618]	[0.133,44.581]	[0.553,2.351]	[-0.830,0.995]
Other race/ethnicity	*reference*				
West	1.351*	0.048	0.535	1.762***	-0.074
	[0.999,1.827]	[-0.314,0.409]	[0.142,2.014]	[1.160,2.676]	[-0.438,0.290]
Southeast	1.149	-0.075	1.001	1.311	-0.064
	[0.821,1.608]	[-0.503,0.353]	[1.000,1.000]	[0.881,1.952]	[-0.467,0.339]
Midwest	1.241	0.179	0.398	1.362	0.006
	[0.889,1.734]	[-0.172,0.530]	[0.101,1.565]	[0.907,2.047]	[-0.418,0.430]
Southeast	0.923	0.025	0.230**	0.737	-0.331*
	[0.675,1.262]	[-0.321,0.371]	[0.067,0.796]	[0.503,1.079]	[-0.708,0.047]
Northeast	*reference*				
High school diploma	0.753	-0.113	0.894	0.487*	-0.071
	[0.410,1.385]	[-0.812,0.587]	[0.106,7.518]	[0.216,1.100]	[-0.794,0.651]
Some college	0.824	0.084	0.464	0.826	-0.11
	[0.605,1.122]	[-0.320,0.489]	[0.116,1.862]	[0.548,1.246]	[-0.555,0.334]
Associates degree	0.648**	-0.171	1.282	0.579**	-0.056
	[0.439,0.955]	[-0.720,0.379]	[0.268,6.141]	[0.380,0.882]	[-0.492,0.379]

Bachelors degree	0.976	0.053	3.037*	1.095	0.278*
	[0.777,1.226]	[-0.227,0.334]	[0.825,11.181]	[0.811,1.477]	[-0.023,0.579]
Graduate degree	*reference*				
Number of physical health conditions	0.937	-0.078	1.791	1.035	0.017
	[0.837,1.049]	[-0.236,0.080]	[0.888,3.612]	[0.904,1.184]	[-0.118,0.151]
Mental health diagnosis	1.152	0.061	1.613	1.106	0.405**
	[0.912,1.455]	[-0.265,0.387]	[0.410,6.339]	[0.788,1.552]	[0.065,0.745]
No chronic conditions	*reference*				
BMI	0.92	0.059	0.469**	0.791***	-0.158**
	[0.818,1.034]	[-0.087,0.204]	[0.249,0.884]	[0.681,0.919]	[-0.315,-0.002]
Heavy smoker (≥6 packs per day)	0.933	0.254	0.439	1.104	0.15
	[0.622,1.400]	[-0.257,0.764]	[0.072,2.680]	[0.596,2.042]	[-0.307,0.606]
Light smoker (<6 packs per day	1.363	0.438*	0.122**	1.652	0.205
	[0.800,2.322]	[-0.051,0.926]	[0.016,0.914]	[0.713,3.824]	[-0.574,0.985]
Non-smoker	*reference*				
Heavy drinker (≥7 drinks per week)	0.636**	-0.305	0.957	0.74	-0.36
	[0.425,0.952]	[-0.848,0.237]	[0.205,4.461]	[0.437,1.254]	[-0.950,0.231]
Light drinker (<7 drinks per week)	0.893	-0.181	2.52	0.932	0.084
	[0.728,1.094]	[-0.444,0.083]	[0.808,7.860]	[0.717,1.212]	[-0.194,0.362]
Non-drinker	*reference*				
Heavy exerciser (≥3 times per week)	1.07	0.052	0.952	1.390*	0.092

	[0.800,1.431]	[-0.296,0.400]	[0.235,3.854]	[0.979,1.974]	[-0.292,0.476]
Light exerciser (<3 times per week)	0.874	-0.113	0.923	1.025	-0.071
	[0.648,1.178]	[-0.474,0.248]	[0.244,3.494]	[0.698,1.506]	[-0.461,0.319]
Non-exerciser	*reference*				
Mindfulness level (MAAS)	1.001	0.146	1.697	0.843	0.024
	[0.678,1.479]	[-0.333,0.625]	[0.143,20.106]	[0.537,1.323]	[-0.500,0.548]
Extraversion	0.892**	-0.096	1.661*	0.947	0.047
	[0.802,0.993]	[-0.230,0.037]	[0.934,2.953]	[0.817,1.098]	[-0.095,0.189]
Agreeableness	0.931	0.006	1.144	1.002	-0.001
	[0.839,1.033]	[-0.124,0.135]	[0.696,1.882]	[0.877,1.145]	[-0.134,0.133]
Conscientiousness	1.063	-0.02	0.767	0.947	0.023
	[0.960,1.176]	[-0.162,0.123]	[0.438,1.343]	[0.837,1.072]	[-0.104,0.150]
Neuroticism	0.993	-0.057	1.818*	1.119	0.021
	[0.884,1.116]	[-0.218,0.104]	[0.892,3.704]	[0.964,1.298]	[-0.134,0.175]
Openness	1.013	0.027	1.004	0.925	-0.038
	[0.913,1.124]	[-0.102,0.155]	[0.560,1.803]	[0.808,1.059]	[-0.164,0.088]
Intrinsic motivation for meditation (IMI)	1.059	-0.14	4.070***	1.752***	0.301***
	[0.947,1.185]	[-0.317,0.037]	[2.311,7.168]	[1.482,2.071]	[0.139,0.464]
Perceived barriers to meditation (DMPI)	0.973	-0.044	0.737	0.938	-0.094
	[0.860,1.101]	[-0.189,0.102]	[0.491,1.105]	[0.814,1.080]	[-0.236,0.049]
Perceived stress (PSS)	0.921	-0.017	0.962	0.878*	0.044
	[0.823,1.030]	[-0.156,0.122]	[0.544,1.702]	[0.766,1.006]	[-0.097,0.185]
State anxiety (STAIY1)	*removed*				

Trait anxiety (STAIY2)	*removed*				
Depressive symptoms (CESD)	*removed*				
N	304	304	304	304	304