

**DEVELOPING A SMARTPHONE APPLICATION FOR DEPRESSION:
TRACKING RISK AND WELLNESS FACTORS**

by
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A thesis submitted to the Faculty of the University of Delaware in partial fulfillment
of the requirements for the degree of Master of Arts in Psychology

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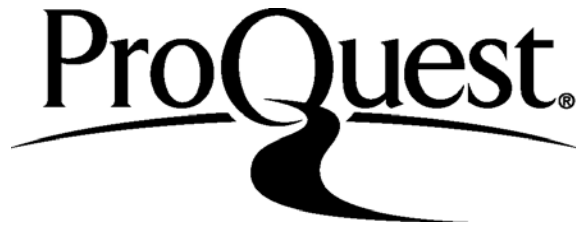
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ABSTRACT

In a time of growing connectivity, technological advances in smartphone capabilities have come to the attention of mental health researchers. Smartphones are now widely used to assess and deliver care for a number of different disorders across the mental health spectrum. However, applications (apps) utilize only a small portion of the data that are collected from these phones. Researchers are beginning to take advantage of the wide array of data collected by smartphones to monitor and predict mental health and behavioral change. The current study assessed the feasibility and utility of an Android-based application designed to measure five areas of functioning related to depression: mood, social functioning, cognitive factors, coping, and lifestyle factors, using both actively inputted and passively collected data. Users were one hundred and fourteen college students who completed daily surveys and allowed the app to collect data over a two-week period. Overall, participants were compliant, with rates of completion ranging from 85% to 93% on the daily, weekly, and morning sleep questionnaires. User feedback also indicated that the app was easy to use (95.6%). Pearson correlations were conducted to examine the associations between depression symptoms, average daily negative and positive mood, mood variability, and the active and passive data collected by the app in the five domains of health and wellness. Overall, correlations indicated strong associations between mood-related variables and items in the domains of social functioning, cognitive factors, and lifestyle factors. However, negative and positive emotion word variables from the Linguistic Inquiry Word Count program and the coping variables performed less well, which may indicate the need to improve or remove these items.

Chapter 1

INTRODUCTION

Depression is one of the leading causes of disability worldwide [World Health Organization (WHO), 2012], affecting approximately one out of six adults over a lifespan (Kessler, et al., 2005). This disabling disorder is associated with considerable negative psychosocial effects and also creates a substantial financial burden on the healthcare system and assistance programs (WHO, 2012). Even with the staggering rates of depression, researchers anticipate an increase in prevalence over the next 10 to 15 years (Lecrubier, 2001; Mathers, Boerma, & Ma Fat, 2008; Murray & Lopez, 1997). In addition, depression is often a recurrent disorder; on average, patients will experience four depressive episodes in their lifetime (Judd, 1997; Richards, 2011). Those with three or more prior episodes have a 70-80% chance of another relapse. Even with the best pharmacotherapy and psychotherapy available, relapse estimates range from of 33% to 50% after inter-episode remission (Hollon & Ponniah, 2010; Shea et al., 1998). The increased prevalence of depression and the relatively high rates of relapse also increase the risk of suicidality. Individuals who meet criteria for a current episode of depression are approximately 20 times more likely to attempt and complete suicide compared to non-depressed individuals (Harris & Barraclough, 1997). In a comprehensive review of risk factors for recurrence, researchers proposed that severity of a depressive episode,

marked by suicidal ideation, was a strong predictor of future relapse (Burcusa & Iacono, 2007).

Overall, these data highlight the need to improve the efficacy of treatments for depression, develop better tools to provide ongoing care, and to detect and manage early warning signs of relapse and recurrence. Researchers have already begun this process by adopting a more holistic view of those with depression using technology to reach individuals outside of the therapy room.

1.1 Why Use Smartphones?

Researchers of major depressive disorder have often struggled with an overreliance on retrospective self-report data (Hunt, Auriemma, Cashaw, 2003). In order to circumvent the biases associated with self-reported data, a number of research groups have begun to collect data automatically by smartphones, which allows for more unbiased data collection and the potential for pattern analysis.

The Pew Research group's "Internet Project" revealed that smartphone ownership in the United States has increased from 35% in 2011 to 53% in 2013. Smartphone ownership for adults aged 35 to 64 ranges from 39% to 69%, with the lowest percentages among the older population (Smith, 2013). Researchers are capitalizing on this trend, particularly in delivering treatments via smartphone applications (Depp et al., 2010; Gustafson et al., 2011; LiKamWa, Liu, Lane, & Zhong, 2013; Reger et al., 2013). Other researchers have begun to examine trends in onset and relapse prevention of psychological disorders (Kok et al., 2014; Wang et al., 2014; Wichers et al., 2011).

Smartphone apps have been developed for a number of mental health disorders, but those for depression are more rudimentary, with a focus on basic mood tracking and

delivery of simple cognitive behavioral therapy tools (Luxton et al., 2011). These applications succeed in reaching individuals in a way that few therapeutic interventions have achieved before, but they have not yet realized the full potential of computing power and sheer breadth of information mining possible with the newest mobile devices. More recent applications are beginning to gather and use a wider range of sensing data to identify and monitor depression.

In a recent attempt to model mood and activity, the MoodScope application for iPhones and Androids utilized participant self-report on a basic five-point scale every day for two months (LiKamWa, Liu, Lane, & Zhong, 2013). This mood modeling system and the survey items were based on the Circumplex mood model of functioning, a Cartesian system measuring high and low activity and mood and their intersections (Russell, 1980). As in the current study, researchers collected information on location, phone calls, applications used, texts messages, and emails. Overall, communication history (phone calls, emails, and text messages) seemed to differentiate mood most effectively. Personalized modeling using the Circumplex mood model resulted in 93% effectiveness in accurately inferring a participant's mood.

Campbell and collaborators (Lane et al., 2014; Lu et al., 2010) have fused high complexity sensing paradigms with psychological monitoring to develop an application that is similar in scope to the app being developed by our team. The BeWell app (Lane et al., 2014) and a second iteration of the app (StudentLife; Wang et al., 2014) collect a range of sensing data collection, including ambient conversations (audio recordings at set intervals to detect nearby conversations), sleep duration, and accelerometer data. The investigators used these automatic sensing data to develop categories related to social

activity (marked by the detection of nearby conversations), sleep length, and levels of mobility (walking, running, standing). The associations between these variables and ecological momentary assessments (EMAs) were examined in a larger study.

In a sample of undergraduate students, the StudentLife app with integrated MobileEMA was used to measure daily levels of well-being and academic functioning. In a 10-week study, Wang et al. (2014) delivered an average of eight daily EMAs and included advanced calculations of automatic sensing data. The results of the study suggest strong negative correlations between ambient measures of social interaction and depression outcome (PHQ-9), as well as sleep duration and depression outcomes (e.g. the less participants slept the more likely they were to report depressive symptoms). This study included four automatic sensing behavioral classifiers (activity, conversation, sleep and location/co-location) together with psychosocial EMAs of stress, mood, social interactions, exercise, behavior, and variables hypothesized to represent well-being.

The smartphone application evaluated in the current study builds on the BeWell and StudentLife apps and also includes variables designed to assess and monitor factors related to depression risk and psychological health. The ultimate goal is to assess these variables and to provide feedback to those at risk for depression to prevent its onset or relapse. To begin, the current study examines the feasibility of the app and the associations between these risk and wellness variables in a nonclinical sample of college students. The domains of risk and wellness are described below.

1.2 Mental Health and Wellness Domains

Many of the factors that place an individual at increased risk for the onset of depression or relapse are difficult to control in or out of the context of a therapy session,

such as socioeconomic status, family history, and comorbid psychopathology. However, certain risk factors are more malleable, including social support, distorted cognitions, and perception of and reactions to stressful life events (Burcusa and Iacono, 2007). These constructs are closely related to well-being which has been extensively researched (Ryff & Singer, 2008) and incorporated into treatments for depression (Well-Being Therapy; Fava, 1999). The current smartphone app attempts to assess domains relevant to depression, as well as factors that contribute to overall wellness. These domains may serve as important indicators of the onset of a depressive episode, therapeutic progress, or relapse.

The domains assessed by the smartphone app are: mood, social functioning, cognitive factors, coping, and lifestyle factors. Each domain is categorized by various measures of each construct and collected by active data and/or passive data. *Active data* is inputted directly by the participant into the application via survey, whereas *passive data* consists of background processes and recordings using hardware and software features (e.g., text messaging, emails, and call recording) of the smartphone that are accessed by the app.

1.2.1 Mood

Unsurprisingly, sad mood, negative emotionality, and depression are commonly associated. In addition, the manner in which mood behaves can increase the risk of major depressive disorder. Emotional variability (emotional instability; Thompson et al., 2012) of negative emotions (e.g., sadness, anger, anxiety) has been identified as a marker of the onset and maintenance of depression (Peeters, Berkhof, Delespaul, Rottenberg, & Nicolson, 2006; Thompson et al., 2012; Wichers et al., 2010). Wichers et al. (2010)

explored the nature of varying mood over time using diary method assessment. Findings suggest that the pattern of emotional variability, specifically negative affect, and response to environmental factors predicted future negative mood outcomes.

Thompson and colleagues (2012) extended the previously mentioned study by exploring hypothesized connections between emotional instability, emotional inertia (the “extent to which emotions are resistant to change or persist over time”), emotional reactivity, and major depressive disorder (MDD). In their study, emotional instability and reactivity were measured in context to positive and negative self-reported events over the week. Results suggest that those with MDD were characterized as having more negative emotional instability and reactivity compared to controls in response to *positive events*. Conversely, Bylsma, Taylor-Clift, and Rottenberg (2011) and Peeters, Nicolson, Berkhof, Delespaul, and deVries (2003) found that depressed individuals are more likely to have more positive reactions to positive events than non-depressed participants. This may suggest that depressed individuals can experience some form of enhanced mood response to positive daily events (i.e., “mood-brightening” effect; Bylsma et al., 2011).

However, another set of processes can interfere with the maintenance and enhancement of positive emotions. Those who are depressed report more fear of strong emotions, hold more negative beliefs about positive emotions, and engage in more active attempts to dampen or down-regulate positive emotion than do non-depressed controls (Werner-Seidler, Banks, Dunn, & Moulds, 2013). Therefore, the current study included measures of average negative and positive emotion and variability over the two-week study period.

Another way to measure negative and positive emotion that takes advantage of smartphone features is through affective text analysis. Historically, accessing information about the language that participants use was limited to diary-method studies using retroactively recalled reflections. The current study enables the possibility of assessing real-time word usage through texts and emails. This naturalistic data allows for an examination of how people use language to express emotions.

To quantify the percentage of negative and positive emotion words used in text content, the Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, & Francis, 2007) program was used in the current study. The LIWC is a text analysis computer program that uses a well-validated, relatively extensive dictionary to calculate percentages of word use across a variety of categories (Pennebaker, 2011; Pennebaker, Booth, & Francis, 2007; Tausczik & Pennebaker, 2010). This program can be useful for the current application because the LIWC is programmable and automatically integrated into the application on the back end. To our knowledge, this will be the first smartphone application to integrate a linguistic analysis of text messages and emails. Positive and negative emotion word use has been cited in Pennebaker's latest book, *The Secret Life of Pronouns: What Our Words Say about Us* (2011), as a potential marker of depression.

1.2.2 Social Functioning

Lack of social support and social isolation are important risk factors for depression, as well as physical health and morbidity (Hemingway & Marmot, 1999; Holt-Lunstad, Smith, & Layton, 2010; Berkman et al., 2003). Backs-Dermott and colleagues (2010) recently proposed an integrated model of psychosocial factors contributing to depression and found that marked interpersonal difficulties and deficits in social support

contributed significantly to depressive relapse, although only if those difficulties were ongoing (i.e. last more than one month).

The social domain is particularly important to overall health and wellness because of the role social support systems play in mitigating depression relapse. In a large community sample of depressed adults, respondents reported “significantly poorer intimate relationships and less satisfying social interactions” (Fredman et al., 1988; Hirschfeld et al., 2000). While Fredman’s group focused on the quality of social relationships from the perspective of depressed individuals, Weber and colleagues (2012) examined the association between perceived levels of social support and depressive symptoms. Depressive symptoms were related, negatively, to the perception of being supported, generally and by family members. Interpersonal difficulties and low social support are well-documented predictors of the onset of depression and relapse (for a review, see Burcusa & Iacono, 2007).

The ability to measure social functioning has improved as certain features and applications on smartphones have become increasingly popular means of social communication (e.g. Facebook, Twitter, Instagram, text, Skype, FaceTime, and Snapchat). Research on the lexicon of depressed Twitter users has recently been examined. De Choudhury, Gamon, Count, and Horvitz (2013) asked self-identified depressive individuals and controls to access their public Twitter account feeds. Using linguistic count methods, results suggest that self-identified depressed individuals tend to use more negative emotion words and self-attention (egocentric) language. In addition, depressed persons, on average, are likely to disengage from social media on smartphones. Using an innovative method, these researchers determined the level of interaction

between the user and unique individuals, as well as a “prestige ratio” which measures the number of times other Twitter users use the participant’s Twitter handle (e.g., [@MattDamon](#)) in their own tweets. Users in the “depression class” were associated with lower prestige ratios (indicating fewer reciprocal communications), following fewer people, and being followed by fewer people. Taken together, these studies suggest that quality, perceived support, and the level of interaction help define the construct of social engagement, and therefore these variables were included in the smartphone app in the current study.

1.2.3 Cognitive Factors

Depression is characterized by self-criticism, pessimism, worthlessness, and a negative view of self (Disner, Beevers, Haigh, & Beck, 2011). These negative cognitions are often activated in context of negative life events and even mild dysphoric states. The combination of depressive cognitions and emotional responses contributes to rumination, or unproductive and repetitive processing. Rumination makes it difficult for people to disengage from negative information and contributes to hopelessness and the maintenance of depression (Gotlib & Joorman, 2010). The activation of these depressive cognitions in response to negative life events and mood is called cognitive reactivity. More cognitive reactivity in remitted depressives has been demonstrated in lab challenge paradigms and in clinical trial research to be an important predictor relapse after recovery from depression (Beshai et al., 2011).

It is also important to identify positive cognitions that may serve as a buffer or resilience factor to reduce the risk of depression relapse. In a review of risk and protective factors of depression, Haefffel & Grigorenko (2007) noted that in childhood

and adolescence, self-confidence and competence are possible mitigating factors of depression. A recent meta-analysis on low self-esteem in relation to depression and anxiety revealed that self-esteem was a stronger predictor of depression, than depression was of self-esteem (Sowislo & Orth, 2013). This smartphone app will include daily assessment of depressive cognitions and those related to wellness.

1.2.4 Coping/Emotion Regulation

Coping techniques and emotion regulation responses play an important role in most types of psychopathology. They are defined as automatic processes to balance duration, expression, and range of an emotional response (Gross, 2007). There is substantial evidence that maladaptive regulation strategies contribute to the onset, maintenance, and relapse in depression (Aldao, Nolen-Hoeksema, & Schweizer, 2010; Joormann & Quinn, 2014; Joormann & Siemer, 2004).

Two dysfunctional emotion regulation strategies in depression are rumination (Nolen-Hoeksema & Morrow, 1991) and avoidance. The former style of regulation is characterized as unproductive and repetitive thinking about one's problems, negative mood, and sense of worthlessness, defectiveness, and hopelessness. It causes further problems by interfering with healthy mood repair strategies, such as cognitive reappraisal, active coping, and using positive emotions and memories to shift attention (for a review see Joormann & Gotlib, 2010). From an information processing perspective, rumination can be viewed as an overengagement with negatively processed information from environmental triggers.

Avoidant coping styles, which involve cognitive and behavioral disengagement or minimization of stressors, maintain negative information processing biases and

rumination. In a review of avoidance related to depression, Trew (2011) explains that motivation behavior is categorized in two ways, the tendency to approach situations that will yield positive outcomes and to avoid situations that yield negative ones. In depression, both avoidant motivation and approach deficit behaviors reduce the experience of positive events, while simultaneously accentuating negative processing of negative experiences. For instance, a recent daily diary study found that those with higher levels of reported depression tend to cope with stressful situations by avoiding the negative environmentally evocative stimuli (Shahar & Herr, 2011). In the context of a psychotherapeutic treatment, reductions in avoidant behaviors resulted in better outcomes in a depressed population (Hayes, Beavers, Feldman, Laurenceau, & Perlman, 2005). Both avoidance and rumination can also inhibit active problem-solving and productive coping with life stressors and can generate even more stress. In addition, Backs-Dermott and colleagues (2010) report that depressed individuals who engage in emotion-oriented and avoidance-oriented coping behaviors are at greater risk for depressive relapse at one-year follow-up.

Beyond negative coping strategies that can perpetuate depressive thoughts, it is important to assess in the smartphone app positive coping strategies that can promote resilience. Coping strategies such as cognitive reappraisal and “positive meaning making” have been identified as having a strong influence on mood (Folkman & Moskowitz, 2000). Cognitive reappraisal, in particular, has been cited as a moderating factor between stress and depression. A study of 78 females from a Colorado community sample demonstrated the ability to use cognitive appraisal online. Although low-level stressors did not seem to activate the need for cognitive appraisal, women who were

exposed to higher level stress events and utilized cognitive reappraisal were less depressed than those who did not (Troy, Wilhelm, Shallcross, & Mauss, 2010).

Another coping style that might enhance resilience is “savoring” of positive experiences (Seligman, Rashid, & Parks, 2006). Because of the tendency to engage in rumination and avoidance, depressed individuals are often incapable of fully experiencing positive events in their lives. In a savoring induction, participants were asked to recall three events that happened over the week and to reflect on how they could best, “savor these events while they occurred.” Results of the intervention suggest that participants who were able to engage in savoring of their everyday experiences had significant reductions in depressive symptoms and reported negative affect (Hurley & Kwon, 2012).

The smartphone application in the current study incorporates three types of coping strategies (rumination, avoidance, and adaptive coping) into survey items. In an effort to assess coping strategies in response to specific life events, survey items were prompted in context of both the worst and best events that occurred over the week for each student.

1.2.5 Lifestyle Factors (Physical activity and Sleep)

In general, individuals with depression are less active than non-depressed individuals (Camacho et al., 1991). However, regular exercise has been shown to be a mitigating factor in the development of depressive symptoms (Azevedo Da Silva et al., 2012). While direct evidence for exercise as a treatment for depression is still under contentious debate, most researchers agree that studies have demonstrated moderate effects (Dunn Trivedi, Kampert, Clark, & Chambliss, 2005; Cooney, Dwan, & Mead,

2013; Chalder et al., 2012). The benefits of physical activity have shown strong relationships to specific biological factors that are linked to depression, such as sleep.

Lopresti, Hood, and Drummond (2013) developed a model of combined physical activity and sleep factors, which share similar biological functions (Hypothalamic-pituitary-adrenal imbalance, neurotransmitter imbalance, immuno-inflammation). Sleep quality, duration, and disturbance have been studied extensively and have been estimated to occur in up to 90% of depression cases (Tsuno, Besset, & Ritchie, 2004). In a sample of depressed participants, with and without suicidal ideation, poorer sleep quality was associated with greater severity of depressive symptoms and with suicidal ideation (Ağargün, Kara, & Solmaz, 1996). Germain and Kupfer (2008) report that insomnia complaints precede the onset and recurrence of depression in as many as 40% of cases.

Taken together, physical inactivity and sleep disturbance can decrease the resources one has to cope with daily stressors, and they have consistently been identified as predictors of the course of depression (Germain & Kupfer, 2008; Lopresti, Hood, & Drummond, 2013; Mason & Harvey, 2014).

1.3 The Current Study

The current study aims to test the feasibility and utility of an Android-based Health and Wellness UDTracker application. Feasibility was measured by total completion rate of active survey data, the ability of the application to accurately record all types of data on a given day, and participant feedback on ease of use/irritability of the application. Items in the five domains of risk and resilience will be correlated with mood-related measures: baseline depression, average daily mood (negative and positive), mood variability (negative and positive), and percentage of emotion words (negative and

positive). This assessment of functionality will help to develop a more streamlined version of the application as we prepare it for use in a clinical population.

Chapter 2

METHOD

2.1 Participants

One hundred and fourteen participants were recruited from the University of Delaware's undergraduate research subject pool system, as well as other psychology courses at UD (Psychopathology, Abnormal psychology, and Social Psychology). They were compensated for their time with extra credit or research participation course credit. One student withdrew from the study citing privacy concerns. Those with significant gaps in data (complications with the application which resulted in nonconsecutive days of data collection) or with fewer than seven days of data were not included in the analyses ($n = 19$). After these adjustments, 94 participants were included in the current analyses.

Eligibility criteria for the Health and Wellness UDTracker Android Application study included a minimum age requirement of 18 years, current enrollment in course work at UD, owning a personal Android smartphone, and having access to Wi-Fi at least once daily. Due to the pilot-nature of the study, participants were also asked to agree to all forms of data collection in order to participate.

The sample was 56% female and 44% male and relatively diverse (58.2% Caucasian, 17.2% Asian, 10.7% Black/African American, 2.4% American Indian or Alaskan Native, and 11.5% mixed/other). Approximately 8% of participants identified as

being ethnically Hispanic or Latino/Latina but varied on racial identification. The mean age of participants was 19.36 years ($SD = 2.16$; range = 18 to 31).

2.2 Study Design

2.2.1 Phases of the Study

The Android Health and Wellness UDTracker app study was divided into three phases. *Phase I* (Baseline) was an in-person visit which included the consent procedures, completion of baseline measurements, and installation and tutorial of the app. *Phase II* (Data Collection Period) began the day following the baseline visit. The data collection period lasted 24 hours a day, or as long as the participants' phones were on, for 14 days. *Phase III* (Termination) was an in-person visit scheduled as close to the last day of the data collection as possible. During the termination visit, students were asked to complete a written feedback form, while the researchers uninstalled the application. Participants were debriefed about the aims of the study, explaining the hypothesized connections between passive and active data collection, as well allowing time for the removal of the application and reconfiguration of previous phone functionalities.

2.2.2 Smartphones

Students with any manufacturer or model of Android smartphone were invited to participate in the study. Participants had a wide variety of models and “ages” of their devices. While previous studies of smartphone applications have been constrained to a singular model of an Android device (Lane et al., 2014; Wang et al., 2014), our program is versatile and has been tested with a variety of Android smartphones and individualized settings. The most common model of smartphone used in the current study was the

Samsung Galaxy S4 (31.4%), and the majority of phones were under two years old (80.9%).

2.2.3 UD Health and Wellness App “UDTracker”

The application is designed to capture actively inputted data and collect data recorded passively through the smartphones automated functions. The active data collection was accumulated from three separate surveys administered on the smartphone. The application is fairly easy to access and navigate. Located under the “Apps” feature on Android phones, the app has an icon-driven graphical user interface (GUI), which allows students to access daily, sleep, or weekly surveys. The GUI also allows participants to access the passive data toggling features. The toggling feature enables students to turn off tracking of specific types of data collection (e.g., SMS, Call Recording, Sensors, Location) for specified intervals of time ranging from 15 minutes to 6 hours.

The app consisted of three questionnaires, the *daily*, *sleep*, and *weekly questionnaires*. The *daily questionnaire* is 28-item measure assessing multiple domains of wellness. Questions were presented as radio buttons or slider style. Students received a pop-up reminder on their smartphones at 8:00 PM EST and were instructed to complete the survey as close to that time as possible. The *sleep questionnaire* was a 5-item survey of quality and duration of sleep adapted from the Pittsburgh Sleep Quality Index, indicating amount and quality of sleep (PSQI; Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). Students received a pop-up reminder on their smartphones at 8:00 AM EST and were instructed to complete the survey as soon as possible when they awoke each morning. The final app survey was the *weekly questionnaire*, which asked students

to reflect on the “BEST” and “WORST” events of the week by providing a short typed answer in a text box or an audio recorded answer. Additional questions about coping styles and mood were assessed in context of each of the identified events. Participants received a pop-up reminder on their smartphones at 10:00 AM EST on days 7 and 14 and were instructed to complete the survey as close to that time as possible.

While participants could access the surveys manually through the GUI, a pop-up reminder feature allowed them to link directly into each type of survey. To navigate the surveys, participants are required to swipe from screen to screen answering radio button, slider, text box, and audio recording question types. The app was equipped with an automatic updating system that allowed for real time bug repair. If a student experienced an application crash (defined as a sudden discontinuation of the Health and Wellness UDTracker app), a crash report was generated and transmitted to the app’s developer. The developer would create a patch and enable the automatic update feature, which allows participants to update the app just as they would any other application on their phone.

2.3 Measures

2.3.1 Depression and Mood

The Beck Depression Inventory-II (BDI-II), which measures the frequency and intensity of depression symptoms experienced over a two-week period (Beck, Steer, & Brown 1996), was administered at the baseline visit. This measure was modified, removing the suicide item (item 9) resulting in total score possibility ranging between 0 and 60.

Mood was assessed by the Positive and Negative Affect Scale (PANAS; Watson, Clark, & Tellegen, 1988), which measures a participant's identification with affect descriptors (e.g., enthusiastic, angry, excited). PANAS items were measured in the *daily* and *weekly* surveys. Three positive ("happy", "enthusiastic", and "calm") and three negative ("nervous", "angry", and "sad") were summed in their respective categories to create *daily positive affect* (D-PA) and *daily negative affect* (D-NA) composites. These composites were averaged over 14 days for each student. *Positive* and *negative affective variability* scores were calculated as standard deviations of each respective affective valence over the 14-day collection period. The PA and NA composites were also created in the context of the "WORST" and "BEST" self-identified events by each student *weekly survey* on days 7 and 14. Scores were averaged across the two days.

To test the utility of the Linguistic Inquiry Word Count system (LIWC; Pennebaker, 1997), *positive emotion* and *negative emotion* dimensions were calculated based on text in both text messages and emails each day. Values from the LIWC program are calculated as total percentage of negative and positive emotion word use divided by the total number of words. These scores were averaged over the 14 day period for each participant.

2.3.2 Social functioning

Participants were also asked to indicate the level of social interaction in the *daily survey*. Items related to length of time interacting with others (*Duration of social interaction*; five-point scale, 0 = *None* to 4 = *More than 2 hours*) and whether those interactions were positive or negative (*Perception of social interaction*; seven-point scale, 0 = *Very negative* to 6 = *Very positive*). Total number of communications (sum of

total number of texts, emails, and phone calls) were assessed passively. All three measures were averaged across the 14 days for each participant.

2.3.3 Cognitive factors

Four items of the BDI-II were included in the *daily survey* to assess daily self-criticism, pessimism, worthlessness, and self-dislike. These items were summed and then averaged over 14 days for each participant to constitute the *depressive cognitions* variable. Items from the Psychological Well-being Scale (PWB; Ryff & Keyes, 1995) was used to create an *adaptive cognitions* variable. Summed scale items from the PWB included the participants' ability to handle situations in life, sense of confidence, positive view of self, and a sense of direction or purpose. Again, this variable was averaged over 14 days for each participant.

2.3.4 Coping/Emotion regulation

Three main components of coping and emotion regulation (*avoidant coping*, *rumination*, and *positive coping*) were assessed using items from the COPE scale (Carver, Scheier, & Weintraub, 1989) and the Responses Styles Questionnaire, short form (*RSQ-SF*; Treynor, Gonzalez, & Nolen-Hoeksema, 2003). Coping strategies were elicited by the *weekly survey* in the context of the best and worst events over the week. The COPE measures an individual's positive and negative coping responses to stressful situations. Items are rated on a four-point scale ranging from 0= *I didn't do this at all* to 3= *I did this a lot*. A composite score for *avoidant coping* was created using items that measure experiential avoidance (i.e. avoiding negative thoughts or feelings) as well as behavioral avoidance (i.e. engaging in maladaptive alcohol or drug use, giving up dealing with the situation, avoiding action to make the situation better, and denial). The *rumination*

variable was assessed by using the total score of the RSQ-SF, which assesses the tendency to ruminate in response to sad or depressed mood. Finally, *positive coping* was measured based on a composite score of all positively valenced coping strategies of the COPE (cognitive reappraisal, social support, use of humor, distraction, acceptance, seeking comfort in religion, seeking guidance, and planning) on the same four-point scale as the negative coping responses. These measures were gathered on days 7 and 14 and averaged over those two days.

2.3.5 Lifestyle factors

As both quality of sleep and physical activity have been indicated as important factors in mental health, these constructs were assessed daily as part of the *daily* and *sleep* questionnaires. The *sleep quality* item was measured on a six-point scale (0 = *Very bad* to 4 = *Very good*). Physical activity was differentiated by duration of light, moderate, and intense activity. *Light activity* was exemplified by, but not limited to, “leisurely walking or cycling, gardening.” *Moderate activity* was defined as, “brisk walking, or cycling, yoga/Pilates.” Finally, *intense activity* was defined as, “running, vigorous cycling, swimming laps.” Participants could indicate multiple levels of intensity, and responses were rated on a five-point scale (1 = *None* to 5 = *More than 90 minutes*).

2.3.6 Feedback

The final measure was administered at the termination visit. The *feedback summary* was a qualitative and quantitative measure which asked students about the usability of the app (0 = *Not at all* to 3 = *Easy to use*), as well as how irritating the app was (0 = *Not at all* to 3 = *Very irritating*). It prompted participants to qualitatively reflect on whether or not they felt the application was easy to use, irritating, affected the way

they behaved, particular features they enjoyed, if they had any feedback about the design or use, and any suggestions for possible improvements. Qualitative responses were categorized and consensus-coded by graduate and undergraduate research assistants.

Chapter 3

RESULTS

3.1 Feasibility analyses

Participants who were excluded initially because of survey completion rates less than 50% and participants with discontinuous data entry were reintegrated into the dataset for the feasibility analyses ($n = 113$). Participants completed the majority of the daily surveys, with 85.8% of students completing seven or more surveys. Completion rates of the sleep survey were the highest overall, with 92.9% of students finishing seven or more surveys during the 14-day data collection period. The completion of the weekly surveys was more variable, with 85% of the sample completing one or both of the weekly surveys (43.4% completing both, 41.6% completing one of the two weekly surveys over the 14-day period), and 15% missing both weekly surveys.

At the conclusion of the study, students were asked for their feedback about the usability of the application. Participants were asked to provide qualitative and quantitative feedback about the ease of use, difficulties, application crashes, and suggestions for application modification. Qualitative answers were coded by the study coordinator and two undergraduate research assistants using an adapted method of Clara Hill's Consensual Qualitative Research (CQR; Hill, Thompson, & Williams, 1997) coding paradigm. The CQR method is a systematic method for creating categories and core ideas. Categories were created from each survey item (see Table 1) and core ideas,

subsumed under the previously mentioned categories, consisted of groupings of similar responses from participants. Each rater independently categorized written responses into core ideas under the umbrella categories. The three coders then met as a group to discuss the generated core idea groupings and reached consensus on the final categories (*ease of use, irritation, effect on behavior, likable features, and improvements*) and coded core ideas. Inter-rater agreement was calculated between two raters for each category. Reliability was good overall, $\kappa \geq .79$ on all five categories (ReCal2; Freelon, 2013).

Feedback about the usability of the app was positive. The two quantitative items of the feedback form showed that most participants reported that the app was “easy to use” (95.6%) and found it “a little” to “not at all” irritating (90.3%). Students reported, qualitatively, irritation with: 1) the monotony of answering the same survey items (15%), 2) overly-frequent pop-up notifications (9%), and 3) drain on battery life (8%). When asked about what they liked about the app, some participants reported enjoying the app’s user-friendliness platform (40%) and pop-up reminders feature (17%) and that the app enhanced self-reflection and awareness of behavior (16%). When asked how the app might be improved, students suggested more variety in the survey questions (23%), fewer crashes/bugs/freezes (9%), and some had suggestions for new technical features (13%).

3.2 Domain analyses

Because this feasibility study is an early step in the development of a wellness and lifestyle tracking app to help prevent depression relapse, the focus of the analyses was on the associations between mood-related variables and actively and passively collected data in each of the domain variables. Bivariate Pearson correlations were calculated between

the mood-related variables and variables in the five domains of risk and wellness. Table 2 presents the intercorrelations of all study variables organized by domain.

3.2.1 Mood

Mood was measured in three ways: baseline depression scores on the BDI-II, average negative and positive mood over the 14-day study period, mood variability (standard deviation of negative and positive mood ratings over the 14 days), and average percentage of negative and positive emotion words used in texts and emails. As expected, baseline depressive symptoms were significantly correlated with more average daily negative affect (D-NA) and less daily positive affect (D-PA). The mood variability variables were not associated with initial BDI scores. Negative affect variability (V-NA) was strongly related to more daily NA and less daily PA and also with more variability in PA (V-PA). Overall, the LIWC dimensions of positive and negative emotions were not significantly associated with the majority of mood variables. However, negative emotions word use was positively associated with baseline depression scores and V-NA.

3.2.2 Social functioning

In the social domain, correlations were examined between the duration, perceived quality, and number of social interactions and the mood variables (baseline levels of depression, average reported daily mood, and mood variability). As seen in Table 1, duration of time spent with others was significantly associated with less D-NA and more D-PA, but not with any of the other mood variables. More positive quality social interactions were strongly correlated with more positive daily mood and also with lower negative daily mood and negative mood variability. The total number of communications a person had over the day (total of emails, texts, and phone calls) was positively

associated with daily negative mood (D-NA), both negative and positive mood variability (V-NA), and with negative and positive emotion word use. Number of social interactions was not significantly correlated with D-PA or depressive symptoms at baseline.

3.2.3 Cognitive factors

Cognitive functioning variables included depressive and adaptive cognitions, which were negatively associated with one another. Unsurprisingly, depressive cognitions were positively correlated with baseline depression, D-NA, V-NA, and with negative emotion word usage. Adaptive cognitions were negatively correlated with depressive symptoms and D-NA, as expected, and they were also associated with more D-PA. Neither cognitive functioning variable was associated with the LIWC dimensions or V-PA.

3.2.4 Coping/Emotion regulation

In the social domain, correlations were examined between the duration, perceived quality, and number of social interactions and the mood variables (baseline levels of depression, average reported daily mood, and mood variability). As seen in Table 1, duration of time spent with others was significantly associated with less D-NA and more D-PA, but not with any of the other mood variables. More positive quality social interactions were strongly correlated with more positive daily mood and also with lower negative daily mood and negative mood variability. The total number of communications a person had over the day (total of emails, texts, and phone calls) was positively associated with daily negative mood (D-NA), both negative and positive mood variability (V-NA), and with negative and positive emotion word use. Number of social interactions was not significantly correlated with D-PA or depressive symptoms at baseline.

3.2.5 Lifestyle factors (Physical activity and Sleep)

Sleep quality and physical activity were included in the lifestyle factors domain. Physical activity was divided into three levels: light, moderate, and intense, and each was measured in duration of time spent engaging activities categorized in that level. Reported quality of the previous night's sleep was positively related to D-PA and negatively related to baseline depressive symptoms and negative emotion word usage in texts and emails. Light activity was positively associated with D-PA and with no other daily mood variables. Moderate activity was positively associated with D-PA and less variability in positive affect (V-PA). Finally, intense activity did not correlate significantly with any daily measures of mood.

Table 1
CQR coding of feedback questionnaire

Categories	Core Ideas	Percentage Endorsed
Do you have any other comments related to how easy the app was to use?	1- Reminders	27.36
	2- Ease of question understandability	2.83
	3- Format/look	13.21
	4- Technical functioning	38.68
	5- Speed	0.94
	6- Crashes	2.83
	7- None or N/A	12.26
	8- Survey length	1.89
Do you have any other comments related to how irritating the app was to use?	1- Bugs or crashes/Freezes	2.91
	2- Length of surveys/frequency	3.88
	3- Repetitiveness of questions/boring	15.53
	4- Reminder frequency	9.71
	5- App functionality failures	6.80
	6- None or N/A	26.21
	7- Timing of surveys/notifications	2.91
	8- Battery drainage	7.77
	9- Upgrades	4.85
	10- Phone issues/email issues	4.85
	11- Not irritating	6.80
	12- Formatting/look	1.94
	13- Other	5.83
Did using this app affect your behavior in any way? If yes, how?	1- No	56.30
	2- Behavioral awareness/modification	11.76
	3- Cognitive awareness/modification	5.88
	4- Emotional awareness/modification	10.08
	5- General awareness/reflection	8.40
	6- Activity on phone	7.56
What did you like about this app?	1- Reminders	16.99
	2- Ease of question/understandability	6.54
	3- Format/look	9.15
	4- Technical functioning/useability	40.52
	5- Speed	5.23
	6- Other	2.61
	7- Created reflection/tracking behavior	16.34
	8- Non-interfering/low time burden	2.61
What might we do to improve this app?	1- Crashes, bugs, freezes	9.40
	2- Question Variability/wording	23.08
	3- Format/look	9.40
	4- Technical functioning/useability	13.68
	5- Timing of reminders/surveys	4.27
	6- Frequency of reminders/surveys	5.13
	7- None, or N/A, everything's fine	18.80
	8- Length of survey	2.56
	9- Updates	3.42
	10- Battery life	5.13
	11- Response period	4.27
	12- Feedback option	0.85

Table 2
Summary of Intercorrelations, Means, and Standard Deviations for Five Domains of Risk and Wellbeing

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	
1 Baseline BDI-II Total	---																									
2 NA Composite ^{1‡}	.32 ^{**}	---																								
3 PA Composite ^{1‡}	-.36 ^{***}	-.36 ^{***}	---																							
4 NA variability ^{1‡}	.20	.62 ^{***}	-.28 ^{**}	---																						
5 PA variability ^{1‡}	-.03	.24 [*]	-.10	.38 ^{***}	---																					
6 LIWC: Negative emotion ^{1‡}	.29 ^{**}	.17	.00	.21 [*]	.10	---																				
7 LIWC: Positive emotion ^{1‡}	.04	-.08	.11	-.12	.05	.04	---																			
8 Duration-social interactions ^{2‡}	-.05	-.22 [*]	.34 ^{**}	-.19	.01	.08	-.09 ⁻	---																		
9 Quality of social interactions ^{2‡}	-.04	-.20 [*]	.56 ^{***}	-.23 [*]	-.19	.05	.06	.56 ^{***}	---																	
10 Number of communications ^{2‡}	.09	.21 [*]	-.08	.39 ^{***}	.24 [*]	.23 [*]	.23 [*]	.19	.04	---																
11 Depressive cognitions ^{3‡}	.49 ^{***}	.42 ^{***}	.39 ^{***}	.29 ^{**}	.04	.35 ^{**}	-.14	-.11	-.16	.15	---															
12 Adaptive cognitions ^{3‡}	-.37 ^{***}	-.28 ^{**}	.51 ^{***}	-.19	-.03	-.13	.13	.20	.42 ^{***}	-.04	-.42 ^{***}	---														
13 Avoidant coping ⁴⁰	-.18	-.12	.21	-.24 [*]	-.30 ^{**}	-.07	-.02	.15	.19	.06	-.19	.08	---													
14 Rumination coping ⁴⁰	.31 ^{**}	.17	-.20	.13	-.14	-.01	-.10	-.22 [*]	-.13	-.01	.32 ^{***}	-.41 [*]	.12	---												
15 Positive coping ⁴⁰	.14	.06	.13	.01	-.04	-.03	.00	.24 [*]	.22 [*]	-.06	.08	-.05	.40 ^{***}	.39 ^{***}	---											
16 Worst event: NA ⁴⁰	.23 [*]	.30 ^{**}	.07	.23 [*]	.20	.12	.15	.07	.11	.17	.20	-.24 [*]	.14	.46 ^{***}	.44 ^{***}	---										
17 Worst event: PA ⁴⁰	-.02	-.01	.09	-.05	-.29 ^{**}	-.05	-.12	-.13	-.16	-.25 [*]	-.07	-.05	.25 [*]	.17	.08	-.26 [*]	---									
18 Best event: Avoidance ⁴⁰	.14	.26 [*]	-.22 [*]	.25 [*]	-.13	.04	-.04	-.43 ^{***}	-.35 ^{***}	-.11	.29 ^{**}	-.22 [*]	.01	.12	-.12	-.06	.49 ^{***}	---								
19 Best event: Savoring ⁴⁰	-.01	.06	.44 ^{***}	.02	.07	.03	.03	.29 ^{**}	.44 ^{***}	.06	-.12	.24 [*]	.06	-.07	.30 ^{**}	.17	-.15	-.43 ^{***}	---							
20 Best event: NA ⁴⁰	.17	.22 [*]	-.17	.21	-.06	.06	-.24 [*]	-.22 [*]	-.14	-.10	.11	-.02	.07	.00	-.03	-.05	.28 ^{**}	.48 ^{***}	-.27 [*]	---						
21 Best event: PA ⁴⁰	-.03	.10	.33 ^{**}	.04	.21 [*]	.06	.08	.18	.40 ^{***}	.02	-.03	.24 [*]	.13	-.07	.26 [*]	.32 ^{**}	-.17	-.21	.46 ^{***}	-.20	---					
22 Sleep quality ^{2‡}	-.33 ^{***}	-.13	.37 ^{***}	-.07	.06	-.22 [*]	.04	.18	.27 ^{**}	-.16	-.37 ^{***}	.32 ^{**}	.02	-.16	.07	-.16	.12	-.14	.05	-.12	.12	---				
23 Light activity ^{2‡}	-.07	-.16	.26 [*]	-.16	-.18	.05	.10	.21 [*]	.16	-.05	-.13	.18	.19	.06	.41 ^{***}	.07	.05	-.13	.17	-.05	.12	.22 [*]	---			
24 Moderate activity ^{2‡}	-.19	-.02	.22 [*]	-.06	-.24 [*]	-.01	.03	.17	.19	.10	-.03	.16	.30 ^{**}	.09	.26 [*]	.19	.22 [*]	.11	.03	-.03	.21	.05	.50 ^{***}	---		
25 Intense activity ^{2‡}	-.08	-.01	.14	-.05	-.08	.06	.00	.16	.08	.10	.05	.13	.27 [*]	.20	.17	.07	.32 ^{**}	.08	-.10	.00	.06	-.17	.09	.57 ^{***}	---	
M	10.21	1.34	5.71	1.26	1.89	1.73	6.36	3.21	4.69	32.93	0.87	7.65	5.24	7.30	10.42	6.11	0.67	0.06	2.35	0.95	8.72	2.77	1.58	0.93	0.83	
SD	7.88	1.14	1.71	0.71	0.66	0.70	2.25	0.74	0.77	34.81	1.23	2.32	1.65	5.45	4.21	2.55	1.22	0.27	0.81	1.19	1.80	0.47	1.09	0.89	0.97	

Note. ¹Mood, ²Social Functioning, ³Cognitive Factors, ⁴⁰Coping, ^{1‡}Lifestyle factors, ^{2‡}Scale administered weekly, ^{3‡}Scale administered daily, *p < .05, **p < .01, ***p < .001

Chapter 4

DISCUSSION

4.1 Summary of Findings

The current study investigated the feasibility of an Android application developed to track functioning in five domains: mood, social functioning, cognitive factors, coping, and lifestyle factors associated with risk for depression, as well as variables that might reduce risk. The correlations between the domain variables and baseline depression, average daily mood over the 14-day study period, and mood variability were examined to assess the utility of the domain variables in the app. The Health and Wellness UDTracker application was largely successful in both usability and effectively recording and capturing data. Participants reported that the app was straightforward, easy to use, and user friendly. Completion rates for daily, sleep, and at least one weekly survey were high. Participant feedback indicated a range of suggestions for improvements, including the need to minimize battery usage and more dynamic methods of assessing survey items. As the ultimate target population for this application is individuals with depression, it is important that the app collect data passively without user input and burden, but also assess some areas of functioning with active data input and reflection. At this point in development, a goal was to get a naturalistic snapshot of participants' functioning without altering their behavior. Most

participants reported that the app did not influence their daily behavior, although some reported that it did help them to reflect about the day, sleep habits, behaviors, cognitions, and emotions.

Across all domains, correlations between the domain variables and baseline depressive symptoms and the negative and positive mood variables (average daily mood, mood variability, and emotion word use) were moderate to strong. Within the mood domain, results suggest good concordance between depressive symptoms and daily reported affect in expected directions. Consistent with findings from Thompson et al. (2012) and Wichers et al. (2010), negative mood variability was also associated with average daily negative affect, although it was not associated with baseline depression symptoms. We expected that the LIWC program would provide another measurement of mood, but it was largely unassociated with mood ratings except that more negative word use was associated with higher baseline depressive symptoms and with negative mood variability. The measures of average daily mood and mood reactivity showed important associations with the domain variables, but the LIWC negative and positive emotion words usage variables were less useful.

In the social functioning domain, each of the variables showed some association with the mood variables. Passive data collection of total number of communications as a measure of social interaction seems to be a particularly valuable tool, as it was associated with more daily negative mood, variability of both negative and positive mood, and more negative and positive emotion words. The strong relationship between higher perceived quality of interaction and positive daily mood is

consistent with Weber and colleagues' (2010) finding that stronger social support networks are associated with more self-esteem and confidence, and fewer depressive symptoms (Weber et al., 2010). Thus, the social functioning variables were particularly useful and showed associations with both positive and negative mood. The LIWC emotion word variables, again, were largely unassociated with social functioning variables, apart from the total number of communications variable.

The cognitive factors, depressive and adaptive cognitions, appear to be two of the strongest correlates of mood and depression symptoms. Depressive cognitions showed associations with negative mood variables and with higher baseline depressive symptoms, and adaptive cognitions showed associations with positive mood and lower baseline depressive symptoms. These items were fairly easy to rate each day and yielded useful patterns of associations with mood.

In general, the coping variables did not perform as expected and might need to be re-evaluated for inclusion in the app. Avoidance in response to the worst events over the 14-day period negative was not associated with daily negative affect, but was significantly related to lower levels of both negative and positive variability. Avoidance was also correlated with more positive emotion in response to the negative event. This set of findings could be especially informative, as avoidant coping seemed serve a stabilizing function in the face of negative life events during the study period, at least in this nonclinical population. These findings are inconsistent with the literature on the negative effects of avoidance in depression (Trew, 2011) and suggest that these items be re-evaluated. It is also possible that this event-specific method of

assessing coping yields different information than more general avoidant coping strategies. The ruminative coping variable performed better and was associated with baseline depression and with negative reported affect during the worst event of the week. These findings are consistent with research suggesting that ruminative processing can perpetuate engagement in experiencing of negative affect (Joormann & Gotlib, 2010). Positive coping strategies were largely unassociated with mood or depressive symptoms. An unexpected finding was that the positive coping strategies were associated with more avoidance and rumination.

The role of avoidance and savoring seemed to be associated with mood in the context of positive experiences. Avoidance in response to positive events was correlated with more daily negative mood and negative mood variability, as well as with less daily positive mood. These findings are consistent with research suggesting that people who are depressed report more fear of strong emotions and engage in more active attempts to dampen or down-regulate positive emotion than do non-depressed controls (Werner-Seidler et al., 2013) . In contrast, savoring was significantly correlated with higher daily levels of positive affect.

Lifestyle factors (physical activity and sleep) were more closely related to daily reported positive mood than to negative mood variables. It is unsurprising that physical activity and positive affect are related, given that on average depressed persons are less likely to be active (Camacho et al, 1996) and physical activity has been cited as a mitigating factor of the development of depression (Azevedo Da Silva et al., 2001). Furthermore, the quality of an individual's sleep shows clear links with

depression onset and relapse (Germain & Kupfer, 2008; Mason & Harvey, 2014), and its association with daily positive mood in the current study suggests that it might also have to potential to increase resilience.

These correlational analyses are a first step to identifying which components in each of the five domains might be useful tools in highlighting risk for depression and level of wellness. Many of the components in each domain were associated with mood and depression symptoms, although some coping factors were not associated with baseline depression symptoms and were associated with both positive and negative mood variables in unexpected ways. One of the features of questionable utility is the LIWC program. While the LIWC program could be a useful tool to integrate automatically into the app system, many of the analyses yielded no significant relationships between emotion language that participants used and their well-being. However, there are other dimensions of the LIWC program that may be explored. Literature suggests a strong association between inward focus of language, such as using egocentric pronouns “I” and “me”, and higher levels of depression (Pennebaker, 2011). Another LIWC category of interest is the “discrepancy” dimension. The discrepancy category is comprised of words such as, *can't*, *couldn't*, *would*, and *wish*. In a treatment study of depression, discrepancy words were associated with treatment improvement and mastery, or the feeling of control in one's environment (Van der Zanden et al., 2014). Future studies can include a broader range of the LIWC categories that might show stronger associations with depression and negative emotion.

4.2 Study Limitations

There are several limitations to consider in the current study related to generalizability to the intended target population, selection bias, limiting factors of the application, and issues with different types of measurement. Thus far, the application has only been examined in a non-clinical population. Although approximately 20% of students in the sample met criteria for mild to severe levels of depression symptoms ($\text{BDI-II} \geq 14$), it will be important to test the app with a full range of depression scores and participant ages. The correlational design was used as a first examination of the associations between average ratings of variables across the 14-day study period. This approach identified variables that showed associations with the mood variables and others that were less useful. These initial analyses can point to variables that might need to be refined or deleted from the app. For instance, the LIWC emotion word categories showed less consistent associations with the domain variables than the other mood variables, such as average daily mood and mood variability. After further development and testing of that app, it also will be useful to examine day-to-day associations between variables using multilevel modeling approaches.

While the Health and Wellness UDTracker application was generally well-received by this student sample, this may not be the case in a depressed sample. An obstacle in successfully implementing this app with a depressed population may be the user's adherence to daily survey completion. Depression is characterized by anhedonia, low motivation, low energy (APA, 2014), and also diminished reward responsivity (Pizzagalli et al., 2008). A major concern will be the app's ability to keep

depressed individuals interested, engaged, or invested in it. Well-developed fitness applications and online dieting programs might serve as useful models of apps that both monitor and provide feedback, which might also enhance reward and motivation.

Most fitness programs chart progress and graph weekly consumptions of calories, miles run, or sit-ups completed (e.g., MyFitnessPal and SHealth). Feedback may be an especially effective tool, given previous research that suggests that feedback programs can be useful even in difficult-to-treat areas of psychopathology such as substance abuse (Gustafson et al., 2008). For this reason, our group has drafted a feedback template that provides basic information (e.g. number of social interactions, activity level) that can be graphed and that can combine the data to yield an overall level (color coded) of risk and resilience. This will require a number of evaluation trials and multivariate statistics to identify the best combination of predictors of depression and better health.

A factor that can limit the generalizability of the current findings relates to potential differences between Android and iPhone users. Marketing trends indicate that Android smartphones are currently outselling iPhones (iOS platform). Research suggests that Android users tend to be less represented in the 18-24 age bracket (Android- 16% vs. iOS- 19%) and are less wealthy than users of the iOS platform (comScore, 2013). While utilizing an iOS platform seems preferable, the capabilities and security of the application would be prohibitively restrictive. Apple products limit application availability in that all apps must be downloaded on the Apple Store. The Apple Store is potentially an open source and would allow anyone to download our

application. Android phones offer an alternative to Apple's more restrictive method of sharing applications, which allows for better control and security of data. The vast number of possible models of smartphones also brings difficulties adapting the app to the different models and interpreting the passive data (e.g., differences of accelerometer and gyroscope across models of phones).

Another important component that may be a limiting factor in the current study design is the two-week data collection period. This study was intended to examine the feasibility of the app and the intercorrelations between the domain variables in the period of time that will be used in future studies using a two-week burst design. Salthouse and Nesselroade (2010) recommend a burst-design approach to data collection, which takes snapshots of data over a longer time course; for example, two weeks every other month for a year. This maximizes the window to describe change or variability in behavior, while simultaneously reducing burden for participants. This could be especially helpful to offset burden in a depressed sample.

While the collection methods of many passive variables in this study are sophisticated, the tools to analyze them can be limited. This is particularly true in the linguistic analysis of emails and text messages. The LIWC program is largely unable to capture contextually based information (Tausczik & Pennebaker, 2010), especially in an ever increasing text message-based language. For example, words that can be used in multiple contexts or locale-specific idioms can often be miscoded into a single linguistic category on the LIWC program. The word 'sick' can occur in multiple contexts such as, "I found a *sick* dog that was extremely malnourished" or "I found a

sick dog that can do lots of tricks.” Sick in the latter sentence is slang for a positive value or quality, whereas the former indicates illness. This becomes even more salient in a depressed population, where text such as, “I’ll never be *happy*” or, “The pizza shop is right *down* the street” would be coded by the LIWC as a positive and negative emotion, respectively. This coding would not capture the essence of the sentences.

The lack of contextual cues in the passive data is not limited to the text analysis. For instance, the number of social contacts (daily number of texts, emails, or phone calls) was conceptualized as an indicator of engagement with others, but it is not clear for instance, whether the engagement is due to distress that the person was experiencing or to seeking enjoyment and pleasurable contact.

4.3 Future Directions

4.3.1 Passive data training

The Health and Wellness UDTracker application has a number of features that were not included in this paper because data were not yet available. In addition to the surveys and passive data collected on emails, texts, and phone calls, the application collects information about the location of the phone (GPS and Wi-Fi), orientation and movement of the phone (accelerometer and gyroscope), voice on phone calls, application type use, and general phone information indicating activity (e.g. power on/off, backlight). The associations between these variables and the mood-related variables will be examined, as in the current set of analyses.

In order to take advantage of all aspects of the passive data collection, training periods are common to establish standardizations for these variables, or “training data”

(Lane et al., 2014; Lu et al., 2010; Ravi, Dandekar, Mysore, & Littman, 2005).

Training periods consist of laboratory testing of certain functionalities, such as accelerometer, gyroscope, or GPS data. During these trials, participants or researchers perform a number of tasks (e.g., standing, sitting, walking, jumping, or running) with real-time data capture denoting changes in activity. Once these trials have been concluded, algorithms can be created and applied to the current data set to identify higher or lower levels of activity.

4.3.2 App improvements

One of the goals of this study was to identify superfluous functionalities to create a more streamlined application that will reduce burden for participants. Participant feedback helped to highlight certain problem areas that can be modified to decrease battery consumption, increase dynamic question banks, and reduce privacy concerns by removing collection of certain features, which were rarely used during the two-week period (e.g., emails). Some features of the phone are measured every five minutes for 30 seconds. These functionalities (GPS, Wi-Fi access, App access, and accelerometer) tend to draw heavily on power supply but yield precise data for that small window. In a training data study for accelerometers (study aimed at differentiating types of activity based on certain phone functionalities), researchers suggest that a shorter window, approximately 5 seconds, is adequate to interpret accelerometer data accurately (Ravi, Dandekar, Mysore, & Littman, 2005). If the duration of these data collection bursts can be minimized, it may help conserve battery.

4.3.3 Feedback

Unrelated to phone functioning, improvements of the graphical user interface are also indicated. To facilitate continual engagement of the user over longer periods of time, dynamic data collection may include variation in question types such as visual exemplar selection, Cartesian plane sorting, or sentence completion. As mentioned above, a limitation of the application in its current state is the repetitiveness of survey items. This barrier can be particularly troublesome for depressed individuals with avoidant features who may find the repetition too burdensome.

As the ultimate intent for this application is to reduce relapse in depression, we have created a draft of a feedback system that will be computed and delivered by the app. The feedback system will consist of weekly generated reports of the five areas of functioning highlighted in this paper. Akin to modern day intelligence testing or other models of factor analysis, the feedback system will utilize individualized items to compute a composite score and generate an overall score for the target week. Participants will be able to draw comparisons week to week in each of the five domains. Generated feedback may also serve as the basis for setting and monitoring goals and for activating information on relevant therapeutic skills. The results of the feedback can serve as a monitoring tool, often used in many cognitive treatments (Beck, Rush, Shaw, & Emery, 1979). In order to successfully integrate the feedback system, an estimation of item incremental validity or contribution to a broader factor should be conducted and would also serve to streamline the surveys by eliminating ineffective or irrelevant items.

The current feasibility study raises many questions and suggests domain items that might warrant reconsideration or revision, the application has been shown to be an effective data collection tool. The Health and Wellness UDTracker application will require more development and testing, but a number of the passive and active variables are showing associations with baseline depression symptoms and mood-related variables. The findings from this initial study suggest possibilities for improving app functionality and streamlining the variables in the domains of risk and wellness. This application, and others like it, might help to expand the ways in which treatment and prevention programs are delivered, stepping into the world of dissemination of implementation science.

REFERENCES

- Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review, 30*(2), 217-237. doi:10.1016/j.cpr.2009.11.004
- American Psychiatric Association (2013). *Diagnostic and statistical manual of mental disorders: DSM-5*. Washington, D.C.: American Psychiatric Association.
- Azevedo Da Silva, M., Singh-Manoux, A., Brunner, E. J., Kaffashian, S., Shipley, M. J., Kivimäki, M., Nabi, H. (2012). Bidirectional association between physical activity and symptoms of anxiety and depression: The Whitehall II study. *European Journal of Epidemiology, 27*(7), 537-46. doi:10.1007/s10654-012-9692-8
- Backs-Dermott, B. J., Dobson, K. S., & Jones, S. L. (2010). An evaluation of an integrated model of relapse in depression. *Journal of Affective Disorders, 124*(1-2), 60-67. doi:10.1016/j.jad.2009.11.015
- Beck, A.T., Rush, A.J., Shaw, B.F., & Emery, G. (1979). *Cognitive therapy of depression*. New York: Guilford.
- Beck, A.T., Steer, R.A., & Brown, G.K. (1996). *Manual for the Beck Depression Inventory-II*. San Antonio, TX: Psychological Corporation.
- Berkman, L. F., Blumenthal, J., Burg, M., Carney, R. M., Catellier, D., Cowan, M. J., ...Schneiderman, N. (2003). Effects of treating depression and low perceived social support on clinical events after myocardial infarction: The enhancing recovery in coronary heart disease patients (ENRICH) randomized trial. *JAMA: Journal of the American Medical Association, 289*(23), 3106-3116. doi:10.1001/jama.289.23.3106
- Beshai, S., Dobson, K. S., Bockting, C. L. H., & Quigley, L. (2011). Relapse and recurrence prevention in depression: Current research and future prospects. *Clinical Psychology Review, 31*(8), 1349-1360. doi:10.1016/j.cpr.2011.09.003

- Burcusa, S. L. & Iacono, W. G. (2007). Risk for recurrence in depression. *Clinical Psychology Review*, 27(8), 959-985. doi:10.1016/j.cpr.2007.02.005
- Buysse, D. J., Reynolds III, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh sleep quality index: A new instrument for psychiatric practice and research. *Psychiatry Research*, 28(2), 193-213. doi:10.1016/0165-1781(89)90047-4
- Bylsma, L.M., Taylor-Clift, A., & Rottenberg, J. (2011). Emotional Reactivity to Daily Events in Major and Minor Depression. *Journal of Abnormal Psychology*, 120(1), 155-167. doi:10.1037/a0021662
- Camacho, T. C., Roberts, R. E., Lazarus, N. B., Kaplan, G. A., & Cohen, R. D. (1991). Physical activity and depression: Evidence from the alameda county study. *American Journal of Epidemiology*, 134(2), 220-31.
- Carver, C. S., Scheier, M. F., & Weintraub, J. K. (1989). Assessing coping strategies: A theoretically based approach. *Journal of Personality and Social Psychology*, 56, 267-283. doi:10.1037/0022-3514.56.2.267
- Chalder, M., Wiles, N. J., Campbell, J., Hollinghurst, S. P., Hasse, A. M., Taylor, A. H., Fox, K.R., Costelloe, C., Searle, A., Baxter, H., Winder, R., Wright, C., Turner, K. M., Calna, M., Lawlor, D. A., Peters, T. J., Shard, D. J., Montgomery, A. A., & Lewis, G. (2012). Facilitated physical activity as a treatment for depressed adults: Randomised controlled trial. *BMJ (Clinical Research Ed.)*, 344(2758), 1-13. doi:10.1136/bmj.e2758.
- comScore Inc. (2013). *Mobile Future in Focus 2013*. Retrieved from <https://www.comscore.com/Insights/Presentations-and-Whitepapers/2013/2013-Mobile-Future-in-Focus2>.
- Cooney, G., Dwan, K., & Mead, G. (2014). Exercise for depression. *Journal-American Medical Association*, 311(23), 2432-2433. doi:10.1001/jama.2014.4930.
- Craighead, W. E., Miklowitz, D. J., & Craighead, L. W. (2013). *Psychopathology: History, Diagnosis, and Empirical Foundations*, 2nd Ed. Hoboken, NJ: John Wiley and Sons., Inc.
- De Choudhury, M., Gamon, M., Counts, S., & Horvitz, E. (2013). Predicting depression via social media. *Proceedings of the Seventh International AAAI Conference on Weblogs and Social Media*, Bellevue, WA. 128-137.

- Depp, C. A., Mausbach, B., Granholm, E., Cardenas, V., Ben-Zeev, D., Patterson, T.L., Lebowitz, B. D., & Jeste, D. V. (2010). Mobile interventions for severe mental illness: Design and preliminary data from three approaches. *The Journal of Nervous and Mental Disease*, 198(10), 715-721. doi:10.1097/NMD.0b013e3181f49ea3.
- Dey, S., Roy, N., Xu, W., Choudhury, R. R., & Nelakuditi, S. (2014). AccelPrint: Imperfections of accelerometers make smartphones trackable. *NDSS Symposium 2014*, San Diego, CA.
- Disner, S. G., Beevers, C. G., Haigh, E. A., & Beck, A. T. (2011). Neural mechanisms of the cognitive model of depression. *Nature Reviews Neuroscience*, 12(8), 467-77. doi: 10.1038/nrn3027.
- Dunn, A. L., Trivedi, M. H., Kampert, J. B., Clark, C. G., & Chambliss, H. O. (2005). Exercise treatment for depression. *American Journal of Preventive Medicine*, 28(1), 1-8. doi:10.1016/j.amepre.2004.09.003
- Fava, G. A. (1999). Well-being therapy: conceptual and technical issues. *Psychotherapy and Psychosomatics*, 68(4), 171-179. doi:10.1159/000012329
- Folkman, S., & Moskowitz, J. T. (2000). Positive affect and the other side of coping. *American Psychologist*, 55(6), 647-654. doi:10.1037/0003-066X.55.6.647
- Fredman, L., Weissman, M. M., Leaf, P. J., & Bruce, M. L. (1988). Social functioning in community residents with depression and other psychiatric disorders: Results of the New Haven epidemiologic catchment area study. *Journal of Affective Disorders*, 15(2), 103-122.
- Freelon, D. (2013). ReCal OIR: Ordinal, interval, and ratio intercoder reliability as a web service. *International Journal of Internet Science*, 8(1), 10-16.
- Germain, A., & Kupfer, D. J. (2008). Circadian rhythm disturbances in depression. *Human Psychopharmacology: Clinical and Experimental*, 23(7), 571-585. doi:10.1002/hup.964
- Geschwind, N., Nicolson, N. A., Peeters, F., van Os, J., Barge-Schaapveld, D., & Wichers, M. (2011). Early improvement in positive rather than negative emotion predicts remission from depression after pharmacotherapy. *European Neuropsychopharmacology*, 21, 241-247. doi:10.1016/j.euroneuro.2010.11.004

- Gotlib, I. H. & Joormann, J. (2010). Cognition and depression: Current status and future directions. *Annual Review of Clinical Psychology*, 6, 285-312. doi:10.1146/annurev.clinpsy.121208.131305.
- Gross, J. J. (2007). *Handbook of emotion regulation*. New York: Guilford Press.
- Gustafson, D. H., Shaw, B. R., Isham, A., Baker, T., Boyle, M. G., & Levy, M. (2011). Explicating an evidence-based, theoretically informed, mobile technology-based system to improve outcomes for people in recovery for alcohol dependence. *Substance use & Misuse*, 46(1), 96-111. doi:10.3109/10826084.2011.521413.
- Haefffel, G. J., & Grigorenko, E. L. (2007). Cognitive vulnerability to depression: Exploring risk and resilience. *Child and Adolescent Psychiatric Clinics of North America*, 16(2), 435-448. doi:10.1016/j.chc.2006.11.005
- Harris, E. C., & Barraclough, B. (1997). Suicide as an outcome for mental disorders. A meta-analysis. *The British Journal of Psychiatry*, 170(3), 205. doi:10.1192/bjp.170.3.205
- Hayes, A. M., Beevers, C. G., Feldman, G. C., Laurenceau, J.-P., & Perlman, C. (2005). Avoidance and processing as predictors of symptom change and positive growth in an integrative therapy for depression. *International Journal of Behavioral Medicine*, 12(2), 111-22.
- Hemingway, H., & Marmot, M. (1999). Psychosocial factors in the aetiology and prognosis of coronary heart disease: systematic review of prospective cohort studies. *BMJ: British Medical Journal*, 318(7196), 1460-1467.
- Hill, C. E., Thompson, B. J., & Williams, E. N. (1997). A guide to conducting consensual qualitative research. *Counseling Psychologist*, 25(4), 517-72.
- Hirschfeld, R. M., Montgomery, S. A., Keller, M. B., Kasper, S., Schatzberg, A. F., Möller, H. J., Healy, D., Baldwin, D., Humble, M., Versiani, M., Montenegro, R., & Bourgeois M. (2000). Social functioning in depression: A review. *The Journal of Clinical Psychiatry*, 61(4), 268-75.
- Hollon, S. D., & Ponniah. K. (2010). A review of empirically supported psychological therapies for mood disorders in adults. *Depression and Anxiety*, 27(10), 891-932. doi:10.1002/da.20741.

- Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social Relationships and Mortality Risk: A Meta-analytic Review. *PLoS Medicine*, 7(7), e1000316. doi:10.1371/journal.pmed.1000316
- Hunt, M., Auriemma, J., & Cashaw, A. C. (2003). Self-report bias and underreporting of depression on the BDI-II. *Journal of Personality Assessment*, 80(1), 26-30. doi: 10.1207/S15327752JPA8001_10
- Hurley, D. B., & Kwon, P. (2012). Results of a study to increase savoring the moment: Differential impact on positive and negative outcomes. *Journal of Happiness Studies*, 13(4), 579-588. doi:10.1007/s10902-011-9280-8
- Joormann, J., & Gotlib, I. H. (2010). Emotion regulation in depression: Relation to cognitive inhibition. *Cognition & Emotion*, 24(2), 281-98. doi:10.1080/02699930903407948.
- Joormann, J., & Quinn, M. E. (2014). Cognitive processes and emotion regulation in depression. *Depression and Anxiety*, 31(4), 308-315. doi:10.1002/da.22264
- Joormann, J., & Siemer, M. (2004). Memory accessibility, mood regulation, and dysphoria: Difficulties in repairing sad mood with happy memories? *Journal of Abnormal Psychology*, 113(2), 179-188. doi:10.1037/0021-843X.113.2.179
- Judd, L. L. (1997). The clinical course of unipolar major depressive disorders. *Archives of General Psychiatry*, 54(11), 989-91.
- Kessler, R. C., Berglund, P., Demler, O., Jin, R., Merikangas, K. R., & Walters, E.E. (2005). Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the national comorbidity survey replication. *Archives of General Psychiatry*, 62(6), 593-602. doi:10.1001/archpsyc.62.6.593
- Kok, G., Bockting, C., Burger, H., Smit, F., & Riper, H. (2014). Mobile cognitive therapy: Adherence and acceptability of an online intervention in remitted recurrently depressed patients. *Internet Interventions*, 1(2), 65-73. doi:10.1016/j.invent.2014.05.002
- Lane, N., Lin, M., Mohammad, M., Yang, X., Lu, H., Cardone, G., . . . Choudhury, T. (2014). BeWell: Sensing sleep, physical activities and social interactions to promote wellbeing. *Mobile Networks and Applications*, 19(3), 345-359. doi:10.1007/s11036-013-0484-5.
- Lecrubier, Y. (2001). Prescribing patterns for depression and anxiety worldwide. *Journal of Clinical Psychiatry*, 62(Suppl13), 31-36.

- LiKamWa, R., Liu, Y., Lane, N. D., & Zhong, L. (2013). MoodScope: building a mood sensor from smartphone usage patterns. In *Proceeding of the 11th annual international conference on Mobile systems, applications, and services* (MobiSys '13). ACM, New York, NY, USA, 389-402. doi:10.1145/2462456.2464449
- Lopresti, A. L., Hood, S. D., & Drummond, P. D. (2013). A review of lifestyle factors that contribute to important pathways associated with major depression: Diet, sleep and exercise. *Journal of Affective Disorders, 148*(1), 12-27. doi:10.1016/j.jad.2013.01.014
- Lu, H., Yang, J., Liu, Z., Lane, N.D. Choudhury, T., & Campbell, A.T. (2010). The Jigsaw continuous sensing engine for mobile phone applications. In *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems* (SenSys '10). ACM, New York, NY, USA, 71-84. doi:10.1145/1869983.1869992
- Luxton, D. D., McCann, R. A., Bush, N. E., Mishkind, M. C., & Reger, G. M. (2011). MHealth for mental health: Integrating smartphone technology in behavioral healthcare. *Professional Psychology: Research and Practice, 42*(6), 505-512. doi:10.1037/a0024485
- Mason, E. C., & Harvey, A. (2014). Insomnia before and after treatment for anxiety and depression. *Journal of Affective Disorders, 168*, 415-21. doi:10.1016/j.jad.2014.07.020
- Mathers, C., Boerma, T., & Ma Fat, D. (2008). The global burden of disease: 2004 update. Geneva, Switzerland: World Health Organization. Retrieved from http://www.who.int/healthinfo/global_burden_disease/GBD_report_2004update_full.pdf
- Murray C.J., & Lopez, A. D. (1997). Alternative projections of mortality and disability by cause 1990-2020: Global burden of disease study. *Lancet, 349*(9064), 1498-504. doi:10.1016/S0140-6736(96)07492-2
- Nolen-Hoeksema, S., & Morrow, J. (1991). A prospective study of depression and posttraumatic stress symptoms after a natural disaster: The 1989 Loma Prieta earthquake. *Journal of Personality and Social Psychology, 61*(1), 115-21.
- Nolen-Hoeksema, S. (2000). The role of rumination in depressive disorders and mixed anxiety/depressive symptoms. *Journal of Abnormal Psychology, 109*(3), 504-11. doi:10.1037/10021-843X.109.3.504

- Paffenbarger, R. S., Lee, I.-M., & Leung, R. (1994). Physical activity and personal characteristics associated with depression and suicide in American college men. *Acta Psychiatrica Scandinavica*, 89, 16-22. doi:10.1111/j.1600-0447.1994.tb05796.x
- Peeters, F., Berkhof, J., Delespaul, P., Rottenberg, J., & Nicolson, N. A. (2006). Diurnal mood variation in major depressive disorder. *Emotion*, 6(3), 383-91. doi:10.1037/1528-3542.6.3.383
- Pennebaker, J. W., Booth, R. J., & Francis, M. E. (2007). *Operator's manual linguistic inquiry and word count: LIWC2007*, LIWC.net.
- Pennebaker, J. W. (2011). *The secret life of pronouns: What our words say about us*. New York: Bloomsbury Press.
- Pennebaker, J. W. (1997). Writing about emotional experiences as a therapeutic process. *Psychological Science*, 8(3), 162-166.
- Pizzagalli, D. A., Iosifescu, D., Hallett, L. A., Ratner, K. G., & Fava, M. (2008). Reduced hedonic capacity in major depressive disorder: Evidence from a probabilistic reward task. *Journal of Psychiatric Research*, 43(1), 76-87. doi:10.1016/j.jpsychires.2008.03.001
- Ravi, N., Dandekar, N., Mysore, P. & Littman, M.L. 2005. Activity recognition from accelerometer data. In *Proceedings of the 17th conference on Innovative applications of artificial intelligence - Volume 3 (IAAI'05)*, Bruce Porter (Ed.), Vol. 3. AAAI Press 1541-1546.
- Reger, G. M., Hoffman, J., Riggs, D., Rothbaum, B. O., Ruzek, J., Holloway, K. M., & Kuhn, E. (2013). The ``PE coach" smartphone application: An innovative approach to improving implementation, fidelity, and homework adherence during prolonged exposure. *Psychological Services*, 10(3), 342-349. doi:10.1037/a0032774
- Richards, D. (2011). Prevalence and clinical course of depression: A review. *Clinical Psychology Review*, 31(7), 1117-1125. doi:10.1016/j.cpr.2011.07.004
- Russell, J.A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161-1178.
- Ryff, C., & Keyes, C. (1995). The structure of psychological well-being revisited. *Journal of Personality and Social Psychology*, 69(4), 719-27.

- Ryff, C., & Singer, B. (2008). Know thyself and become what you are: A eudaimonic approach to psychological well-being. *Journal of Happiness Studies*, 9(1), 13-39. doi:10.1007/s10902-006-9019-0
- Salthouse, T. A., & Nesselroade, J. R. (2010). Dealing With Short-term Fluctuation in Longitudinal Research. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 65B(6), 698–705. doi:10.1093/geronb/gbq060
- Seligman, M. E. P., Rashid, T., & Parks, A. C. (2006). Positive psychotherapy. *American Psychologist*, 61(8), 774-788. doi:10.1037/0003-066X.61.8.774
- Shahar, B. & Herr, N. R. (2011). Depressive symptoms predict inflexibly high levels of experiential avoidance in response to daily negative affect: A daily diary study. *Behavior Research and Therapy*, 49, 676-681. doi:10.1016/j.brat.2011.07.006
- Shea, M. T., Elkin, I., Imber, S. D., & Sotsky, S. M. Watkins, J.T., Collins, J.F., Pilkonis, P.A., Beckham, E., Glass, D.R., Dolan, R.T., Paroloff, M.B. (1992). Course of depressive symptoms over follow-up: Findings from the national institute of mental health treatment of depression collaborative research program. *Archives of General Psychiatry*, 49(10), 782-787. doi:10.1001/archpsyc.1992.01820100026006
- Smith, A. (2013). Smartphone Ownership- 2013 Update- *Pew Research Center's Internet and American Life Project*. Retrieved from <http://www.pewinternet.org/2013/06/05/smartphone-ownership-2013/>
- Sowislo, J. F. & Orth, U. (2013). Does low self-esteem predict depression and anxiety? A meta-analysis of longitudinal studies. *Psychological Bulletin*, 139(1), 213-240. doi:10.1037/a0028931
- Tausczik, Y. & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1), 24-54. doi:10.1177/0261927X09351676
- Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuhl, M., Jonides, J., & Gotlib, I. H. (2012). The everyday emotional experience of adults with major depressive disorder: Examining emotional instability, inertia, and reactivity. *Journal of Abnormal Psychology*, 121(4), 819-29. doi:10.1037/a0027978

- Trew, J. L. (2011). Exploring the roles of approach and avoidance in depression: An integrative model. *Clinical Psychology Review, 31*(7), 1156-1168. doi:10.1016/j.cpr.2011.07.007
- Troy, A. S., Wilhelm, F. H., Shallcross, A. J., & Mauss, I. B. (2010). Seeing the silver lining: Cognitive reappraisal ability moderates the relationship between stress and depressive symptoms. *Emotion, 10*(6), 783-795. doi:10.1037/a0020262
- Treynor, W., Gonzalez, R., & Nolen-Hoeksema, S. (2003). Rumination reconsidered: A psychometric analysis. *Cognitive Therapy and Research, 27*(3), 247-259.
- Tsuno, N., Besset, A., & Ritchie K. (2005). Sleep and depression. *The Journal of Clinical Psychiatry, 66*(10), 1254-69. doi:10.4088/JCP.v66n1008
- Van Der Zanden, R., Curie, K., Kramer, J., Van Londen, M., Steen, G., & Cuijpers P. (2014). Web-based depression treatment: Associations of clients word use with adherence and outcome. *Journal of Affective Disorders, 160*, 10-13. doi:10.1016/j.jad.2014.01.005
- Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., & Campbell, A.T. (2014). Proceedings of the 2014 ACM International Joint Conference / Pervasive and Ubiquitous Computing (UbiComp '14). *Studentlife*. ACM, 2 Penn Plaza, Suite 701, New York, NY 10121-0701, USA.
- Watson, D., Clark, L. A., & Tellegen A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*(6), 1063-70.
- Weber, S., Puskar, K. R., & Ren, D. (2010). Relationships between depressive symptoms and perceived social support, self-esteem, & optimism in a sample of rural adolescents. *Issues in Mental Health Nursing, 31*(9), 584-588. doi:10.3109/01612841003775061
- Werner-Seidler, A., Banks, R., Dunn, B. D., & Moulds, M. L. (2013). An investigation of the relationship between positive affect regulation and depression. *Behaviour Research and Therapy, 51*(1), 46-56. doi:10.1016/j.brat.2012.11.001
- Wichers, M., Peeters, F., Geschwind, N., Jacobs, N., Simons, C. J. P., Derom, C, ...van Os, J. (2010). Unveiling patterns of affective responses in daily life may improve outcome prediction in depression: A momentary assessment study. *Journal of Affective Disorders, 124*(1-2), 191-195. doi:10.1016/j.jad.2009.11.010

Wichers, M., Simons, C. J. P., Kramer, I. M. A., Hartmann, J. A., Lothmann, C., Myin-Germeys, I., van Bemmelen, A. L., Peeters, F., Delespaul, P., van Os, J. (2011). Momentary assessment technology as a tool to help patients with depression help themselves. *Acta Psychiatr Scand* 124, 262–272. doi:10.1111/j.1600-0447.2011.01749.x

World Health Organization (2012). *Sixty-fifth world health assembly 2012*. Retrieved from <http://www.who.int/mediacentre/events/2012/wha65/journal/en/index4.html>.

Appendix

HUMAN SUBJECTS REVIEW BOARD APPROVAL LETTER



RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE: April 24, 2014

TO: Adele Hayes, Ph. D.
FROM: University of Delaware IRB

STUDY TITLE: [375698-4] Daily cognitive, emotional, and behavioral patterns of undergraduates: A smartphone feasibility study

SUBMISSION TYPE: Amendment/Modification
** Amendment Request to reopen the feasibility study to run an additional 100 subjects*

ACTION: APPROVED
APPROVAL DATE: April 24, 2014
EXPIRATION DATE: January 15, 2015
REVIEW TYPE: Full Committee Review

Thank you for your submission of Amendment/Modification materials for this research study. The University of Delaware IRB has APPROVED your submission. This approval is based on an appropriate risk/benefit ratio and a study design wherein the risks have been minimized. All research must be conducted in accordance with this approved submission.

This submission has received Full Committee Review based on the applicable federal regulation.

Please remember that informed consent is a process beginning with a description of the study and insurance of participant understanding followed by a signed consent form. Informed consent must continue throughout the study via a dialogue between the researcher and research participant. Federal regulations require each participant receive a copy of the signed consent document.

Please note that any revision to previously approved materials must be approved by this office prior to initiation. Please use the appropriate revision forms for this procedure.

All SERIOUS and UNEXPECTED adverse events must be reported to this office. Please use the appropriate adverse event forms for this procedure. All sponsor reporting requirements should also be followed.

Please report all NON-COMPLIANCE issues or COMPLAINTS regarding this study to this office.

Please note that all research records must be retained for a minimum of three years.

Based on the risks, this project requires Continuing Review by this office on an annual basis. Please use the appropriate renewal forms for this procedure.

If you have any questions, please contact Nicole Farnese-McFarlane at (302) 831-1110 or nicolefm@udel.edu. Please include your study title and reference number in all correspondence with this office.