Understanding Psychological Well-Being From the Behavioral Perspective

Understanding Psychological Well-being from the Behavioral Perspective

Jun Lin Flora Or

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Abstract

Despite the great burden of mood disorders, much of the treatment gap remains due to under-recognition. One way to alleviate this burden would be to target unhealthful behaviors that are more prevalent among those who experience symptoms of mood disorders. This dissertation aims to evaluate new ways to measure and to understand behaviors related to psychological well-being drawing from the fields of behavioral economics, marketing, and engineering in a systematic review (Paper 1), a mixed methods study (Paper 2), and an online survey and experiment (Paper 3). Paper 1 is a systematic review that evaluated the most up-to-date evidence on the feasibility of smartphone applications as a research tool for monitoring mood disorders. Using nine bibliographic databases, we identified 30 relevant studies that attempted to measure and quantify the five common phenotypic categories in the context of mood disorders: social activity, physical activity, sleep, voice, and mobility. Common limitations that impact the robustness of statistical inferences include sparse or lack of clinical assessments as gold standards, small sample size, and data incompleteness. There is high potential but limited evidence in using smartphone data to monitor mood disorders. In paper 2, we evaluated the motivations to use Electronic Nicotine Delivery Systems (ENDs) by conducting logistic regressions and thematic analyses on demographics, intention to quit, and experience with ENDs from a commercial online panel to evaluate the motivations to use ENDs. We identified health, image, enjoyment, and utility as the key motivation to use ENDs. With approximately half of the respondents cited non-health reasons, the reasons and preferences for ENDS varied by smoking status and types of ENDs used. In paper 3, we evaluated the relationships among depression, health behaviors, and intertemporal decisions that involve costs and rewards across different points in time. We found that sub-threshold depression was associated present bias but not impatience; whereas, high risks for depression was not associated with present bias or impatience. When primed, those who were depressed were more likely to take up commitment devices than those who were healthy.

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Smartphone Applications for Monitoring Mood Disorders

(Paper 1)

Flora Or, M.H.S.

Harvard T.H. Chan School of Public Health

Abstract

Background: Despite the great burden of mood disorders, much of the treatment gap remains due to under-recognition. The increasing prevalence of smartphone ownership creates an opportunity to better monitor behavioral phenotypes that are relevant to mood disorders. This review is aimed to evaluate the most up-to-date evidence on the feasibility of smartphone apps as a research tool for monitoring mood disorders.

Methods: We conducted the systematic search in nine bibliographic databases: Embase, PsycINFO, Web of Science, PubMed, CINAHL, EconLit, PAIS, ABI and INSPEC using search terms that capture the concepts of mood disorders and smartphone applications.

Results: The 30 included studies attempted to measure and quantify the following five phenotypic categories in the context of mood disorders: social activity, physical activity, sleep, voice, and mobility. Most included studies speculated that increased frequency in these phenotypes would indicate onset or relapse of a manic episode, and vice versa for major depressive episode. Common limitations that impact the robustness of statistical inferences include sparse or lack of clinical assessments as gold standards, small sample size, and data incompleteness.

Conclusions: There is high potential but limited evidence in using smartphone data to monitor moo disorders. Both internal and external validity of included studies were limited. Future studies should consider issues related to selection bias, information that can be learned from pattern of missing data, and within-person designs.

Mood disorders create great burden, yet much of the burden remains unaddressed globally (Kohn et al., 2004; Murray et al., 2013, Whiteford et al., 2013). The reasons for treatment gap include lack of awareness, limited access to care, denial of symptoms, stigma, and ineffective care (Kohn et al., 2004; Corrigan et al., 2002; Corrigan et al., 2009). Traditionally, the diagnosis and monitoring of mood disorders rely heavily on individuals' recall of symptoms and behaviors elicited during clinical interviews or in completing paper and pencil questionnaires. Recent studies have shown that recall bias in mood symptoms exist for recall periods as short as one day (Shiffman et al., 2008; Torous et al., 2015). In addition to unintentional biases, patients might have an incentive to misrepresent their symptoms to avoid hospitalization or changes in medication. Patients are more likely to consult their clinicians during a depressive episode rather than a manic episode, leading to misdiagnosis of bipolar disorder as unipolar depression (Hirschfeld, 2001; Bowden et al., 2014). Most current clinical practices are targeted at "an average patient," which often leads to ineffective treatments. The increasing prevalence of smartphones and the advances in smartphone technology might create opportunities for more personal, precise, and scalable screening, monitoring, and diagnosis of mood disorders. We define "screening" as early identification of risk for mood disorders to monitor change in symptoms or treatment outcomes over time, and we define "diagnosis" as the determination of the state of health by a clinician. (Težak, Kondratovich, & Mansfield, 2010). While no existing device has the capability to diagnose mood disorders, a typical smartphone has built-in accelerometer, touchscreen, GPS, camera, and Bluetooth and Wi-Fi that enable digital phenotyping (Onnela & Rauch, 2016). Digital Phenotyping refers to "the moment-by-moment quantification of the individual-level human phenotype in situ using data from smartphones or other personal digital devices." Research in this area is still in its infancy, and most investigations are pilot studies (Torous et al., 2015). Existing reviews of smartphone technologies for mood disorders are limited to those that primarily use this technology to field surveys, either using mobile web, phone calls or text messages (SMS) to solicit responses. There are some reviews that are specific to smartphone applications (apps) designed to screen, monitor and manage symptoms of mood disorders, all of which have appeared in the past three years (e.g., aan het Rot et al., 2012, Shen et al., 2015, Plaza et al., 2013, Martinez-Perez et al., 2013; Torous et al., 2015). To date, there is insufficient data to evaluate the effectiveness of smartphone apps to monitor mental health (Plaza et al., 2013; Donker et al., 2013; Mohr et al., 2013; Seko et al., 2014). The studies we reviewed suggested that smartphone apps have tremendous potential to advance mental health research and practice. As the scientific literature in this area has grown rapidly in the past two years, this review is aimed to evaluate the most up-to-date evidence on the feasibility of smartphone apps as a research tool for monitoring mood disorders.

Method

With the help of a professional librarian, we conducted the systematic search in nine bibliographic databases: Embase, PsycINFO, Web of Science, PubMed, CINAHL, EconLit, PAIS, ABI and INSPEC. We used controlled vocabularies (e.g., MESH terms) including "mobile applications," "cell(ular) phones," "mobile device," "software applications," and text words including iPhone, iPad, Android, Android tablets, Blackberries to identify studies that used smartphone as a research platform. To identify literature on mood disorders, we used controlled vocabulary including "mood disorders," "affective disorders," "depression (emotion)," "dysthymic disorder," "endogenous depression," "postpartum depression," "recurrent depression," "treatment resistant depression," "bipolar disorders," "major depression," "mania," "seasonal affective disorders," along with synonyms of these conditions as text words appearing in abstracts or titles in our searches. We combined searches for the respective topic with a logical "AND" to identify literature at the intersection of smartphone applications and mood disorders. We did not impose limits on publication date, and we last updated this search on January 22, 2017. We submitted requests through the library for studies that were not immediately available. Unpublished studies are included in this review. Two authors (FO and JS) screened the titles, abstracts and texts based on the following inclusion and exclusion criteria.

Inclusion Criteria

We include articles that meet all the inclusion criteria: (1) documented empirical studies (2) were written in English; (2) used passive smartphone data; (3) were aimed at screening or monitoring mood disorders; (4) were conducted in humans.

Exclusion Criteria

We excluded titles or abstracts written in languages other than English. We also excluded non-empirical studies (i.e., comment, opinion or narratives) or empirical studies that involved non-human subjects, as well as studies that used “app” in a different meaning (i.e., abbreviation for other objects or concepts). In order not to duplicate previous reviews, we excluded studies that used ecological momentary assessment (EMA) because a comprehensive review on studies using electronic self-monitored mood has been recently published (Maria Faurholt-Jepsen, Munkholm, Frost, Bardram, & Kessing, 2016). To ensure specificity and relevance of this rapidly progressing area of research inquiry, we excluded computer-based, web-based, or text-based studies, and effects of smartphone use (e.g., addiction). Since therapeutic smartphone apps involve functions that greatly differ from those designed to monitor mood disorders, we also excluded studies that used apps for treatment purposes. Figure 1.1 depicts the flowchart of the study selection process.

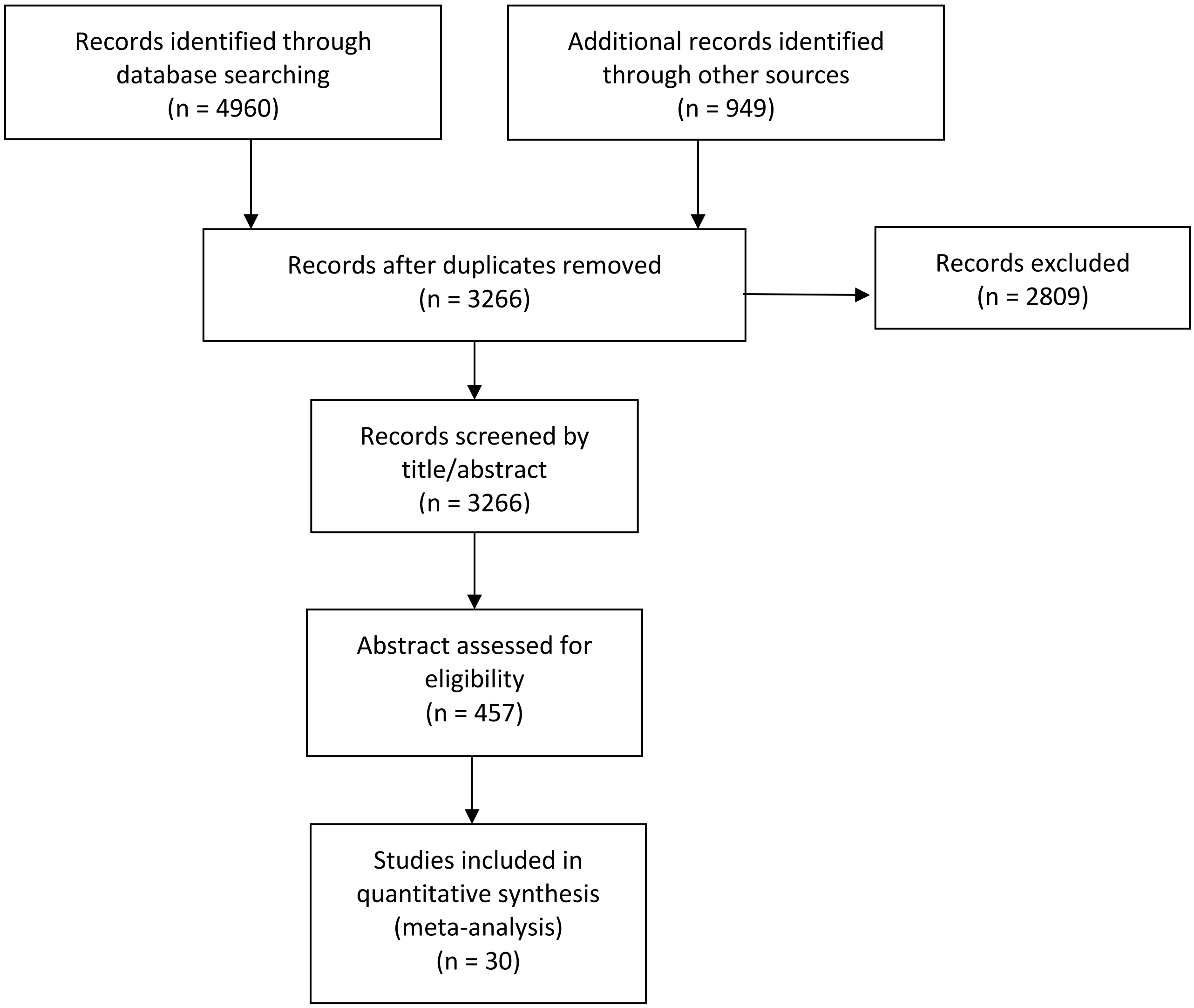

Figure 1.1 Flowchart of Studies Selection

Results

The nine database searches identified a total of 4960 articles. We removed 1694 duplicates based on authors and titles. We screened 3266 articles based on the inclusion and exclusion criteria listed in the previous section. We excluded 2809 publications by titles or abstracts. We assessed the abstracts of the remaining 457 records and included 30 studies conducted in various parts of the U.S. or Europe in the current review. Included studies recruited clinical patients in the hospital, clinical patients in the community, and non-clinical participants for studies that lasted from one week to one year in their respective countries. These included studies to evaluate the feasibility of using smartphone sensors, including GPS, accelerometer, and Wi-Fi and Bluetooth to monitor variation in mood disorder symptoms. The incentive structure varied in the types of payment (i.e., financial vs. goods), amount, and qualifying requirements across studies. A number of studies did not offer financial incentives for participation (M. Faurholt-Jepsen, Frost, et al., 2014; M. Faurholt-Jepsen et al., 2015);(A. Grünerbl, Oleksy, P., Bahle, G., Haring, C., Weppner, J., & Lukowicz, P. , 2012; V. Osmani, Maxhuni, A., Grünerbl, A., Lukowicz, P., Haring, C., & Mayora, O. , 2013). The incentives across studies were listed in Table 1.1. The included papers evaluated a total of 16 unique apps that aimed to monitor mood disorders. Six of the apps were aimed at monitoring bipolar disorders in clinical cohorts, and the remainder of the apps aimed to screen for depression in community settings, such as among university students and users of craigslist which is an American classified advertisement website. Table 1.2 summarizes the functionality and characteristics of these apps.

Table 1.1 Overview of Included Studies

Study, country, n	**Adherence**	**Duration**	**App**	**Condition (diagnostic criteria)**	**Inpatient/outpatient/community**	**Incentive**
Abdullah et al., 2016, U.S. (n=7)	NA	4 weeks	Mood Rhythm	Bipolar disorders (clinically diagnosed, criteria not specified)	Outpatient	$50 for each week of participation, $25 for each completed questionnaire and $50 for the final interview. Patient compensation was not contingent on adherence to the daily protocol of use.
Giudi et al., 2015, France (n=1)	NA	14 weeks	PSYCHE	Bipolar II (DSM-IV-TR)	Outpatient	NA
Grunerbl et al., 2015, Austria (n=10)	19 - 71 out of 84 datasets per patient per day	12 weeks	MONARCA	Bipolar (ICD 10)	Inpatient/ outpatient	NA
Karam et al., 2014, U.S.(n=6)	NA	6 months	PRIORI	Bipolar disorders (clinically diagnosed, criteria not specified)	Outpatient	NA
Maxhuni et al., 2016, Austria	NA	12 weeks	MONARCA	Bipolar (ICD 10)	Inpatient/ outpatient	NA

(n=5)						
Muaremi et al., 2014, Austria (n=12)	NA	12 weeks	MONARCA	Bipolar disorders (clinically diagnosed, critiera not specified)	Inpatient/ outpatient	NA
Osmani et al., 2015, Austria (n=12)	NA	12 weeks	MONARCA	Bipolar disorders (clinically diagnosed, critiera not specified)	Inpatient/outp atient	NA
Faurholt-Jepsen, et al., 2016a, Denmark (n=29)	NA	12 weeks	MONARCA	Bipolar (ICD 10)	Outpatient	No compensation
Dang et al., 2016, Germany (n=4)	NA	1 week	Fine	MDD (clinically diagnosed, criteria not specified)	Outpatient	NA
Beiwinkel et al., 2016, Germany (n=13)	55.7% (no clinician feedback); activity: 78.2%; social data 56.1%	12 months	SIMBA	Bipolar (DSM-IV)	Outpatient	NA
Ben-Zeev et al., 2015, US (n=47)	One-time self-assessment at week-10 was 78%	10 week	FOCUS	Healthy/MDD (NA)	Community	T-shirts and raffle of multiple Jawbone UP wristbands, and Google Nexus smartphone at various weeks

Faurholt-Jepsen, et al., 2014, Denmark (n=17)	Daily self-assessment (10-week) 87 (with clinician feedback)	3 months	MONARCA	Bipolar (ICD 10)	Outpatient	No compensation
Faurholt-Jepsen, et al., 2015, Denmark (n=61)	NA	6 months	MONARCA	Bipolar (ICD 10)	Outpatient	No compensation
Frost et al., 2013, Denmark, (n=6)	Daily self assessment 91% (with clinician feedback)	6 months	MONARCA 2.0	Bipolar disorders (clinically diagnosed, criteria not specified)	Outpatient	No compensation
Grunerbl et al., 2012, Austria (n=10)	NA	8weeks	MONARCA	Bipolar disorders (clinically diagnosed, criteria not specified)	Inpatient/ outpatient	Study phone
Grunerbl et al., 2014, Austria (n=12)	NA	12 weeks	MONARCA	Bipolar (ICD 10)	Inpatient/outpatient	NA
Osmani et al., 2013, Austria (n=9)	NA	3 months	MONARCA	Bipolar (ICD 10)	Inpatient/outpatient	NA
Prociow et al., 2012, UK (n=4 healthy, 1 bipolar)	NA	2 weeks	NA	Healthy/bipolar (self-identified)	Outpatient	NA
Saeb et al., 2015a, US (n=28)	NA	2 weeks	Purple Robot	Healthy/MDD (self-identified)	Community	NA

Asselbergs et al. 2016, Netherlands (n=27)	daily self-assessment 88.8%	6 weeks	iYouVU	Healthy/MDD (self-identified)	Community	EMA response rates ≥50%: €20; rates ≥75%: €35; rates ≥95%: €47.50
Braun et al., 2016, Germany and Spain (n=36)	NA	2 weeks	VoiceApp	Healthy/MDD (self-identified)	Community	NA
Canzian et al., 2016, UK, (n=28)	Mood Traces	2 weeks	MoodTraces	Healthy/MDD (self-identified)	Community	One winner of a Nexus 5 mobile phone and five winners that have received a 10 pounds Amazon voucher each among all the participants that have completed the daily questionnaire at least 50 times in a two-month span.
Farhan et al., 2016a, US (n=79)	NA	Undetermined	LifeRhythm	Healthy/MDD (self-identified/DSM-5)	Community	$15 Amazon gift card for every two weeks of active

						participation
Farhan et al., 2016b, US (n=60)	NA	10 weeks	StudentLife	Healthy/MDD (self-identified)	Community	NA
Faurholt-Jepsen, et al., 2016b, Denmark (n=28)	NA	12 weeks	MONARCA	Bipolar (ICD 10)	Outpatient	NA
Gideon, et al., 2016, US (n=37)	NA	6-12 months	PRIORI	Bipolar disorders (clinically diagnosed, criteria not specified)	Outpatient	NA
Hung et al., 2016, Taipei (n=28)	NA	2 weeks	iHOPE	Healthy (self-identified)	Community	NA
Saeb et al., 2016, US (n=48)	NA	10 weeks	StudentLife	Healthy/MDD (self-identified)	Community	NA
Saeb et al., 2015b, US (n=18)	NA	2 weeks	Purple Robot	Healthy/MDD (self-identified)	Community	$35 per week
Wahle et al., 2016, Switzerland and Germany (n=126)	22.2% provided 2 self assessment for >4 weeks	8 weeks	MOSS	Healthy/MDD (self-identified)	Community	NA

Table 1.2. Overview of Smartphone Applications

App	Plat-form	Passive Data Streams	Bipolar or MDD	Commercial	Personal vs. Study Phone
MONARCA	Android	Audio, communication, GPS and accelerometer	Bipolar	No	Personal or study phone
MONARCA 2.0	Android	Audio, communication, GPS, accelerometer, phone usage	Bipolar	No	NA
Mood Rhythm	iOS/ Android	Audio, communication, GPS, accelerometer, Wi-fi, network	Bipolar	No	Study phone
PRIORI	Android	Audio	Bipolar	No	Study phone
PSYCHE	Android	Audio	Bipolar	No	NA
SIMBA	Android	GPS, communication, network	Bipolar	NA	Study phone
Fine	Android	Communication, GPS and accelerometer, phone usage	MDD		Study phone
FOCUS	Android	Audio, GPS, accelerometer, Wi-fi, light sensor	MDD	No	Study phone
iHOPE	Android	Communication and phone usage	MDD	No	Personal phone
iYouVU	Android	Communication, accelerometer, phone usage, phone camera log	MDD	No	Personal phone
LifeRhythm	iOS/ Android	GPS, accelerometer, network	MDD	No	Personal phone
MoodTraces	Android	GPS	MDD	Yes	Personal phone
MOSS	Android	Communication, GPS, accelerometer, phone usage, schedule	MDD	No	NA
Purple Robot	Android	GPS, phone usage	MDD	Yes	Study phone
StudentLife	iOS/ Android	Audio, communication, GPS and accelerometer, phone usage, light sensor	MDD	No	Personal or study phone
VoiceApp	Android	Audio	MDD	No	NA

Data completeness

Incompleteness of data appeared to be a common problem in most reviewed studies. In general, there are two types of missingness in smartphone data – planned and unplanned. Planned missingness occurs when the sensors (e.g., GPS) are programmatically triggered only at certain times to save battery (Asselbergs et al., 2016; Canzian & Musolesi, 2015). In contrast, unplanned missingness occurs either because of technical issues, or non-adherence. Adherence is generally defined by the extent to which participants engage in the behavior of interest as instructed by the researcher(s) over a defined period of time (Dunbar, 1984). The reviewed studies applied the definition of adherence differently, including the extent to which participants had their phone sensors enabled, or the proportion of completed survey-based self-assessment or clinical assessment. Most studies claimed smartphone apps to be excellent disease management tools because they require little input from the patients and, in addition, individuals in the general population often carry their phones on them (Prociow, Wac, & Crowe, 2012b). Studies also reported surprise at the large amount of missing data from different smartphone data streams. Missing data was typically due either to patients turning off phone sensors to conserve the smartphone battery or reduced frequency of using a study phone over time (Asselbergs et al., 2016; Dang, Mielke, Diehl, & Haux, 2016; A. Grunerbl et al., 2015). Some included studies (66.7%) used study phones rather than personal phones, and we speculate that this might be a reason for missing data. The ways individuals use their personal phones might be different from how they use study phones, and additional complication might result from assigning participants test phones that are different from their own personal phones (Belisario, 2015). Existing literature suggests that patients refuse to use study phones to make phone calls and do not carry study phones on them at all times (D. Ben-Zeev, E. A. Scherer, R. Wang, H. Xie, & A. T.

Campbell, 2015; M. Frost, Doryab, A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. , 2013; A. Grunerbl et al., 2015; A. Muaremi, Gravenhorst, Grunerbl, Arnrich, & Troster, 2014).

Adherence to completing self-assessments varied across different incentive structures; see Table 1.1. The adherence rate of completing a one-time self-assessment at week-10 was 78% in a student sample, where adherence was incentivized by raffling of technological products (D. Ben-Zeev, E. A. Scherer, et al., 2015). In contrast, the adherence rate for self-assessment and not deleting the app on the smartphones for four weeks or more was 22.2% in a community sample where the subjects did not receive any financial incentive. Bipolar patients seemed to respond positively to non-monetary incentive, such as in-app badges, and they completed self-assessment of daily social rhythm more frequently than the minimum requirement (Saeed Abdullah, 2016). The adherence rate of bipolar patients' daily self-assessment who received feedback from clinicians ranged from 88 to 91% (M. Faurholt-Jepsen, Vinberg, et al., 2014; M. Frost, Doryab, A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. , 2013), while bipolar patients who did not receive any feedback completed self-reports 55.7% of the time (Beiwinkel et al., 2016).

Another reason for incomplete data was that some of the reviewed studies excluded data either because of its low quantity or low quality. In a 12-week observational study where each bipolar patient was expected to generate 84 datasets from GPS, accelerometer, call and text logs and microphone, only 19 to 71 smartphone datasets per patient were used in the data analysis (A. Grunerbl et al., 2015). When smartphone audio, call and text logs were not considered, 35 to 71 smartphone datasets were included in the analysis (A. Grunerbl, Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P., 2014). In a 12-month study in bipolar inpatients, physical activity data from GPS, accelerometer, and sensors for cell towers were only complete 78.2% of the time, and social activity data from communication logs of the study phones were available on 56.1% of days (Beiwinkel et al., 2016). In a clinical sample, the shortage of smartphone data was partially explained by patients switching off smartphone sensors and by authors excluding data that they deemed unsuitable for training and testing when ground truth of the patients' clinical states is missing or when there was a lack of change in mood states among patients (A. Grunerbl, Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P., 2014; A. Muaremi et al., 2014). In community samples, data from 30-50% of the participants were excluded from the analysis because there were insufficient self-assessment data (Asselbergs et al., 2016; Hung, Yang, Chang, Chiang, & Chen, 2016; S. Saeb et al., 2015).

Phenotypes and Mood Disorders

The included studies attempted to measure and quantify the following five phenotypic categories in the context of mood disorders: social activity, physical activity, sleep, voice, and mobility. Most included studies speculated that increased frequency in these phenotypes would indicate onset or relapse of a manic episode, and vice versa for major depressive episode. Table 1.3 maps these five phenotypes onto the types of smartphone data evaluated in the included studies and onto the symptoms of mood disorders described in the Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM 5). Some studies used only one sensor to quantify several phenotypes, while other studies used multiple sensors to ascertain a given phenotype. Many included studies stated as their goals to inform diagnosis and monitoring of mood disorders but not to replace clinical diagnosis. In fact, many of the studies had clinician involvement to ensure the clinical relevance of smartphone passive data. As seen in Table 1.3, the manifestation of mood disorders not only involves changes in behaviors that can potentially be assessed by smartphone data, but also in symptoms that cannot be assessed by smartphone data. We have organized this review on the feasibility of monitoring mood disorders using smartphone data by the following phenotypes: sleep, social activity, voice, mobility, and physical activity.

Table 1.3. Mapping of Phenotypes on Smartphone Data Sources and DSM 5 criteria

Phenotypes	**Smartphone Data Sources**	**Symptoms of Major Depressive Episode**	**Symptoms of Manic Episode**
Social Activity	Microphone, GPS, Wi-Fi, communication log	Diminished interest in nearly all activities most of the day	Increased goal-directed activity; increased talkativeness
Mobility	GPS, accelerometer, microphone, Bluetooth, sensor for cell towers	Fatigue or decreased energy	Increased goal-directed activity; distractibility
Physical Activity	Accelerometer	Psychomotor agitation or retardation; fatigue or decreased energy	Increased psychomotor agitation
Sleep	Screen time, GPS, Wi-Fi, communication log, light sensors	Insomnia or hypersomnia	Decreased need for sleep
Voice	Microphone	Depressed mood	Persistent elevated, expansive, or irritable mood; increased talkativeness; flight of ideas or racing thoughts;
Other symptoms	NA	Significant change in weight or appetite; inappropriate guilt or feelings of worthlessness; difficulty concentrating or making decisions; recurrent thoughts of death, suicidal thoughts, plans, or attempts	Increased in risky beha inflated self-esteem or grandiosity

Sleep

Although sleep plays a significant role in the development, progression, and treatment of major depressive disorders (Association, 2013; Lopresti, 2013), only two studies monitored sleep using smartphone data (D. Ben-Zeev, E. A. Scherer, et al., 2015; Farhan, Lu, et al., 2016). Ben-zeev et al. (2015) used "lock" duration of the touch screen, stationary time per accelerometer reading, ambient silence recorded by the microphone, and ambient darkness detected by light sensor to approximate daily sleep duration in a student sample, while Farhan (2016b) used light sensor to infer sleep duration. While the obtained estimates were not verified by actigraphy, the approach in Ben-zeev et al. (2015) yielded similar results to self-reports (D. Ben-Zeev, E. A. Scherer, et al., 2015). Both studies used PHQ9 as the clinical outcome for depression in student samples. The reported associations between sleep inferred by smartphone data and PHQ9 score were inconsistent across the time in Ben-zeev et al. (2015), whereas Fanhan (2016b) reported more normal sleep patterns among those in the cluster of participants who had lower PHQ9 score.

Social Activity

The manifestation of mood disorders in terms of social activity include diminished interest in nearly all activities on most days or social isolation in a major depressive episode and increased goal-directed activity or talkativeness in a manic episode (Association, 2013; Cacioppo John T., 2006). Most studies speculated that social activities would increase during manic episodes and decrease during depressive episodes (Beiwinkel et al., 2016; Farhan, Lu, et al., 2016; A. Grünerbl, Oleksy, P., Bahle, G., Haring, C., Weppner, J., & Lukowicz, P. , 2012). While social activity generally referred to being surrounded by one or more individuals and having any type of interaction with them, the operational definitions of social activity greatly varied across the studies. Some of the studies used smartphone data from communication logs, Bluetooth, and microphones to capture some aspects of social activity from conversations that took place in-person or over the phone, and time spent in crowded places or in quiet places (Beiwinkel et al., 2016; D. Ben-Zeev, E. A. Scherer, et al., 2015; Farhan, Yue, et al., 2016; M. Faurholt-Jepsen, Frost, et al., 2014; M. Faurholt-Jepsen et al., 2015; M. Frost, Doryab, A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. , 2013; A. Grunerbl et al., 2015; A. Grünerbl, Oleksy, P., Bahle, G., Haring, C., Weppner, J., & Lukowicz, P. , 2012; Prociow et al., 2012b). Other studies used the detection of human speech in the ambient noise by the smartphone microphone as a proxy for social interaction in community samples. For example, the microphone was activated every 2 minutes and would remain activated when human speech was detected to record the duration of the human speech a subject was exposed to daily (D. Ben-Zeev, E. A. Scherer, et al., 2015; Farhan, Yue, et al., 2016). Ben-zeev et al., (2015) did not collect raw audio data from detected human speech but processed them destructively in real time to protect privacy of individuals who produced those speeches (D. Ben-Zeev, E. A. Scherer, et al., 2015). One study used Bluetooth as a proxy for the frequency of exposure to certain individuals, and to crowds in a community sample, based on the specific devices detected and the number of devices detected, respectively (Prociow et al., 2012b). The authors presumed that a large number of devices detected in a single scan would suggest a crowded location, such as a bus stop or a city center, thus reflect the subject's social activity levels (Prociow et al., 2012b).

For bipolar patients, the studies mostly ascertained social activities based on call and text logs in the context of manic or depressive symptoms (Beiwinkel et al., 2016; M. Faurholt-Jepsen, Frost, et al., 2014; M. Faurholt-Jepsen et al., 2015; M. Frost, Doryab, A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. , 2013). Some variables of interests include daily call times, call durations, and number of unique contacts (A. Grunerbl et al., 2015; A. Muaremi et al., 2014; V. Osmani, 2015). The major strength of call and text logs is data completeness independent of sensors, which the subjects may switch off. The major limitations of using call and text metadata in reviewed studies are two-fold. First, while communication has migrated from call and text to various social media e.g., Facebook, Instagram, the studies reviewed were unable to incorporate these data in the understanding of social activity. Secondly, 16.7-40% of the patients did not make calls with the study phone assigned to them (A. Grünerbl et al., 2015; Amir Muaremi, Gravenhorst, Grünerbl, Arnrich, & Tröster, 2014). While there was some evidence to suggest that reduced number of text messages was associated with increased depressive symptoms (Beiwinkel et al., 2016), the relationship between calling and texting behavior and severity of illness may be nonlinear. For instance, mildly depressed patients had longer and a greater number of calls relative to those who were severely depressed and also those who were healthy (A. Grünerbl, Oleksy, P., Bahle, G., Haring, C., Weppner, J., & Lukowicz, P. , 2012).

Voice

Variations in speech patterns might be indicative of persistent elevated, expansive, or irritable mood; increased talkativeness; flight of ideas or racing thoughts in mania, and low mood in depression (Association, 2013). Speech recordings from therapy session and vocal exercise have shown promising clinical utility for mental illness in the past (Cummins, 2015)*,* which leads to the question whether smartphone audio data captured from daily life could offer important clinical insights in diagnosing mood disorders. Common statistical audio features, such as number of conversations, speaking length, pitch, and volume, were used to ascertain clinically relevant outcomes, such as mood and social rhythm. Moreover, the completeness of smartphone audio data was strongly affected by patients’ adherence to carrying and using the study phones as prescribed. Despite this limitation, included studies found that audio features from daily calls were able to classify patients into one of the seven possible mood states, ranging from severe depression to severe mania, with a classification accuracy of 70-80% (A. Grunerbl et al., 2015; A. Maxhuni, Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. , 2016; A. Muaremi et al., 2014; V. Osmani, 2015). Audio features resulted in classification accuracy similar to that of call and text metadata, and a fusion of both data streams did not necessarily improve the classification accuracy (69-83%) (A. Grunerbl et al., 2015; A. Muaremi et al., 2014; V. Osmani, 2015). However, the cost and quality of data collection differ between these two data streams. Smartphone audio data are more voluminous to collect, often involve legal as well as ethical considerations, and may require strong incentives over long time periods, while call and text metadata tend to be more readily available (although only on Android devices, not on iOS) and complete. In addition, audio data seem to differ in clinical utility by the context of the recording. Audio data collected from clinical interviews by phone were found to better differentiate depression and hypomania from euthymic state, whereas audio data collected from calls outside of clinical assessment had difficulties differentiating depression from euthymia (Karam et al., 2014). Smartphone audio data collected during personal calls on the day of participant's clinical assessment did not improve mood-state classification from clinical assessment alone (Gideon, Provost, & McInnis, 2016; Karam et al., 2014). Furthermore, contrary to the expectation that increased speech frequency was associated only with (hypo)mania, increased speech frequency in audio was also observed during the transition from hypomania to depression (Guidi et al., 2015) and the correlations between audio features and mood were relatively weak (S. Abdullah et al., 2016; Guidi et al., 2015). The findings in the reviewed papers suggest that GPS and accelerometer data potentially provide superior performance in classifying or predicting clinically relevant outcomes without the burden of collecting audio data from patients (A. Grunerbl et al., 2015; A. Maxhuni, Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. , 2016; A. Muaremi et al., 2014; V. Osmani, 2015). We summarize studies that used smartphone audio data to monitor mood disorders in Table 1.4.

Table 1.4. Summary of Smartphone Audio Data in Monitoring Mood Disorders

Study, country (n)	Duration	App	Data Source	Clinically Relevant Outcome	Methods	Audio Findings	Additional Findings
Braun et al., 2016, Germany and Spain (n=36)	2 weeks	VoiceApp	Speech recorded of text reading	HAMD-17	Unspecified correlation between HAMD score and audio data	r>0.80 between audio features and HAMD 65-75% of all cases	NA
Faurholt-Jepsen, et al., 2016b, Denmark (n=28)	12 weeks	MONARCA	Phone calls	YMRS and HAMD from biweekly clinical assessment	what methods were used to classify patients into one of the how many possible mood states ranging from X to Y	Classification accuracy of depressed or euthymic state was 0.70 (s.d. 0.13) with a sensitivity of 0.64 (s.d. 0.25), and the classification accuracy for a manic or mixed state versus a euthymic state was 0.61 (s.d. 0.04) with a sensitivity of 0.71 (s.d. 0.09).	Addition of other objective data did not improvement prediction accuracy of audio data alone
Gideon, et al., 2016, US (n=37)	6-12months	PRIORI	Phone calls with clinician and others	YMRS and HAMD from weekly clinical assessment by phone	Support vector machine with linear and radial-basis-function kernel for binary mood state classification	AUC of 0.72±0.20 for mania and AUC of 0.75±0.14 for depression	
Giudi et al., 2015, France (n=1)	14 weeks	PSYCHE	Picture commenting task	Voice segments recorded by a computer	Spearman correlation between mood and audio	Spearman correlation between mood state changes and median absolute deviation of the distribution (0.54, p-value = 0.0392); No statistically significant correlations between audio features and QID or YMRS scales	N/A

Grunerbl et al., 2015, Austria (n=10)	12 weeks	MONARCA	Phone calls	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period of 12 weeks using HAMD and YMRS	Naive Bayes classifier and other classifiers, such as k-nearest neighbors, were used to classify patients into one of the 7 classes ranging from mania to depression.	Classification accuracy 70%	Classification accuracy using call data 66%
Karam et al., 2014, U.S.(n=6)	6 months	PRIORI	Phone calls with clinicians and others	Weekly clinical assessment using YMRS and HAMD by phone with trained clinicians of mood state over the past week	Support vector machine with linear and radial-basis-function kernel for binary mood state classification	AUC for audio-based classification of hypomania (depression): clinical evaluation calls trained with clinical evaluation calls 0.81 ± 0.17 (0.67 ± 0.18); unstructured calls trained with audio data from clinical evaluation calls on the same day 0.61 ± 0.09 (0.49 ± 0.08); unstructured calls trained with clinical evaluation calls the day before or after 0.47±0.05 (0.52 ± 0.09).	N/A

Maxhuni et al., 2016, Austria (n=5)	12 weeks	MONARCA	Phone calls	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period of 12 weeks using HAMD and YMRS	Implementation of several classifiers (e.g., random forest, support vector machine, k-nearest neighbors) was used to classify patients into one of the 7 classes ranging from mania to depression.	Classification accuracy using spectral characteristics 82% or emotional characteristics 82%	Classification accuracy using accelerometer data 81% – 85%; accelerometer and audio data combined: 79%-86%
Muaremi et al., 2014, Austria (n=12)	12 weeks	MONARCA	Phone calls	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period of 12 weeks using HAMD and YMRS	Support vector machine, logistic regression, random forest and neural networks were used to classify patients into one of the 7 classes ranging from mania to depression.	Classification accuracy using conversation characteristics 78% or patient voice characteristics 80%	Classification accuracy using call data 77%; combination of all data streams 83%
Osmani et al., 2015, Austria (n=12)	12 weeks	MONARCA	Phone calls	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period of 12 weeks using HAMD and YMRS	Naïve Bayes classifier, k- nearest neighbors, search tree, and a conjunctive rule learner were used to detect change at the individual level.	Classification accuracy 70%	Classification accuracy using accelerometer data 72%; GPS 81%; combination of GPS and accelerometer 76%; call data 66%; combination of call and audio 69%

Mobility

The reviewed literature speculated symptoms of mood disorders to be intricately linked with mobility. Depressive symptoms, such as loss of motivation, social withdrawal, and decreased social and physical activity were expected to be associated with decreased distance traveled, change in location patterns, and time spent indoors. In contrast, the relationship between mania and mobility was expected to be in the opposite direction. Studies that evaluated mobility data aimed to provide patients insights into their disease (M. Frost, Doryab, Faurholt-Jepsen, Kessing, & Bardram, 2013), to pre-empt mood episodes (Prociow, Wac, & Crowe, 2012a), and to explore the potential of passive data in monitoring individuals with bipolar disorder. In some studies, GPS data were used with or without data from other sensors (e.g., accelerometer, microphone, etc.) to ascertain changes in social rhythms (Saeed Abdullah, 2016) and to study mood in bipolar patients (A. Grunerbl, Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P., 2014). Other studies investigated the relationship between daily stress as well as depression severity and behavioral movement in community samples recruited from craigslist (S. Saeb et al., 2015) or from the student body of a university (D. Ben-Zeev, E. A. Scherer, et al., 2015; Farhan, Lu, et al., 2016; Farhan, Yue, et al., 2016). The duration of these studies ranged from 2 weeks to 6 months. The location variables used in these studies varied depending on the sensors employed, data processing, and analytic approaches. Location data from GPS were often summarized into distance travelled, number of location clusters (Saeed Abdullah et al., 2016; Dror Ben-Zeev, Emily A Scherer, Rui Wang, Haiyi Xie, & Andrew T Campbell, 2015; Gruenerbl et al., 2014), time spent outdoor relative to time spent indoor (A. Grünerbl et al., 2012), and regularity of travel patterns (S. Saeb et al., 2015) on a 24-hour cycle. When GPS data were unavailable, the studies used number of cell towers detected, wearable light sensors that distinguish between outdoor natural and indoor artificial light sources, and detection of Bluetooth devices tied to known locations to monitor mobility in clinical samples of bipolar patients and in community samples of healthy subjects.

Analyses of mobility data were largely exploratory in nature. Common approaches to investigate the association between statistical summaries of location data (e.g., distance traveled, home stay) and clinical outcomes, such as PHQ-9 score, YMRS and HAMD, in both clinical and community samples, were standard statistical methods, such as linear regression, (Dror Ben-Zeev et al., 2015; A. Grünerbl et al., 2012; Sohrab Saeb, Mi Zhang, Christopher J Karr, et al., 2015). Exploratory analysis using t-tests suggested that circadian movement, normalized entropy, location variance, home stay, phone usage duration, and phone usage frequency were different between individuals with PHQ9 scores of 5 or greater and those whose PHQ9 score was less than 5 in a community-based sample recruited from craigslist (Sohrab Saeb, Mi Zhang, Christopher J Karr, et al., 2015). Findings of correlational analyses between mobility data, including circadian movement, location variance, normalized entropy and home stay, and depression score suggested that inactivity and reduced regularity in daily routines were associated with higher depression score (Sohrab Saeb, Mi Zhang, Mary Kwasny, et al., 2015). While PHQ9 is a clinically relevant screening tool for depression, it is not a diagnostic tool that determines whether the participants meet criteria for clinical depression.

In studies that used machine learning to predict clinical outcomes (i.e., social rhythm, current and future mood, PHQ9 score) related to mood disorders, bipolar patients were found to have stable social rhythm (SRM<3.5, unstable; SRM>=3.5, stable) using number of location clusters, distance traveled, frequency of conversation inferred from audio data, and duration of non-sedentary activity calculated over each day. Abdullah et al. (2016) performed feature ranking to assess the important of each feature, where least-contributing features to the model were discarded until the most important features remained, and they found location cluster and total distance traveled over a day to be the most important features (Saeed Abdullah et al., 2016). Another study that used machine learning and included summary statistics such as time spent outdoors, distance traveled, entropy, percentage of time spent at home was able to predict mood state with 80%-87% accuracy (Farhan, Lu, et al., 2016; A. Grünerbl et al., 2012). However, addition of accelerometer did not improve the prediction accuracy of mood states (A. Grünerbl et al., 2012). Notwithstanding the potential of using smartphone location data to diagnose mood disorders, there were several limitations, such as high proportion of missing data and sparse ground truth data.

Physical Activity

Traditionally, subjective reports of changes in physical activity have been used in mood disorders to ascertain depressive symptoms, such as loss of energy, psychomotor retardation, and symptoms of mania, including irritability, excessive energy, reduction in the need of sleep, and psychomotor agitation or acceleration (A. Maxhuni, Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. , 2016). The advancement of mobile technology provides an opportunity to overcome the limitations of patient self-reports on physical activity (e.g., recall bias) by using smartphone accelerometer data, which has been used to monitor bipolar disorders in clinical samples (Saeed Abdullah et al., 2016; M. Frost et al., 2013; A. Grünerbl et al., 2015; A. Grünerbl et al., 2012; A. Maxhuni et al., 2016; V. Osmani et al., 2013; Prociow et al., 2012a) and to screen for depression in community samples (D. Ben-Zeev, E. A. Scherer, et al., 2015; Sohrab Saeb, Mi Zhang, Mary Kwasny, et al., 2015). The studies monitored the physical activity of bipolar patients from 2 weeks to 6 months and the physical activity of community members for 2-10 weeks. Smartphone accelerometer data was often summarized into ratio of stationary to sedentary duration (Saeed Abdullah, 2016) or the ratio of time spent moving to the time with little or no movement (D. Ben-Zeev, E. A. Scherer, et al., 2015; Farhan, Yue, et al., 2016; A. Grünerbl et al., 2012). Passive data were summarized into daily estimates or estimates for pre-defined intervals of the day (morning, afternoon, evening, and night) (V. Osmani et al., 2013). One study excluded data on dates with clinical visits. Two challenges in processing accelerometer data were the physical orientation of the phone and to determine whether the person was being stationary or not carrying the phone in times of movement. To address issues of phone orientation, which was largely unknown to the researchers, rotationally invariant statistical summaries were used in the analysis (Dror Ben-Zeev et al., 2015; A. Grünerbl et al., 2015; V. Osmani et al., 2013). To define stationary states, studies used pre-determined threshold to distinguish lack of movement from missing data. For example, complete lack of movement (A. Grunerbl, Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P., 2014) or movement slower than $1km/h$ were interpreted as the phone not being on the patient (Farhan, Yue, et al., 2016; Sohrab Saeb, Mi Zhang, Mary Kwasny, et al., 2015). In one study, this threshold was derived experimentally (D. Ben-Zeev, S. M. Schueller, et al., 2015). Findings regarding the clinical validity of using smartphone accelerometer data to diagnose mood disorders were mixed. Among bipolar patients, daily sedentary time was found to be weakly correlated with mood and moderately correlated with self-assessed energy score, and it was the third most important feature in predicting stability of social rhythm using support vector machine (Saeed Abdullah et al., 2016). Based on Pearson correlation between physical activity levels (i.e., low, moderate, high) and mood states, the authors concluded that there was insufficient evidence to determine whether daily accelerometer data were associated with depressed or manic mood.

However, physical activity in the morning was associated with mood scores much more strongly than daily activity levels (V. Osmani et al., 2013). Rather than evaluating activity level on a daily basis or predefined intervals of the day (morning, afternoon, evening, and night), one study used smartphone acceleration data during phone conversation and semi-supervised learning, which resulted in over 80% prediction accuracy in mood states (A. Maxhuni et al., 2016). We summarize studies that used smartphone accelerometer data to monitor mood disorders in Table 1.5.

Table 1.5. Summary of Studies Using Smartphone Accelerometer Data

Study, country, n	App	Duration	Clinically Relevant Outcome	Methods	Physical Activity Findings
Abdullah et al., 2016, U.S. (n=7)	Mood Rhythm	4 weeks	Self-report on Social Rhythm Metric (5 items)	Support vector machine with linear kernel using recursive feature elimination	Non-sedentary duration ranked 3rd in predicting stable vs. unstable status
Grunerbl et al., 2015, Austria (n=10)	MONARCA	12 weeks	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period of 12 weeks using HAMD and YMRS	Naive Bayes classifier and other classifiers, such as k-nearest neighbors, were used to classify patients into one of the 7 classes ranging from mania to depression.	Classification accuracy 70%
Maxhuni et al., 2016, Austria (n=5)	MONARCA	12 weeks	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period of 12 weeks using HAMD and YMRS	Implementation of several classifiers (e.g., random forest, support vector machine, k-nearest neighbors) was used to classify patients into one of the 7 classes ranging from mania to depression.	Classification accuracy using time domain 80.78% or frequency domain 84.54%
Osmani et al., 2015, Austria (n=12)	MONARCA	12 weeks	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period	Naïve Bayes classifier, k-nearest neighbors, search tree, and a conjunctive rule learner were used to detect change at the individual level.	Classification accuracy 72%

			of 12 weeks using HAMD and YMRS		
Ben-Zeev et al., 2015, US (n=47)	FOCUS	10 week	Self-report on PHQ9 at the end of study period	Penalized functional regression of active period on depression	The association was small and non-significant (b= 0.00031; p=0.61)
Frost et al., 2013, Denmark, (n=6)	MONARCA 2.0	6 months	Self-report on mood from highly depressed (-3) to highly manic (+3) daily	chi-square correlations between objective data (phone usage, social activity, physical activity, and mobility) self-reported mood score	Physical activity was not highly correlated with mood scores
Grunerbl et al., 2012, Austria (n=10)	MONARCA	8weeks	Daily self-report on activity of daily life and psychiatric assessment every 3 weeks using HAMD, ADS, and MSS	Descriptive statistics of motion ratio in manic, euthymic, depressed states; linear regression of motion ratio on mood states	Mean increase of 21.3% motion ratio in the transition from depression to euthymic state and a reduction of 33.7% motion ratio in the transition from mania to euthymic state; motion ratio correlated with self-assessment within 90% confidence interval in bipolar patients in a linear regression.
Grunerbl et al., 2014, Austria (n=12)	MONARCA	12 weeks	Psychiatric assessment every 3 weeks over a period of 12 weeks using HAMD, ADS, and MSS	Implementation of several classifiers (e.g., Naïve Bayes, k-nearest neighbor, j48 search tree, conjunctive rule learner) were used to classify patients into one of the 7 classes ranging from mania to depression.	Classification accuracy 72%

Osmani et al., 2013, Austria (n=9)	MONARCA	3 months	Psychiatric assessment and psychological state examination were performed every 3 weeks over a period of 3 months using HAMD and YMRS	Pearson correlation coefficient between physical activity levels (none, moderate, high) during each daily interval (overalll, morning, afternoon, evening, respectively) and psychiatric evaluation scores	Much stronger correlation between the individual daily intervals than there is for the overall activity levels
Asselbergs et al. 2016, Netherlands (n=27)	iYouVU	6 weeks	Self-report on mood from low (-2) to high (+2) 5 times a day	Personalized mood prediction models were trained using forward stepwise regression (FSR) of phone usage, communication log and percentage of duration performing "high activity"	Correct cross-validated predictions of the personalized models 55% to 76%.
Farhan et al., 2016a, US (n=79)	LifeRhythm	undetermined	DSM5 based clinical assessment at the initial screening and self-report on PHQ9	Pearson's correlation between percentage of time being active or percentage of time being inactive and PHQ9 score	Non-significant correlation (correlation and p-value were not reported)
Farhan et al., 2016b, US (n=60)	StudentLife	10 weeks	self-report on PHQ9	Support vector machine to classify people into clusters based on daily averages and trends of physical activity, light information, conversation, and location data, as well as variability in location	People in the low PHQ9 group were more active as compared to people in the high PHQ9 group

Wahle et al., 2016, Switzerland and Germany (n=126)	MOSS	8 weeks	Binary outcome based on biweekly self-report on PHQ9 using a cut-off of 11	Random Forest and Support Vector Machine leave-one-out cross validation using Wi-fi, accelerometer, GPS and phone usage data	Classification accuracy: 59.1% - 60.1%

External Validity

To understand the applicability of lessons learned from the included studies, we evaluated the response rate, recruitment period, and sample characteristics. The inclusion and exclusion criteria of participants, including symptom manifestation and severity, varied across studies, which made comparisons difficult. In Austria and Demark, bipolar patients who met ICD-10 criteria for bipolar disorder were recruited to participate. In Austria, inpatients who were willing and able to meet the study's demands, e.g., using a smartphone, were recruited by the ward psychiatrists to participate in the 12-week observational study (A. Grunerbl et al., 2015; A. Grünerbl, Oleksy, P., Bahle, G., Haring, C., Weppner, J., & Lukowicz, P. , 2012; A. Grunerbl, Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P., 2014; A. Maxhuni, Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. , 2016; A. Muaremi et al., 2014; Osmani, 2015; V. Osmani, Maxhuni, A., Grünerbl, A., Lukowicz, P., Haring, C., & Mayora, O. , 2013). Among a total of 12 patients who were enrolled in the trial, two dropped out and one of them had no state change (Osmani, 2015). While most patients stayed overnight and received therapy at the facility, they were free to move around the hospital compound and the town close by, i.e., they were not on lock-down. Most of the participants were released from the facility one to two weeks after the start of the trial based on medical advice independent of one's participation in research (A. Grunerbl, Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P., 2014). This observational study might offer some degree of external validity for patients with moderate severity of bipolar disorder who are about to be discharged from psychiatric facility, although it is not clear to what extent the findings might be generalizable to bipolar patients with different severity of illness. The amount of time required to complete recruitment, and the response rate to the study, was not reported. On the other hand, a randomized controlled trial in Demark demonstrated the practical challenge of recruiting patients in an outpatient setting. In a three-month trial, the response rate and retention rate were promising: 17 out of 21 patients (70%) recruited were enrolled in the study. Only three individuals refused to participate as they were unwilling to use an Android study phone, one person was lost to follow-up, and no one dropped out of the study (M. Faurholt-Jepsen, Frost, et al., 2014). The external validity of this study is unclear, however, because only a third of the sample were employed, while the rest were on sick leave, unemployed, underemployed, or disabled. In a six-month trial supported by the same app and patients from the same clinic, more unanticipated challenges in enrollment were reported. The recruitment took 18 months. Approximately one third of the 113 Danish-speaking patients who met clinical eligibility to participate in the study refused to do so for reasons including unwillingness to use an Android study phone, unwillingness to participate in research, or unwillingness to devote the time required (M. Faurholt-Jepsen et al., 2015). In the U.S., there were two separate pilot studies with bipolar patients in two locations (Michigan and Pennsylvania). Only one out of nine enrolled patients did not use the app, and data for one patient proved to be unusable.

In a four-week study, all patients were euthymic (S. Abdullah et al., 2016), which again raises the question of external validity. In the 6-12-month study, enrollees were diagnosed with Bipolar I disorder, with a history of rapid cycling (i.e., four or more episodes a year of mania, hypomania, or depression) (Karam et al., 2014). Two studies conducted in the U.S. ascertained depression in (under)graduate students (D. Ben-Zeev, E. A. Scherer, et al., 2015) and in a community sample recruited from Craigslist (S. Saeb et al., 2015). The generalizability of these studies is uncertain, as students may exhibit very different behavioral patterns as compared to working young adults or older adults who do not spend the majority of their time on campus.

Individuals who volunteer to participate in research studies posted on Craigslist may be a self-selected group, i.e., they may be more receptive with mobile health intervention than the general population.

Conclusions

The area of inquiry regarding the use of smartphone to monitor mood disorders is in its infancy, and most of the publications reviewed are pilot studies. Comparison of results across studies is difficult due to differences in the sample characteristics, incentive structures, measures, and methods. Included studies often used different models of study phones to collect different combinations of sensor data to evaluate the respective phenotype, using different gold standards. Common limitations across studies include sparse or lack of clinical assessments as gold standards and data incompleteness, which led to the challenges in data management and analytic approaches as documented here. See Table 1.6 for a list of limitations and potential solutions.

Table 1.6. Limitations and Potential Solutions

Limitations	**Proposed Solutions**
Sparse or no clinical data	Use clinical calls
Non-adherence in passive data (e.g., refusal to use study phone to call, turning off sensors)	Use personal phone instead of study phones, develop apps in both Android and iOS platforms, customize app to extend battery life, reminder to charge phone nightly
Non-adherence in self-assessment	Clinician feedback, reminders, in-app badges, financial Incentives or lottery
Individual differences in phone use	Survey prior to passive data collection, within-subject designs
Small sample size	Increase recruitment period
Selection bias	Infer missingness in data analysis
Limited internal validity	Transparent and meticulous reporting of data management and analysis to ensure reproducible research

We speculate that there is considerable selection bias of subjects given that many eligible individuals with mood disorder diagnoses refused to participate in the studies due to unwillingness to use an Android study phone, unwillingness to participate in research, or unwillingness to devote the time required (Ben-Zeev et al., 2015; Frost, 2013; Faurholt-Jepsen et al., 2015; A. Grunerbl et al., 2015; Muaremi et al., 2014). Most existing studies provided participants with study phones, but we suspect that participants use study phones and personal phone differently. The use of smartphone apps that support both Android and iOS phones would facilitate the use of personal rather than study phones (Farhan, Yue, et al., 2016), thus reducing data incompleteness and erratic usage due to unfamiliarity with the device. Some of the studies provided participants with study phones because the participants did not own smartphones compatible with the apps (Saeb, Lattie, Schueller, Kording, & Mohr, 2016). There was a lack of information on whether the participants who were given study phones owned a smartphone prior to being enrolled into the research studies. Since provision of smartphones would constitute a major intervention for those individuals who did not own smartphones, we recommend that future studies in smartphone-based digital phenotyping exclude these participants due to the unreliability of the collected data .

Besides habits and familiarity with preferred smartphones, we speculate that both mere forgetfulness during healthy states or diminished ability to function during severe mood states could all lead to non-adherence, such as forgetting to charge the smartphone. Future studies could consider scheduled reminders (e.g., reminder to charge phones before bed time) to address forgetfulness in charging the smartphone, customize apps to extend battery power (Beiwinkel et al., 2016) or provision of monetary or in-app incentives, e.g., badges, or battery charging cases to reduce data incompleteness due to battery issues. While data tend to be less complete for GPS data due to battery drainage, communication logs are considerably cheaper to collect and readily available on Android devices, yet they have not been fully utilized in existing studies.

In addition to selection bias, the uncertainty of mood states associated with missing observations brings into the question the internal validity of the collected data. It was challenging to assess the robustness of statistical conclusions of the included studies due to missing data. For instance, authors of the studies excluded data from their analyses when data were deemed unsuitable for training models (e.g., unavailable ground truth data were missing, lack of change in mood states among patients) (A. Grunerbl, Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P., 2014; A. Muaremi et al., 2014). A study using a community sample excluded data from half of the participants in the analysis stage because data were not available more than 50% of the time for them(S. Saeb et al., 2015). Most of the included studies did not consider the validity of statistical inferences in the presence of missing data. To evaluate the robustness of the statistical conclusions and to ensure reproducibility of the studies, future research should ensure transparent and meticulous reporting of data processing and analyses. We conjecture that data in these studies is not be missing at random but, instead, missingness is likely associated with the outcome of interest, the state or condition of the subject (Wahle, Kowatsch, Fleisch, Rufer, & Weidt, 2016), which is a matter that requires further enquiry in the future.

While most included studies expected the intensity of phenotypes to increase from severe depression (-3) to normal state to severe mania (+3), many included studies presented counterintuitive results with respect to digital phenotypes and mood disorders. Contrary to the expectation that heightened physical activity would be associated with worsening of mania and improvement of depression, some studies found that increased physical activity was associated with the alleviation of both depressive and manic symptoms. Other studies found a non-linear relationship between social activity and depression severity, where increased length and number of calls occurred in mildly depressed patients in comparison to those who were severely depressed and those who were in a euthymic state. Similarly, frequency of speech was found to increase with the onset of both (hypo)mania and depression. Future research should avoid overly simplistic model specifications in modeling the complex behavioral variations of mood disorders. In addition, multiple data streams should be used to infer a person's mood state. For instance, preoccupation with phone may be a sign of depression, and future research could consider coupling phone communication data with GPS-based location data to see to more accurately infer the mood state of a participant.

Studies that involved within-subject designs observed patterns of activities that differed from the patterns seen in between-subject designs (Beiwinkel et al., 2016; A. Grünerbl et al., 2012). For instance, the individual differences in the range of observations across mood states ranged from 35-2700% in one study (A. Grünerbl et al., 2012). Potential reasons for these variations in usage patterns might be participants' work schedules or habits of phone use. For instance, a respondent who works day-shifts would be expected to exhibit a different mobility pattern throughout the day as compared to another respondent who works the night-shift. Given the variation in expected mobility patterns throughout the day or the week, it would be meaningful to stratify mobility data into week days and weekends (Saeb et al., 2016). The lack of information on the participants' work schedule and habits of phone usage led to challenges in making valid inferences. This challenge not only applies to ascertaining mobility and physical activity, data but also to social activity. For instance, text and call logs would be a less valid indicator for social activity for people who use social media as primary forms of communications, although within-subject comparisons over time would be valid also for these individuals. We believe that it would be useful to survey participants about their habits prior to the start of the study, and it also seems that some comparisons are best carried out longitudinally using within-person analyses. While it is certainly feasible and potentially very promising to use smartphone data for studying mood disorders, it is important to be mindful about issues surrounding selection bias, data management, and analytic approaches. While most included studies focused on the association between self-reports and passively collected smartphone data, we believe that another line of potentially fruitful enquiry is to use passively collected smartphone data to predict clinical events or crises, such as hospitalization, self-harm, or suicide. Reliance on passive data also means that these future studies could involve large sample sizes over long study periods, which could help alleviate some of the concerns that are, understandably given the novelty of the field, present in the current studies.

References

Abdullah, S., Matthews, M., Frank, E., Doherty, G., Gay, G., & Choudhury, T. (2016). Automatic detection of social rhythms in bipolar disorder. *Journal of the American Medical Informatics Association, 23*(3), 538-543.

Abdullah, S., Matthews, M., Frank, E., Doherty, G., Gay, G., & Choudhury, T. (2016). Automatic detection of social rhythms in bipolar disorder. *J Am Med Inform Assoc, 23*(3), 538-543. doi:10.1093/jamia/ocv200

Asselbergs, J., Ruwaard, J., Ejdys, M., Schrader, N., Sijbrandij, M., & Riper, H. (2016). Mobile phone-based unobtrusive ecological momentary assessment of day-to-day mood: an explorative study. *Journal of Medical Internet Research, 18*(3).

Association, A. P. (Ed.) (2013). *Diagnostic and statistical manual of mental disorders* (5 ed.). Arlington, VA: American Psychiatric Publishing.

Beiwinkel, T., Kindermann, S., Maier, A., Kerl, C., Moock, J., Barbian, G., & Rössler, W. (2016). Using smartphones to monitor bipolar disorder symptoms: a pilot study. *JMIR Ment Health, 3*(1).

Belisario, J. S. M. J. J., Huckvale K, O'Donoghue J, Morrison CP, Car J. (2015). Comparison of self-administered survey questionnaire responses collected using mobile apps versus other methods. *Cochrane Database Syst Rev, 27*(7).

Ben-Zeev, D., Scherer, E. A., Wang, R., Xie, H., & Campbell, A. T. (2015). Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. *Psychiatr Rehabil J, 38*(3), 218.

Ben-Zeev, D., Scherer, E. A., Wang, R., Xie, H., & Campbell, A. T. (2015). Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. *Psychiatr Rehabil J, 38*(3), 218-226. doi:10.1037/prj0000130

Ben-Zeev, D., Schueller, S. M., Begale, M., Duffecy, J., Kane, J. M., & Mohr, D. C. (2015). Strategies for mHealth Research: Lessons from 3 Mobile Intervention Studies. *Administration and Policy in Mental Health and Mental Health Services Research, 42*(2), 157-167. doi:10.1007/s10488-014-0556-2

Cacioppo John T., H. M. E., Waite Linda J., Hawkley Louise C., Thisted Ronald A. . (2006). Loneliness as a Specific Risk Factor for Depressive Symptoms: Cross-Sectional and Longitudinal Analyses. *Psychology and Aging, 21*, 140-151.

Canzian, L., & Musolesi, M. (2015). *Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis.* Paper presented at the Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing.

Cummins, N., Scherer, S., Krajewski, J., Schnieder, S., Epps, J., & Quatieri, T. F. . (2015). A review of depression and suicide risk assessment using speech analysis. *Speech Communication, 71*, 10-49.

Dang, M., Mielke, C., Diehl, A., & Haux, R. (2016). Accompanying Depression with FINE-A Smartphone-Based Approach. *Stud Health Technol Inform, 228*, 195.

Dunbar, J. (1984). Adherence measures and their utility. *Controlled Clinical Trials, 5*(4), 515-521.

Farhan, A. A., Lu, J., Bi, J., Russell, A., Wang, B., & Bamis, A. (2016). *Multi-view Bi-Clustering to Identify Smartphone Sensing Features Indicative of Depression.* Paper presented at the Connected Health: Applications, Systems and Engineering Technologies (CHASE), 2016 IEEE First International Conference on.

Farhan, A. A., Yue, C., Morillo, R., Ware, S., Lu, J., Bi, J., . . . Wang, B. (2016). *Behavior vs. Introspection: Refining prediction of clinical depression via smartphone sensing data.* Paper presented at the 7th Conference on Wireless Health, WH.

Faurholt-Jepsen, M., Frost, M., Vinberg, M., Christensen, E. M., Bardram, J. E., & Kessing, L. V. (2014). Smartphone data as objective measures of bipolar disorder symptoms. *Psychiatry Res, 217*(1-2), 124-127. doi:10.1016/j.psychres.2014.03.009

Faurholt-Jepsen, M., Munkholm, K., Frost, M., Bardram, J. E., & Kessing, L. V. (2016). Electronic self-monitoring of mood using IT platforms in adult patients with bipolar disorder: A systematic review of the validity and evidence. *BMC Psychiatry, 16*(1), 7.

Faurholt-Jepsen, M., Ritz, C., Frost, M., Mikkelsen, R. L., Christensen, E. M., Bardram, J., . . . Kessing, L. V. (2015). Mood instability in bipolar disorder type I versus type II-continuous daily electronic self-monitoring of illness activity using smartphones. *J Affect Disord, 186*, 342-349. doi:10.1016/j.jad.2015.06.026

Faurholt-Jepsen, M., Vinberg, M., Frost, M., Christensen, E. M., Bardram, J., & Kessing, L. V. (2014). Daily electronic monitoring of subjective and objective measures of illness activity in bipolar disorder using smartphones--the MONARCA II trial protocol: a randomized controlled single-blind parallel-group trial. *BMC Psychiatry, 14*, 309. doi:10.1186/s12888-014-0309-5

Frost, M., Doryab, A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. (2013). *Supporting disease insight through data analysis: refinements of the monarca self-assessment* *system.* Paper presented at the Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing.

Frost, M., Doryab, A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. . (2013). *Supporting disease insight through data analysis: refinements of the monarca self-assessment system.* Paper presented at the Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing.

Gideon, J., Provost, E. M., & McInnis, M. (2016). *Mood state prediction from speech of varying acoustic quality for individuals with bipolar disorder.* Paper presented at the Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on.

Gruenerbl, A., Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., . . . Lukowicz, P. (2014). *Using smart phone mobility traces for the diagnosis of depressive and manic episodes in bipolar patients.* Paper presented at the Proceedings of the 5th Augmented Human International Conference.

Grünerbl, A., Muaremi, A., Osmani, V., Bahle, G., Oehler, S., Tröster, G., . . . Lukowicz, P. (2015). Smartphone-based recognition of states and state changes in bipolar disorder patients. *IEEE J Biomed Health Inform, 19*(1), 140-148.

Grunerbl, A., Muaremi, A., Osmani, V., Bahle, G., Ohler, S., Troster, G., . . . Lukowicz, P. (2015). Smartphone-based recognition of states and state changes in bipolar disorder patients. *IEEE J Biomed Health Inform, 19*(1), 140-148. doi:10.1109/jbhi.2014.2343154

Grünerbl, A., Oleksy, P., Bahle, G., Haring, C., Weppner, J., & Lukowicz, P. (2012). *Towards smart phone based monitoring of bipolar disorder.* Paper presented at the Proceedings of the Second ACM Workshop on Mobile Systems, Applications, and Services for HealthCare.

Grünerbl, A., Oleksy, P., Bahle, G., Haring, C., Weppner, J., & Lukowicz, P. . (2012). *Towards smart phone based monitoring of bipolar disorder.* Paper presented at the In Proceedings of the Second ACM Workshop on Mobile Systems, Applications, and Services for HealthCare.

Grunerbl, A., Osmani, V., Bahle, G., Carrasco, J. C., Oehler, S., Mayora, O., ... & Lukowicz, P. (2014). *Using smart phone mobility traces for the diagnosis of depressive and manic episodes in bipolar patients.* Paper presented at the In Proceedings of the 5th Augmented Human International Conference.

Guidi, A., Salvi, S., Ottaviano, M., Gentili, C., Bertschy, G., de Rossi, D., . . . Vanello, N. (2015). Smartphone Application for the Analysis of Prosodic Features in Running Speech with a Focus on Bipolar Disorders: System Performance Evaluation and Case Study. *Sensors (Basel), 15*(11), 28070-28087. doi:10.3390/s151128070

Hung, G. C.-L., Yang, P.-C., Chang, C.-C., Chiang, J.-H., & Chen, Y.-Y. (2016). Predicting Negative Emotions Based on Mobile Phone Usage Patterns: An Exploratory Study. *JMIR Res Protoc, 5*(3).

Karam, Z. N., Provost, E. M., Singh, S., Montgomery, J., Archer, C., Harrington, G., . . . Ieee. (2014). ECOLOGICALLY VALID LONG-TERM MOOD MONITORING OF INDIVIDUALS WITH BIPOLAR DISORDER USING SPEECH *2014 Ieee International Conference on Acoustics, Speech and Signal Processing*. New York: Ieee.

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. . *J Affect Disord, 148*(1), 12-27.

Maxhuni, A., Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. (2016). Classification of bipolar disorder episodes based on analysis of voice and motor activity of patients. *Pervasive and Mobile Computing, 31*, 50-66.

Maxhuni, A., Muñoz-Meléndez, A., Osmani, V., Perez, H., Mayora, O., & Morales, E. F. . (2016). Classification of bipolar disorder episodes based on analysis of voice and motor activity of patients. *Pervasive and Mobile Computing*.

Muaremi, A., Gravenhorst, F., Grunerbl, A., Arnrich, B., & Troster, G. (2014). Assessing Bipolar Episodes Using Speech Cues Derived from Phone Calls. In P. Cipresso, A. Matic, & G. Lopez (Eds.), *Pervasive Computing Paradigms for Mental Health* (Vol. 100, pp. 103-114). Berlin: Springer-Verlag Berlin.

Muaremi, A., Gravenhorst, F., Grünerbl, A., Arnrich, B., & Tröster, G. (2014). *Assessing bipolar episodes using speech cues derived from phone calls.* Paper presented at the International Symposium on Pervasive Computing Paradigms for Mental Health.

Onnela, J.-P., & Rauch, S. L. (2016). Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. *Neuropsychopharmacology*.

Osmani. (2015). Smartphones in Mental Health: Detecting Depressive and Manic Episodes. *Ieee Pervasive Computing, 14*(3), 10-13.

Osmani, V. (2015). Smartphones in Mental Health: Detecting Depressive and Manic Episodes. *Ieee Pervasive Computing, 14*(3), 10-13.

Osmani, V., Maxhuni, A., Grünerbl, A., Lukowicz, P., Haring, C., & Mayora, O. (2013). *Monitoring activity of patients with bipolar disorder using smart phones.* Paper presented at the Proceedings of International Conference on Advances in Mobile Computing & Multimedia.

Osmani, V., Maxhuni, A., Grünerbl, A., Lukowicz, P., Haring, C., & Mayora, O. . (2013). *Monitoring activity of patients with bipolar disorder using smart phones.* Paper presented at the In Proceedings of International Conference on Advances in Mobile Computing & Multimedia.

Prociow, P., Wac, K., & Crowe, J. (2012a). Mobile psychiatry: towards improving the care for bipolar disorder. *International Journal of Mental Health Systems, 6*(1), 5.

Prociow, P., Wac, K., & Crowe, J. (2012b). Mobile psychiatry: Towards improving the care for bipolar disorder. *International Journal of Mental Health Systems, 6*. doi:10.1186/1752-4458-6-5

Saeb, S., Lattie, E. G., Schueller, S. M., Kording, K. P., & Mohr, D. C. (2016). The relationship between mobile phone location sensor data and depressive symptom severity. *PeerJ, 4*, e2537.

Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study. *J Med Internet Res, 17*(7), e175. doi:10.2196/jmir.4273

Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. *Journal of Medical Internet Research, 17*(7), e175.

Saeb, S., Zhang, M., Kwasny, M., Karr, C. J., Kording, K., & Mohr, D. C. (2015). *The relationship between clinical, momentary, and sensor-based assessment of depression.* Paper presented at the Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare.

Saeed Abdullah, M. M., Ellen Frank, Gavin Doherty, Geri Gay, Tanzeem Choudhury. (2016). Automatic Detection of Social Rhythms in Bipolar Disorder. *J Am Med Inform Assoc, 23*(3), 538-543.

Težak, Ž., Kondratovich, M. V., & Mansfield, E. (2010). US FDA and personalized medicine: in vitro diagnostic regulatory perspective. *Personalized Medicine, 7*(5), 517-530.

Wahle, F., Kowatsch, T., Fleisch, E., Rufer, M., & Weidt, S. (2016). Mobile sensing and support for people with depression: a pilot trial in the wild. *JMIR Mhealth Uhealth, 4*(3).

For Health or Not For Health:

Motivations To Use Electronic Nicotine Delivery Systems

(Paper 2)

Flora Or, M.H.S.

Harvard T.H. Chan School of Public Health

Abstract

Background: The recent advent of e-cigarette and vaporizer technology has introduced new possibility and concerns for tobacco control. The heterogeneity in the reasons to use found in early studies motivated the current study which aimed to explore the typology of ENDs users by the type of ENDs they used, their stages of change, and by their experience with ENDs.

Methods: We collected data on demographics, intention to quit, and experience with ENDs from a commercial online panel. We identified the key reasons to use ENDs by using thematic analysis and further explored the reasons to use ENDs by their stages of change and by the type of ENDs they used.

Results: The key motivations to use ENDs were health concerns, personal enjoyment, personal image, and pragmatic reasons. Despite harm reduction and quitting being the most frequently cited reasons to use ENDs among those who intended to quit smoking, more than half of the respondents cited non-health reasons including aesthetics, social desirability and ease of use. Motivation to use ENDs also differed by the types of ENDs where vaporizer users cited more hedonic reasons and fewer pragmatic reasons to use ENDs as compared to e-cigarette users.

Discussion: The existing categorization of "typical" ENDs users into either quitting smokers or curious non-smokers who are experimenting with nicotine products may be overly simplistic. While the heterogeneity in motivation found in this study suggested intention to substitute the combustion of tobacco leaf with ENDs on some occasions, the relative harm and benefit of using ENDs remain unknown.

Tobacco poses a major threat to population health globally and in the U.S., increasing the risk of cancer, cardiovascular disease, respiratory disease, and premature death (Clair et al., 2013; Haiman et al., 2006; Lim et al., 2013; Stringhini et al., 2017; US Department of Health and Human Services, 2014). While number of individuals who attempt to quit smoking has increased in the U.S. over time (Gitchell, Shiffman, & Sembower, 2016), smoking cessation remains one of the top priorities in public health(Health & Services, 2014). Counseling and pharmacological interventions, (e.g., antidepressants and nicotine replacement therapies) have been well established as effective smoking cessation strategies (Health & Services, 2014; McDaniel, 2016; Warnier, van Riet, Rutten, De Bruin, & Sachs, 2013), yet many individuals remain unsuccessful in their attempts at cessation (Borland, Partos, Yong, Cummings, & Hyland, 2012).

The recent advent of e-cigarette and vaporizer technology has introduced a new possibility for tobacco control, however their use as cessation aids remains controversial (Abrams, 2014; Cobb, Byron, Abrams, & Shields, 2010). Despite strong opposition from some tobacco control advocates, the availability and popularity of e-cigarettes continue to grow (Ayers, Ribisl, & Brownstein, 2011; Etter, 2010; Giovenco, Hammond, Corey, Ambrose, & Delnevo, 2014; Noel, Rees, & Connolly, 2011). Common concerns raised against promoting e-cigarette and vaporizer use include the potential for dual use rather than replacement, strengthened nicotine addiction, reduced effort in quitting among smokers (Health & Services, 2014; Kalkhoran & Glantz, 2016), and the idea that the devices may serve as a gateway to smoking conventional cigarettes among non-smokers (Primack, Soneji, Stoolmiller, Fine, & Sargent, 2015; Rigotti, 2015). Proponents of e-cigarettes and vaporizers argue that these products deliver nicotine effectively and reduce cravings (Glasser et al., 2016), offer greater appeal and satisfaction than traditional nicotine replacement therapies such as chewing gums (Barbeau

(Barbeau, Burda, & Siegel, 2013), and cause less harm than combustion from smoking conventional cigarettes(Etter, 2015). In the U.K., where e-cigarettes have been evaluated as smoking cessation tools, studies found that e-cigarettes were associated with a higher continuous abstinence rate than nicotine replacement patches (Brown et al., 2013).

Focus groups and exploratory studies have begun to evaluate e-cigarette users' perceptions and motivations for using these devices. For instance, investigators in the U.K., Korea, and the U.S. conducted focus groups to evaluate users' awareness of positive and negative attributes of electronic nicotine delivery systems (ENDS) as well as their reasons for experimentation, continued usage, and discontinued usage (Berg, 2016; Cho, Shin, & Moon, 2011; Ford, MacKintosh, Bauld, Moodie, & Hastings, 2016; Tan, Lee, & Bigman, 2016). Other studies evaluated the reasons to use and to discontinue using e-cigarettes by smoking status among young adults, and the evidence had mixed implications on the relative harm and benefits of these products (Berg, 2016; Kong, Morean, Cavallo, Camenga, & Krishnan-Sarin, 2015; Leventhal et al., 2015). In general, the motivations to use include harm reduction, quitting, absence of offensive smells, reduced costs, and desire to smoke everywhere, while motivations to discontinue use include preference for other tobacco products, health risks, and disapproval by others (Berg, 2016; Kong et al., 2015). Some studies have reported that adolescents and young adults experiment with e-cigarettes as a result of peer influence, (dis)satisfaction with school life, and curiosity about the types of flavors (Berg, 2016; Cho et al., 2011; Ford et al., 2016; Kong et al., 2015; Wagoner et al., 2016). Despite the concerns of potential nicotine addiction and uncertainty with safety, adolescents and young adults viewed the ability to control nicotine dosage and harm reduction as positive attributes of ENDs relative to combustible cigarettes (Wagoner et al., 2016)

Beyond focus groups, public health researchers have attempted to gauge the attitudes of the general public towards ENDs and to understand marketing strategies by analyzing social media content (e.g., Twitter and Youtube) (Dai & Hao, 2016; Harris et al., 2014; Lazard et al., 2016; Paek, Kim, Hove, & Huh, 2014). Other attempts to understand marketing strategies include evaluation of logos, emotional appeal, amount of educational information, and health claims (Banerjee, Shuk, Greene, & Ostroff, 2015; Dai & Hao, 2016).

These initial attempts to characterize the heterogeneity in motivation and demographics of ENDs users suggest opportunities to segment the population based on their characteristics and to reach them with a distinct set of strategies (Kotler, 1979; Reid, Rynard, Czoli, & Hammond, 2015). For instance, the motivation of using ENDs may be dependent on the stages of change in smoking (Prochaska & DiClemente, 1984). The goal of the current study is to explore the typology of ENDs users by the type of ENDs they used, their stages of change, and by their experience with ENDs.

Methods

A convenience sample of consumers was recruited from a commercial online platform to participate in a survey regarding their experience with e-cigarettes or vaporizers June 21-22, 2016. Participants were asked to provide demographic information and were screened for use of e-cigarettes or vaporizers in the past six months. Participants who had used e-cigarettes or vaporizers in the past six months were asked provide information on their intention to quit smoking and their experience using e-cigarettes or vaporizers.

Demographics

Participants were asked to provide information on their gender, age in years, and city and state of residence.

Intention to quit

Participants were asked to describe their intention to quit smoking, with the following response options: "I have never been a smoker," "I was a smoker but I do not smoke anymore (since less than 6 months ago)," "I was a smoker but I do not smoke anymore (since more than 6 months ago)," "I am a smoker and I have made a firm decision to quit smoking in the next 30 days," "I am a smoker and seriously thinking of quitting smoking, but I have not yet decided when," and "I am a smoker and I have absolutely no intention to quit smoking."

Experience e-cigarettes or vaporizers

One free response item was used to elicit participants' opinions regarding their experience with e-cigarettes or vaporizers. The prompt stated: "We'd like to understand your experience with e-cigs and vaporizers. What do you use (e-cig or vaporizer or both)? When do you use it? Why do you use it? Think about the benefits you gain from using."

Thematic analysis

Two coders conducted a thematic analysis to evaluate the participants' qualitative response regarding their experience with e-cigarettes or vaporizers. The lead coder generated a set of *a priori* codes based on the existing literature. Both coders used the *a priori* codes for the first round of coding, and jointly created a codebook by modifying definitions of the *a priori* codes and by adding new codes that emerged from the data.

Quantitative analysis

Quantitative analysis was conducted using STATA13, where each code was converted to a binary variable. The sum of codes within each qualitative response was used to generate the number of distinct needs per user. We conducted Pearson chi-square tests among the identified needs in general, and by gender, age group, and intention to quit. We then repeated the same set of tests stratified by whether participants had experience using e-cigarettes, vaporizers, or both.

Results

Sample Characteristics

A convenience sample of 6725 adults (region: 19.4% northeast; 24.8% Midwest; 37.3% south; 17.1% west; 0.4% other; 1% missing) were screened for e-cigarette or vaporizer use in the past 6 months. Among those who were screened, 830 individuals reported having used e-cigarettes only, 667 individuals reported having used vaporizers only, and 967 reported having used both e-cigarettes and vaporizers, and 4261 reported not having used either in the past six months. Among the 2464 individuals who had used vaporizers or e-cigarettes six months prior to the survey, 2027 reported that they intended to quit smoking. Nearly half of the survey respondents were smokers interested in quitting, including 30.5% of the sample who were seriously thinking about quitting but had not made a decision, and 16.1% had made a firm decision to quit smoking in the next 30 days. We also found that 18.4% of respondents had no intention to quit, 13.1% of the respondents were former smokers who had quit more than six months prior to survey, 7.1% had quit less than six months prior to the survey, and 14.5% of survey respondents had never smoked. Similar to the distribution of stages of change found in (Velicer et al., 2000), approximately half of the sample was in contemplation stage (61%), approximately a fifth of the sample were in preparation stage. However, the proportion of people in the pre-contemplation stage was much smaller in our sample (15%) as compared to the proportion (40%) in (Velicer et al., 2000).

Respondents who had used e-cigarettes or vaporizers in the past six months described their experience with these products. Among 500 respondents who provided a qualitative response, 271 provided meaningful insights. The demographics of these respondents by the types of ENDs they used were as shown in Table 2.1.

Table 2.1. Demographics of E-cig, Vaporizer and Dual Users Who Provided Meaningful Responses (n=271)

	E-cigarettes Use		Vaporizer Use		Dual Use	
	Female (n=54)	Male (n=18)	Female (n=36)	Male (n=11)	Female (n=114)	Male (n=38)
18-34 years	20 37.0%	9 50.0%	23 63.9%	6 54.6%	66 57.9%	20 52.6%
35-50 years	20 37.0%	6 33.3%	11 30.6%	5 45.5%	41 36.0%	15 39.5%
51-66 years	14 25.9%	3 16.7%	2 5.6%	0 0%	7 6.1%	3 7.9%

Motivations

Despite quitting (E-cigarettes: 33.3%; Vaporizers: 42.6%; Dual: 32.9%) and harm reduction (E-cigarettes: 30.6%; Vaporizer: 29.8%; Dual: 26.3%) being the most commonly cited motivations, there was a large group of people who cited other reasons for using ENDs. The four key themes of using ENDs are health concerns, personal image, personal enjoyment, and pragmatic reasons. As expected, respondents cited health reasons such as intention to quit and to reduce harm by controlling the nicotine dosage and by reducing second-hand smoke as reasons to use ENDs. On the other hand, there were a variety of non-health motivations to use ENDs. Personal image was important to ENDs users who preferred to smell cleaner, look better, and to engage in behaviors that were not repulsive to others. Personal enjoyment, including interesting flavors, recreational use, and relaxation, also served as a non-health motivation to use ENDs. Lastly, ENDs users also cited pragmatic reasons to use ENDs, such as ability to smoke anytime, anywhere to satisfy their nicotine cravings, ease of use and transportation, as well as the potential to save money. Table 2.2 contains the list of themes and corresponding codes.

Table 2.2. Definition of *A priori* and emerged codes

Themes	Code	*A priori*/ emerged	Definitions
Enjoyment	Fun	Emerged	Curiosity and appreciation for the novelty of ENDs
Enjoyment	Mood	Emerged	Stress reduction, relaxation, appetite suppressant, enjoyment
Enjoyment	Recreation	*A priori*	Hobby, communal smoking, vaping clouds competition
Enjoyment	Taste	*A priori*	Enjoyment or preference for various flavors of ENDs
Health	Control	Emerged	Ability to increase, decrease, or maintain the dosage of nicotine
Health	Harm reduction	*A priori*	Reduce cough, to smoke less conventional cigarettes, expectation of less harm involved relative to convention cigarettes
Health	Quit	*A priori*	Cessation of conventional cigarettes, prevention of relapse, Maintenance of cessation
Health/ Personal Image	Social	*A priori*	Consideration of people around user, including second hand smoke, reducing smell that may be repulsive to non-smokers, ability to smoke around friends and family
Personal Image	Aesthetic	Emerged	Benefits for personal image, including reduced odor and staining
Pragmatic	Convenien ce	*A priori*	Easy to use, easy to transport, no hassle due to smoke alarm, desire to smoke anytime e.g., run out of conventional cigarettes
Pragmatic	Economic	Emerged	Cost-saving
Pragmatic	Restricted	*A priori*	Enabling smoking in restricted places, desire to smoke anywhere

Table 2.3a. Ranking of Motivations by Type of ENDs

E-cigarette Only (n=72)	Vaporizer Only (n=47)	Dual Use (n=152)
Quit (33.3%)	Quit (42.6%)	Quit (32.9%)
Harm Reduction (30.6%)	Harm Reduction (29.8%)	Harm Reduction (26.3%)
Convenience (20.8%)	Taste (23.4%)	Taste (23.7%)
Restricted (19.4%)	Mood (19.2%)	Restricted (16.5%)
Taste (16.7%)	Recreation (12.8%)	Social (14.5%)
Aesthetic (9.7%)	Economic (10.6%)	Convenience (12.5%)
Economic (9.7%)	Fun (8.5%)	Mood (10.5%)
Mood (4.2%)	Aesthetic (4.3%)	Aesthetic (9.2%)
Social (4.2%)	Dose Control (4.3%)	Economic (8.6%)
Fun (2.8%)	Restricted (4.3%)	Dose Control (4.6%)
Dose Control (1.4%)	Social (4.3%)	Recreation (4.0%)
Recreation (0%)	Convenience (2.1%)	Fun (1.3%)

As seen in Table 2.3, there were similarities and differences between different types of ENDs users. Motivations among e-cigarette users, vaporizer users, and dual users did not differ in terms of aesthetics ($\chi^2 = 1.3, \rho = 0.5$), dosage control ($\chi^2 = 1.5, \rho = 0.5$), economic factors ($\chi^2 = 0.2, \rho = 0.9$), harm reduction ($\chi^2 = 0.5, \rho = 0.8$), cessation efforts ($\chi^2 = 1.6, \rho = 0.5$), or taste ($\chi^2 = 1.5, \rho = 0.5$). Differences between e-cigarette and vaporizer users were common. ENDs users who liked to vape did not necessarily like to use e-cigarettes.

> *"I didn't like E cigs, too strong a taste and required a longer draw. Vaping is an easier draw but difficult to get used to and I'm not a fan of vape shops I find them uncomfortable," said 43-year-old female smoker.*

Responses varied between different types of ENDs users in their endorsement of fun ($\chi^2 = 6.5, \rho < 0.05$), recreation ($\chi^2 = 11.1, \rho < 0.01$), social factors ($\chi^2 = 7.9, \rho < 0.05$), convenience ($\chi^2 = 8.9, \rho < 0.05$), and mood ($\chi^2 = 6.9, \rho = 0.03$) as motivations for use. The difference in motivation to smoke in restricted places was marginally significant between types of products used ($\chi^2 = 5.6, \rho = 0.06$).

Table 2.3b. Ranking of Motivations by Stages of Change

Pre-contemplation (n=30)	Contemplation (n=102)	Preparation (n=41)	Action (n=23)	Maintenance (n=45)	Never Smoker (n=29)
Restricted (40%)	Harm Reduction (35.3%)	Quit (41.5%)	Quit (60.9%)	Quit (55.6%)	Harm Reduction (27.6%)
Harm Reduction (30%)	Quit (31.4%)	Harm Reduction (24.4%)	Taste (34.8%)	Harm Reduction (24.4%)	Taste (24.1%)
Social (16.7%)	Restricted (19.6%)	Taste (19.5%)	Aesthetic (21.7%)	Taste (24.4%)	Mood (20.7%)
Taste (16.7%)	Taste (19.6%)	Convenience (12.2%)	Economic (13.0%)	Mood (15.6%)	Recreation (17.2%)
Convenience (13.3%)	Convenience (18.7%)	Mood (9.8%)	Recreation (13.0%)	Aesthetic (13.3%)	Social (13.8%)
Aesthetic (10.0%)	Economic (12.8%)	Dose Control (7.3%)	Harm Reduction (8.7%)	Convenience (8.9%)	Quit (10.3%)
Quit (10.0%)	Social (11.8%)	Economic (7.3%)	Restricted (8.7%)	Economic (8.9%)	Convenience (6.9%)
Fun (6.7%)	Mood (8.8%)	Recreation (4.9%)	Convenience (4.4%)	Dose Control (6.7%)	Economic (6.9%)
Mood (6.7%)	Aesthetic (6.9%)	Restricted (4.9%)	Social (4.4%)	Fun (4.4%)	Fun (6.9%)
Dose Control (3.3%)	Dose Control (2.9%)	Social (4.9%)	Dose Control (0%)	Restricted (4.4%)	Restricted (6.9%)
Economic (0%)	Fun (2.0%)	Aesthetic (2.4%)	Fun (0%)	Social (4.4%)	Aesthetic (3.5%)
Recreation (0%)	Recreation (1.0%)	Fun (0%)	Mood (0%)	Recreation (2.2%)	Dose Control (0%)

Stages of change

The frequency of motivations cited differed by stages of change. E-cigarette users who had no intention to quit smoking conventional cigarettes reported smoking in restricted places as a motivation to use ENDS more frequently (40.0%) than those who were seriously thinking about quitting but undecided (19.6%) and those who were not current smokers (4.4-6.9%). Vaporizer users who had no intention to quit also reported using ENDs for harm reduction, social desirability, aesthetic, and convenience, as seen in the quote below by a dual user who has no intention to quit conventional cigarettes.

> *"I love my regular cigarettes but with the e-cigs or vaporizers I can do it indoor some places with out offending anyone. E-cigs are for me more to knock the nicotine fit out, while vaporizers with all the flavor e juices available are to me more like a treat. I do not smoke inside my home, I can not stand the stench of cigarettes on everything so I use both vape and e cigs while I am indoors at home as well as in the car and places that smoking is not allowed," said 39-year-old female smoker.*

Unlike END users who were in pre-contemplation stage, harm reduction (35.3%) and quitting (19.6%) were the most commonly presented motivation to use ENDs among individuals who were in the contemplation stage. Almost a third of those who intended to quit smoking in the next 30 days reported quitting as a motivation to use ENDs (41.5%), and over half of the former smokers used either e-cigarettes or vaporizers to prevent relapse and to maintain cessation (55.6-60.9%). Former smokers who were in the maintenance phase often reported success in quitting with elaborate details.

"I had smoked cigarettes for 37 years, had tried quitting several times… Without electronic cigarettes, I would not have been able to stop smoking and probably would be using oxygen at home to breathe. I have been tobacco free for three years and am very happy! I should also mention that I've saved a ton of money. The price of smoking cigarettes is outrageous, the steep price does not prevent people from smoking, The addiction is too strong. The e-liquid, tanks, batteries and other accessories are so much more affordable," said 50-year-old former smoker.

As for never smokers, harm reduction (27.6%) was a leading motivation to use ENDs, followed by taste (24.1%), and mood (20.7%). The motivations to use ENDs differed between e-cigarettes and vaporizers.

Discussion

Using thematic analysis, we identified health and non-health related themes among the reasons to use ENDs. The health themes are quitting and harm reduction, whereas the non-health themes include personal image, personal enjoyment, and pragmatic reasons. Despite quitting and harm reduction being the most frequently cited for using ENDs, over half of the ENDs users cited non-health reasons ranging from relaxation and ease of use, to personal image and social desirability. While this heterogeneity in motivation to use ENDs suggested intention to substitute the combustion of tobacco leaf with vaping on some occasions, it was possible that many tobacco and ENDs dual users are experiencing more harm than smoking tobacco or ENDs alone. The ongoing debate about e-cigarettes often assumes a "typical" ENDS user – either a smoker who is using them to quit smoking, or the adolescent who is experimenting with nicotine products. The heterogeneity of motivations found in this study suggested that this existing categorization of ENDs users may be overly simplistic. There appeared to be different market segments that varied according to stages of change, motivation for use, and types of ENDs.

The reasons of using ENDs for the purpose of harm reduction and quitting seemed to differ across stages of change in terms of desire to quit smoking conventional cigarettes. Among individuals who intended to quit smoking in the next 30 days, 31.1% reported using e-cigarettes to quit smoking, and 30.6% used vaporizers to quit smoking. Instead of targeting ENDs users (e-cigarettes: 21.5%; vaporizers: 31.1%) who were undecided about quitting or had no intention to quit (e-cigarettes: 11.5%; vaporizer: 9.5%) who may experience increased harm as a result of smoking both combustible and ENDs, it is particularly important to target individuals who would like to smoke less and to quit with ENDs. Regulations should ensure the safety of ENDs, so that ENDs can be offered as viable quitting tools in places where tobacco and other quitting aides are sold. The current availabilities of ENDs are limited in pharmacies, gas station convenience stores (Rose et al., 2014; Seidenberg, Hong, Liu, Noel, & Rees, 2012). In Massachusetts, almost majority of pharmacies that sell tobacco also offer nicotine patches, but only 2% offer e-cigarettes (Seidenberg et al., 2012). Nationally, retail availability of e-cigarettes was more common in neighborhoods with higher median household income (Rose et al., 2014), which would potentially widen health disparity in tobacco use. Moreover, traditional cigarettes tended to be sold at a lower price when the availability of e-cigarettes was high (Rose et al., 2014), which would likely shift choices from options with reduced harm. ENDs should be sold next to tobacco products or nicotine patches in pharmacies to promote smoking cessations in current smokers.

The existing literature treats e-cigarettes and vaporizers as interchangeable concepts, yet we found differences in motivations to use different types of ENDs. Consistent with qualitative literature that demonstrated the difference in perception of e-cigarettes and vaporizers (Wagoner et al., 2016), we found preference for e-cigarettes to vaporizers and vice versa. Hedonic reasons to use ENDs were more commonly reported among vaporizer users, whereas pragmatic reasons to use ENDs were more frequently presented among e-cigarette users. To better understand different segments of ENDs users based on their needs, demographics, and intention to quit, future research should explore the differences between e-cigarettes and vaporizers as quitting tools in appeal and in effectiveness for various age groups, using a nationally representative sample. The results of such study could provide insights to improve the content and strategies of Public Service Announcement in targeting relatively homogenous groups in the population, and thus improve its effectiveness.

References

Abrams, D. B. (2014). Promise and peril of e-cigarettes: can disruptive technology make cigarettes obsolete? *Jama, 311*(2), 135-136.

Ayers, J. W., Ribisl, K. M., & Brownstein, J. S. (2011). Tracking the rise in popularity of electronic nicotine delivery systems (electronic cigarettes) using search query surveillance. *American Journal of Preventive Medicine, 40*(4), 448-453.

Banerjee, S. C., Shuk, E., Greene, K., & Ostroff, J. S. (2015). Content analysis of trends in print magazine tobacco advertisements. *Tobacco regulatory science, 1*(2), 103-120.

Barbeau, A. M., Burda, J., & Siegel, M. (2013). Perceived efficacy of e-cigarettes versus nicotine replacement therapy among successful e-cigarette users: a qualitative approach. *Addiction science & clinical practice, 8*(1), 5.

Berg, C. J. (2016). Preferred flavors and reasons for e-cigarette use and discontinued use among never, current, and former smokers. *Int J Public Health, 61*(2), 225-236.

Borland, R., Partos, T. R., Yong, H. H., Cummings, K. M., & Hyland, A. (2012). How much unsuccessful quitting activity is going on among adult smokers? Data from the International Tobacco Control Four Country cohort survey. *Addiction, 107*(3), 673-682.

Brown, C. H., Mohr, D. C., Gallo, C. G., Mader, C., Palinkas, L., Wingood, G., . . . Jacobs, C. (2013). A computational future for preventing HIV in minority communities: how advanced technology can improve implementation of effective programs. *J Acquir Immune Defic Syndr, 63 Suppl 1*, S72-84. doi:10.1097/QAI.0b013e31829372bd

Cho, J. H., Shin, E., & Moon, S.-S. (2011). Electronic-cigarette smoking experience among adolescents. *Journal of Adolescent Health, 49*(5), 542-546.

Cobb, N. K., Byron, M. J., Abrams, D. B., & Shields, P. G. (2010). Novel nicotine delivery systems and public health: the rise of the "e-cigarette": American Public Health Association.

Dai, H., & Hao, J. (2016). Mining social media data for opinion polarities about electronic cigarettes. *Tobacco Control*, tobaccocontrol-2015-052818.

Etter, J.-F. (2010). Electronic cigarettes: a survey of users. *BMC Public Health, 10*(1), 231.

Etter, J.-F. (2015). E-cigarettes: methodological and ideological issues and research priorities. *BMC medicine, 13*(1), 32.

Ford, A., MacKintosh, A. M., Bauld, L., Moodie, C., & Hastings, G. (2016). Adolescents' responses to the promotion and flavouring of e-cigarettes. *Int J Public Health, 61*(2), 215-224.

Giovenco, D. P., Hammond, D., Corey, C. G., Ambrose, B. K., & Delnevo, C. D. (2014). E-cigarette market trends in traditional US retail channels, 2012–2013. *Nicotine & Tobacco Research*, ntu282.

Gitchell, J. G., Shiffman, S., & Sembower, M. A. (2016). Trends in Serious Quit Attempts in the United States, 2009- 2014. *Addiction*.

Glasser, A. M., Collins, L., Pearson, J. L., Abudayyeh, H., Niaura, R. S., Abrams, D. B., & Villanti, A. C. (2016). Overview of Electronic Nicotine Delivery Systems: A Systematic Review. *American Journal of Preventive Medicine*.

Harris, J. K., Moreland-Russell, S., Choucair, B., Mansour, R., Staub, M., & Simmons, K. (2014). Tweeting for and against public health policy: response to the Chicago Department of Public Health's electronic cigarette Twitter campaign. *Journal of Medical Internet Research, 16*(10), e238.

Health, U. D. o., & Services, H. (2014). The health consequences of smoking—50 years of progress: a report of the Surgeon General. *Atlanta, GA: US Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health, 17*.

Kalkhoran, S., & Glantz, S. A. (2016). E-cigarettes and smoking cessation in real-world and clinical settings: a systematic review and meta-analysis. *The Lancet Respiratory Medicine, 4*(2), 116-128.

Kong, G., Morean, M. E., Cavallo, D. A., Camenga, D. R., & Krishnan-Sarin, S. (2015). Reasons for electronic cigarette experimentation and discontinuation among adolescents and young adults. *Nicotine & Tobacco Research, 17*(7), 847-854.

Kotler, P. (1979). Strategies for introducing marketing into nonprofit organizations. *The Journal of Marketing*, 37-44.

Lazard, A. J., Saffer, A. J., Wilcox, G. B., Chung, A. D., Mackert, M. S., & Bernhardt, J. M. (2016). E-Cigarette Social Media Messages: A Text Mining Analysis of Marketing and Consumer Conversations on Twitter. *JMIR Public Health and Surveillance, 2*(2).

Leventhal, A. M., Strong, D. R., Kirkpatrick, M. G., Unger, J. B., Sussman, S., Riggs, N. R., . . . Audrain-McGovern, J. (2015). Association of electronic cigarette use with initiation of combustible tobacco product smoking in early adolescence. *Jama, 314*(7), 700-707.

McDaniel, A. M. (2016). Smoking cessation strategies may increase quit rates among adults of low socioeconomic status. *Evidence-based nursing, 19*(1), 17-17.

Noel, J. K., Rees, V. W., & Connolly, G. N. (2011). Electronic cigarettes: a new 'tobacco'industry? *Tobacco Control, 20*(1), 81-81.

Paek, H.-J., Kim, S., Hove, T., & Huh, J. Y. (2014). Reduced harm or another gateway to smoking? Source, message, and information characteristics of e-cigarette videos on YouTube. *J Health Commun, 19*(5), 545-560.

Primack, B. A., Soneji, S., Stoolmiller, M., Fine, M. J., & Sargent, J. D. (2015). Progression to traditional cigarette smoking after electronic cigarette use among US adolescents and young adults. *JAMA pediatrics, 169*(11), 1018-1023.

Prochaska, J., & DiClemente, C. (1984). Self change processes, self efficacy and decisional balance across five stages of smoking cessation. *Progress in clinical and biological research, 156*, 131.

Reid, J. L., Rynard, V. L., Czoli, C. D., & Hammond, D. (2015). Who is using e-cigarettes in Canada? Nationally representative data on the prevalence of e-cigarette use among Canadians. *Preventive medicine, 81*, 180-183.

Rigotti, N. A. (2015). e-Cigarette use and subsequent tobacco use by adolescents: new evidence about a potential risk of e-cigarettes. *Jama, 314*(7), 673-674.

Rose, S. W., Barker, D. C., D'angelo, H., Khan, T., Huang, J., Chaloupka, F. J., & Ribisl, K. M. (2014). The availability of electronic cigarettes in US retail outlets, 2012: results of two national studies. *Tobacco Control, 23*(suppl 3), iii10-iii16.

Seidenberg, A. B., Hong, W., Liu, J., Noel, J. K., & Rees, V. W. (2012). Availability and range of tobacco products for sale in Massachusetts pharmacies. *Tobacco Control*, tobaccocontrol-2012-050591.

Tan, A. S., Lee, C.-j., & Bigman, C. A. (2016). Comparison of beliefs about e-cigarettes' harms and benefits among never users and ever users of e-cigarettes. *Drug Alcohol Depend, 158*, 67-75.

Velicer, W. F., Prochaska, J. O., Fava, J. L., Rossi, J. S., Redding, C. A., Laforge, R. G., & Robbins, M. L. (2000). Using the transtheoretical model for population-based approaches to health promotion and disease prevention. *HOMEOSTASIS-PRAHA-, 40*(5), 174-195.

Wagoner, K. G., Cornacchione, J., Wiseman, K. D., Teal, R., Moracco, K. E., & Sutfin, E. L. (2016). E-cigarettes, hookah pens and vapes: adolescent and young adult perceptions of electronic nicotine delivery systems. *Nicotine & Tobacco Research*, ntw095.

Warnier, M. J., van Riet, E. E., Rutten, F. H., De Bruin, M. L., & Sachs, A. P. (2013). Smoking cessation strategies in patients with COPD. *European Respiratory Journal, 41*(3), 727-734.

Difficulty of “Now” in Depression and Health Behaviors (Paper 3)

Flora Or, M.H.S.

Harvard T.H. Chan School of Public Health

Abstract

People who suffer from chronic depression are also disproportionately affected a distinct set of health-damaging behaviors that can be involve short-term rewards and long-term costs, which can lead to inconsistencies in intertemporal choices (e.g. smoking, poor sleep, and nutrition). The goal of the current study is to evaluate the relationships among depression, health behaviors, and intertemporal decisions that involve costs and rewards across different points in time. An online sample of participants resided in the U.S. completed the survey (mean age= 36.6 years, SD=11.6; 53% female) (N=1000). The pattern of financial time preference among those at medium risks for depression was similar to the patterns found in health individuals who were primed with sadness. The pattern of time preference was the opposite among those at high risks for depression, suggesting that decision biases in financial decisions under the influence of additional depressive symptoms exceeded biases due to sadness alone. Financially, individuals who were at medium risks for depression were more present-based than the healthy controls, while individuals who were at high risks for depression were not present-biased but were less likely to be impatient as compared to healthy controls. Behaviorally, present bias was more pronounced in health behaviors (nutrition, sleep, and physical activity) than in financial choices among those who were at medium risks for depression. In our experiment, we found that knowledge alone was insufficient to change either self-report interest in commitment devices or clicking of the hyperlink to obtain more information on commitment devices.

Keywords: depression, time preference, health behaviors, commitment devices

Time preference is intricately related to health and well-being. Higher discount rates are empirically associated with a variety of damaging behaviors such as smoking, gambling, substance use, risky sexual behaviors, reliance on credit cards, while low discount rates are associated with positive behaviors e.g., exercise, savings and healthy diets (Baker et al., 2008; Chabris et al., 2008b; Chivers et al., 2012; Meier & Sprenger, 2010). Epidemiologically, these are the very same behaviors that contribute to early mortality among depressed individuals (Jackson, Knight, & Rafferty, 2010; Murphy et al., 2008). Not only are depressed individuals more susceptible to tobacco use, poor diet, physical inactivity and alcohol consumption, which are leading causes of death in the U.S.. (Dolye et al., 2014; Faith et al., 2011; Mokdad et al., 2004; Grant, 1995; Regier et al., 1990), depressed individuals also have a tendency to withdraw from social networks, resulting in diminishing quality of social relationships (Allgöwer, Wardle, & Steptoe, 2001). It is possible that depressed individuals undertake unhealthy behaviors (e.g., smoking, impulsive shopping) as self-medication or coping strategies (Ziedonis et al., 2008; Dierker et al., 2002; Lejoyeux & Weinstein, 2010).

In experimental studies, primed sadness in healthy samples leads stronger preference for reward now to later regardless of length of delay as compared to those who have been primed with neutral emotions (Lerner, Li, & Weber, 2013). The relationship between depression and time preference is understudied, though sadness is often a perpetual state of emotion experienced in the midst of depression, as negative affect lingers and intensifies given various cognitive vulnerabilities (Hankins 2001). The Appraisal Tendency Framework (ATF) posits that incidental emotion influences the depth and content of thoughts more specifically than global valence (i.e., good vs. bad mood) and in ways that that follow emotion-specific appraisal tendencies (Han, Lerner & Keltner, 2000). Incidental emotions are emotions that are felt at the time of decision making which may have little to do with the choice under consideration, yet can play a role in judgment and choice. Han, Lerner & Keltner (2000) proposed that the process would apply to both momentary and dispositional emotions. Prior work suggests that appraisal tendencies map onto six dimensions, namely pleasantness, anticipated efforts, attentional activity, control and responsibility (Smith & Ellsworth, 1985). While sadness, anger, fear, disgust, contempt and frustration are all unpleasant emotions, sadness distinctly exerts an irrevocable feeling of loss which leads to reward replacement (Lazarus, 1991; Lerner, Small, & Loewenstein, 2004) The appraisal dimensions of sadness include extreme unpleasantness, uncertainty, avoidance, and diminished attentional activity and anticipated effort. Sadness is distinct from other emotions by the extremely appraisal of heightened situational control and diminished personal control. The content effects of sadness include high valuation and reward seeking (despite heightened risks) in terms of valuation, distrust, infrequent cooperation, and tendency to blame. Confirming the ATP prediction that sadness promotes reward seeking behaviors and diminishes self-control, experimental studies have found that primed sadness leads to preference for financial rewards now compared to later, regardless of length of delay, but does not appear to affect delta discounting (i.e. choices between two later options) (Lerner, Li, & Weber, 2013). Existing studies on time preference and depression are limited to studies with small sample size. Some clinical studies' findings were consistent with the ATF predictions, such that people who experienced uni- and bi-polar depression tended to experience greater present bias and impatience as compared to healthy controls (Pulcu et al., 2014; Takahashi et la., 2008). By contrast, other clinical studies found that discount rates were not significantly associated with depression severity in older adults (Dombrovski et al., 2011).

In the context of health behaviors and depression, we speculate that present bias would occur when current self focuses on instant relief by means of unhealthful behaviors (e.g., snacking), greatly discounting well-being in future in the short-horizon, but would have a different set of preferences for one's future self in the long-horizon. Specifically, individuals might intend to maintain and improve their well being in the long run, but are unable to avoid temptation of unhealthy behaviors. Individuals who are aware of their self control problems and are willing to change would sometimes adopt commitment devices that facilitate goal-fulfillment in the future by self-imposing a significant loss as a consequence to failure to execute planned behavior in future (Laibson, 1997). Some examples of commitment device used to promote health behaviors included deposit contract, temptation bundling, (e.g., only watch TV on treadmill), purchasing small packages, serving plate and annual gym memberships (Rogers et al., 2014). While commitment devices effectively address self-control problems, the uptake rate is often low and behavioral strategies to increase uptake are needed (Milkman et al., 2013; Halpern et al., 2015; Schartz et al., 2014; Rogers et al., 2014). Since under-recognition is one of the biggest barriers to seek care in depression, we speculate that information of one's depression status would increase the likelihood of adopting commitment devices in depressed individuals who are suffering from the negative consequences of present bias. The goals of the current study are (1) to evaluate the association between depressive symptoms and time preference; (2) to explore the mechanism linking depression and unhealthful behaviors; (3) to test if the information of one's depression status would improve uptake of commitment devices to improve health behaviors.

Aims and Hypotheses

Our first aim was to evaluate the association between depressive symptoms and time preference (present bias, future bias, and impatience respectively). We hypothesized that moderate risks for depression would be associated with choices consistent with present-biased preferences, while high risks for CESD-R score would be associated with choices inconsistent with present-bias preferences, as compared to low CESD-R score. We also hypothesized that depression would not be associated with impatience or future bias.

Our second aim was to explore the mechanism linking depression and present bias in healthful behaviors (sleep, physical activity, and sleep) using path analysis. We hypothesized that there would be a positive dose-response relationship between CESD-R score and present bias in the respective healthful behavior (direct effect), and that there would be an indirect effect of depression on unhealthful behaviors, where depression affects financial present-bias and financial present-bias would in turn affect present bias in health behaviors (indirect effect).

Our third aim was to test if health message that contains personalized depression status would improve uptake of commitment devices. We hypothesized that, priming of depression status would increase professed interest and uptake of commitment devices among respondents with a CESD-R score >=16.

Method

Sample

We recruited a convenience sample of adults to complete a Human Intelligence Task (HIT) from TurkPrime which integrated with Amazon Mechanical Turk (MTurk) to provide a streamlined process for data collection in social science research (Litman et al., 2016). The HIT involved completing a 5-minute survey on health, behaviors, and financial choices on Harvard Qualtrics anonymously and entering a verification code as proof of completion on mTurk, for a compensation of $.50, and an opportunity to participate in a daily raffle for approximately $20 credit bonus into their amazon payment account. To maximize recruitment speed and to minimize selection bias, we used the HyperBatch feature on TurkPrime which broke down the HIT into multiple smaller HITs recruiting 9 or less participants at a time automatically. MTurk workers who have completed one HIT under the study was disabled from taking subsequent HITs of the same study. We also blocked repeated attempts to complete the survey from the same IP address. The inclusion criteria for participation were English-speaking, aged 18 years or above, residing in the U.S., and an approval rate of 90% or higher on MTurk. MTurk workers who had approval ratings below 90% were excluded to avoid spam. Mturk workers who have completed at least 100 Human Intelligence Tasks (HITs) receive approval ratings that reflect the percentage of completed work that was approved by the requesters. MTurk workers who have completed 0-99 HITs have approval ratings of 100%. Assuming that the distribution of depression among mTurk workers would be similar to that in the general population where the prevalence of depression would be approximately 5% and the prevalence of subthreshold depression would be approximately 25% (Shapiro et al., 2011), we oversampled to ensure sufficient power to evaluate the relationship between depression and time preference in Aim 1 and Aim 2. However, we were underpowered to ascertain the relationship between knowledge of depression status and uptake of commitment devices in Aim 3.

Survey

Participants read a brief description of the study and consented to participate by proceeding with the study on Qualtrics. To ensure thwart spamming, we implemented Completely Automated Public Turing Test to tell Computers and Humans Apart (CATCHA) verification where respondents must correctly type out the character in a picture presented in order proceed with the survey. Participants provided demographics information (age, gender, race, education, and marital status) and whether they were currently taking any medication prescribed by a doctor for mental conditions. Respondents who reported currently taking medication were asked if they were taking antidepressants (e.g., Prozac, Paxil, Celexa, Zoloft), minor tranquilizers (e.g., Valium), medications for bipolar disorders (e.g.,, Lithium), or antipsychotic medication (e.g., Ability, Clozaril, Risperdal, Zyprexa). Respondents also reported whether s/he had received inpatient care in six months prior to the completion of the survey. We used the Center for Epidemiologic Studies Depression Scale – Revised (CESD-R) (Eaton, et al., 2004) to ascertain depression, and a 10-item binary financial choice task to ascertain time preference.

The CESD-R (Eaton, et al., 2004).

The CESD-R is a 20-item self-administered screening test for depression and depressive disorders. These items measured the nine depressive symptoms defined by the American Psychiatric Association Diagnostic and Statistical Manual (DSM-V), including depressed mood, change in appetite, and suicidality. Respondents reported frequency of symptom occurrence in the past two weeks in terms of “not at all or less than 1 day last week,” “one or two days last week,” “three to four days last week,” “five to seven days last week,” or “nearly every day for two weeks.” At the end of this section, we displayed the following psychological support message.

> *“Are you in crisis? Please call 911 or the National Suicide Prevention Hotline at 1-800-273-TALK or go immediately to the nearest emergency room.”*

Upon completion of the CESD-R, the total CESD-R score was automated as the sum of responses to all 20 questions, ranging from zero to three where top two frequency responses were assigned the same value. The sum of the score was computed for the purpose of stratified randomization in the experimental component of the study.

The Financial Choice Task.

We adapted the financial choice task from Toussaert (2014) based on our budget and survey response during the pilot phase of the study. The financial choice task involved two sets of five binary choices between receiving money at different points in time. To ascertain preferences in the short horizon, the first five questions ascertained preferences between sooner options ($20) today and later options ($19.50, $20.50, $21, $21.50, $22.0 respectively) in 3 days. To ascertain preferences in the long horizon, the second set of questions ascertained preferences between sooner options ($20) in 28 days and later options ($19.50, $20.50, $21, $21.50, $22.0 respectively) in 31 days. To motivate thoughtful response, we prefaced this section by the following message on a daily raffle for at least 15 seconds, and enabled delayed submission of response after five seconds of exposure to each question.

> *A BONUS of approximately $20 will be rewarded to one randomly selected person who completes this survey each day. We expect*

your chances of winning the raffle to be 1 in 100.

The ***amount and timing*** *of the reward will be* ***determined by your choices.***

For example, you may be asked to choose between a smaller amount of money which you could receive sooner VERSUS a larger amount which you will need to wait to receive later.

To minimize any priming effect of the depression questions on time preference, we split the CESD-R and the financial choice tasks into 2 halves respectively. Respondents completed the first 10-item of the CESD-R prior to completing 5-item of time preference in the short horizon, and completed the remaining 10-item of the CESD-R prior to completing 5-item of time preference in the long horizon.

Experimental Design

To access the effect of seeing one's depression status on interests and uptake of commitment devices, we stratified respondents by depression status with a cut-off of 16 on the CESD-R score from the previous section, and randomized respondents into one of two treatment arms.

The intervention group was notified of their depression/healthy status prior to a question regarding their interest in signing for an online tool to improve health behaviors. The message regarding their depression/healthy status depended on their CESD-R score from the previous section. We primed individuals of their depressed or healthy status for 15 seconds. We displayed to individuals who had CESD-R score below 16, "According to your survey response, depression is not a problem for you right now," whereas those had CESD-R score of 16 or above, "According to your survey response, you have been experiencing symptoms of depression for more than a few days." We prefaced the questions on commitment devices by "one way to improve your physical and mental health would be to sign a "contract" with yourself to commit to make changes in daily lives (e.g., quit smoking, exercise daily)." Respondents were then asked if s/he was interested in finding out more about free services to make a commitment to better health. Those who professed interest in committement devices received the following invitation.

> *You have indicated that you would like to learn more about a web-based tool to help design commitments to improve your mental health.*
>
> *Please click <u>here</u>** to obtain more information.*
>
> ***This link will open in a new window and will not affect your survey completion.*

The control group was notified of their depression/healthy status <u>after</u> being asked if they were interested in commitment devices and the invitation to obtain more information for clicking a hyperlink.

Survey on Health Behaviors

In order to isolate the effect of seeing one's depression status on the uptake and interest of a commitment device, respondents responded to the following questions on health behaviors adapted from Chabris et al. (2008b) at the end of the survey.

Measure

Sleep.

"In the past 7 days, how often did you go to bed later (i.e., more than one hour) than intended? Every day/ most days/ some days/ few days/ no days"

Eating.

"In the past 7 days, how often did you eat more than you think you should eat e.g., snacking? Every meal/ most meals/ some meals/ few meals/ no meals"

Physical Activity.

"In the past 7 days, how often did you wish to be more physically active (e.g., walking, weight-lifting, working out)? Every day/ most days/ some days/ few days/ no days"

Results

Sample Characteristics

An online sample of participants resided in the U.S. completed the survey (mean age= 36.65 years, SD=11.68; 53.02% female; 79.9% white) (N=1009). Similar to the population estimates, the prevalence of major depressive episode was 3.9% in this sample. Consistent with the epidemiologic evidence of high comorbidity between depression and unhealthful behaviors, over 90% of individuals who were potentially depressed reported inability to achieve intended health behaviors in the past 7 days. Decision biases in financial choices and in heath behaviors exhibited differently in those who had sub threshold depression as compared to those who were depressed.

Classification of Major Depressive Episode (MDE)

We used an algorithm to determine if someone met criteria for major depressive episode (MDE), experienced a probable MDE, possible MDE, subthreshold MDE, or no clinical significance (CESD-R < 16) as described in Eaton et al. (2004). Among indviduals who experienced anhedonia or dysphoria nearly every day for the past two weeks, those who experienced four additional DSM symptom groups nearly every day for the past two weeks met criteria for MDE; those who experienced an additional three DSM symptom group either nearly every day for the past two weeks, or 5-7 days in the past week were considered to have probable MDE, and those who experienced an additional two DSM symptom group either nearly every day for the past two weeks, or 5-7 days in the past week were considered to have possible MDE. We considered those who had probable MDE or met criteria for MDE to be at high risks for depression, those who experienced possible or subthreshold MDE to be at medium risks for depression, and those who no clinical significance at low risk for depression.

Classification of Time Preference

We computed impatience, future bias, and present bias in financial choices as well as health behaviors as binary conditions. In examining financial choices, individual chose a sooner reward in the short horizon and a later reward in the long horizon in one or more instances were considered present-biased, whereas those who chose a later reward in the short horizon and a sooner reward in the long horizon in one or more instances were considered future biased. Individuals who chose a sooner reward instead of a later reward in one or more instances were considered impatient. Individuals who chose a later reward and reverted back to a sooner reward despite additional later reward were considered showing erratic response and were excluded from the analyses involving time preferences in financial choices.

Relationship between Depression and Time Preference

We fitted a series of logistic regressions to evaluation the association between depression and time preference in financial choices and in health behaviors (Table. 3.1a) The relationship between depression and time preference differ by their level of risks for depression and by the types of decisions. In financial choices, individuals who were at medium risks of depression were 1.5 times more likely to be present biased ($p<0.05$) as compared to healthy controls, and while those who experienced high risks for depression did not differ significantly in their likelihood of being present biased. Individuals who experienced medium or high risks for depression were not more likely to be future-biased, as compared to those who were healthy. In contrast, individuals who had high risks for depression were 90% less likely to be impatient as compared to healthy controls ($p<0.01$).

In comparison to financial choices, the magnitude of association between depression and present bias were more pronounced in health behaviors (eating, sleep, exercise). Individuals who were at medium risks for depression were 2-3 times more likely to go to bed more than an hour later than intended, eat more than intended, and wish to be more physically active in the past seven days as compared to healthy controls [OR = 2.3 - 3.3, $p<0.01$]. Individuals who had high risks for depression were three times more likely to go to bed more than an hour later than intended in the past week [OR=3.3, $p<0.01$] but were not more likely to eat more than intended or wish to be more physically active in the past week. Individuals were at high risks for depression were half as likely to wish that they had been more physically active in the past week, as compared to those who were at medium risk for depression [OR=0.5, $p<0.05$].

We replicated the results in linear probability model as shown in Table 3.1b. The results indicated similar patterns where relationship between depression and present bias are more pronounced in health behaviors than in financial choices.

Table 3.1a. Logistic Regressions of Time Preference in Financial Decisions and Health Behaviors on Depression

	Financial Present bias	Financial Future bias	Financial Impatience	Eating Present bias	Sleep Present bias	Exercise Present bias
Med Risk	1.478**	1.122	0.904	2.603***	2.347***	3.328***
Depression	(0.258)	(0.265)	(1.156)	(0.484)	(0.526)	(0.842)
High Risk	1.171	0.819	0.104***	3.313***	1.865*	1.563
Depression	(0.329)	(0.311)	(0.0839)	(1.052)	(0.619)	(0.487)
Male	1.482**	0.582**	0.971	0.838	0.768	0.635**
	(0.240)	(0.138)	(0.769)	(0.129)	(0.134)	(0.114)
Black	0.509**	0.575	0.296	0.530***	0.796	0.935
	(0.156)	(0.246)	(0.326)	(0.128)	(0.221)	(0.285)
Asian	1.441	1.001		0.652	1.925	0.820
	(0.451)	(0.437)		(0.195)	(0.857)	(0.291)
Other	0.667	0.812	0.187	0.826	1.325	0.791
	(0.294)	(0.430)	(0.211)	(0.327)	(0.580)	(0.357)
Age	1.006	1.012	1.045	0.994	0.959***	0.997
	(0.00771)	(0.0102)	(0.0771)	(0.00717)	(0.00727)	(0.00864)
Vocational/	0.536	3.485***	0.424	1.365	2.481*	1.685
Technical School	(0.240)	(1.611)	(0.755)	(0.537)	(1.315)	(0.783)
Some college	1.048	1.311	2.973	0.988	1.286	1.471
	(0.272)	(0.470)	(3.189)	(0.245)	(0.375)	(0.410)
College Graduate	0.902	0.798	5.286	1.512*	1.058	1.669*
	(0.232)	(0.300)	(8.836)	(0.375)	(0.302)	(0.459)
Master’s	0.670	0.769		2.070**	0.888	2.947***
	(0.225)	(0.395)		(0.686)	(0.307)	(1.231)
Doctoral	1.271	0.716		1.515	0.903	1.658
	(0.659)	(0.569)		(0.770)	(0.473)	(0.986)
Married/	1.537**	0.494***	0.494	1.029	0.968	1.050
Living with Partner	(0.281)	(0.122)	(0.410)	(0.179)	(0.187)	(0.210)
Separated/Divorced	2.475***	0.373**		0.752	0.936	1.132
/Widowed	(0.766)	(0.177)		(0.225)	(0.324)	(0.445)
Inpatient	0.864	0.792		0.641*	1.051	0.633
(6 Months)	(0.200)	(0.246)		(0.166)	(0.291)	(0.203)
Constant	0.202***	0.181***	44.30**	3.717***	15.91***	5.111***
	(0.0856)	(0.104)	(65.34)	(1.568)	(7.744)	(2.527)
Observations	920	920	603	1,009	1,009	1,009

Robust Standard Error eform in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Test of difference between coefficients:
Financial Present Bias: $\beta(\text{High Risk Depression}) - \beta(\text{Medium Risk Depression})$
Estimate = .7922676 ; SE = .2878579; Pr > |z| = 0.419
$Financial\ Future\ Bias: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = .7296068 ; SE = .2870403; Pr > |z| = 0.423
$Financial\ Impatience: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = .1567164 ; SE = .1930404; Pr > |z| = 0.132
$Present\ Bias\ in\ Eating: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = 1.272779 ; SE = .4371863; Pr > |z| = 0.483
$Present\ Bias\ in\ Sleep: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = .7949333; SE = .2913649 ; Pr > |z| = 0.531
$Present\ Bias\ in\ Exercise : \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = .4695554 ; SE = .173863 ; Pr > |z| < 0.05

Table 3.1b. Linear Probability Model of Time Preference in Financial Decisions and Health Behaviors on Depression

	Financial Present bias	Financial Future bias	Financial Impatience	Eating Present bias	Sleep Present bias	Exercise Present bias
Med Risk	0.0750**	0.0116	0.0116	0.0116	0.106***	0.132***
Depression	(0.0344)	(0.0247)	(0.0247)	(0.0247)	(0.0249)	(0.0235)
High Risk	0.0293	-0.0185	-0.0185	-0.0185	0.0837**	0.0643
Depression	(0.0518)	(0.0354)	(0.0354)	(0.0354)	(0.0373)	(0.0391)
Male	0.0742**	-0.0501**	-0.0501**	-0.0501**	-0.0375	-0.0584**
	(0.0305)	(0.0221)	(0.0221)	(0.0221)	(0.0247)	(0.0234)
Black	-0.110**	-0.0482	-0.0482	-0.0482	-0.0299	-0.00788
	(0.0425)	(0.0327)	(0.0327)	(0.0327)	(0.0425)	(0.0403)
Asian	0.0699	-0.00307	-0.00307	-0.00307	0.0748*	-0.0213
	(0.0635)	(0.0435)	(0.0435)	(0.0435)	(0.0426)	(0.0492)
Other	-0.0688	-0.0205	-0.0205	-0.0205	0.0265	-0.0309
	(0.0698)	(0.0524)	(0.0524)	(0.0524)	(0.0531)	(0.0652)
Age	0.00118	0.00116	0.00116	0.00116	-0.00677***	-0.000350
	(0.00150)	(0.00107)	(0.00107)	(0.00107)	(0.00129)	(0.00119)
Vocational/	-0.109	0.182**	0.182**	0.182**	0.107**	0.0731
Technical School	(0.0718)	(0.0738)	(0.0738)	(0.0738)	(0.0534)	(0.0593)
Some college	0.00986	0.0274	0.0274	0.0274	0.0313	0.0553
	(0.0515)	(0.0350)	(0.0350)	(0.0350)	(0.0415)	(0.0430)
College Graduate	-0.0192	-0.0177	-0.0177	-0.0177	0.00716	0.0712*
	(0.0504)	(0.0333)	(0.0333)	(0.0333)	(0.0416)	(0.0423)
Master's	-0.0745	-0.0195	-0.0195	-0.0195	-0.0209	0.132***
	(0.0628)	(0.0408)	(0.0408)	(0.0408)	(0.0552)	(0.0492)
Doctoral	0.0560	-0.0255	-0.0255	-0.0255	-0.0240	0.0651
	(0.114)	(0.0635)	(0.0635)	(0.0635)	(0.0901)	(0.0892)
Married/	0.0787**	-0.0667***	-0.0667***	-0.0667***	-0.000316	0.00631
Living with Partner	(0.0331)	(0.0244)	(0.0244)	(0.0244)	(0.0267)	(0.0265)
Separated/	0.179***	-0.0941**	-0.0941**	-0.0941**	-0.00415	0.0165
Divorced	(0.0653)	(0.0414)	(0.0414)	(0.0414)	(0.0571)	(0.0479)
Inpatient	-0.0273	-0.0237	-0.0237	-0.0237	0.0111	-0.0473
(6 Months)	(0.0456)	(0.0336)	(0.0336)	(0.0336)	(0.0340)	(0.0300)
Constant	0.157*	0.151**	0.151**	0.151**	1.009***	0.810***
	(0.0811)	(0.0607)	(0.0607)	(0.0607)	(0.0677)	(0.0660)
Observations	920	920	920	920	1,009	1,009

Robust Standard Error eform in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Test of difference between coefficients:
Financial Present Bias: $\beta(\text{High Risk Depression}) - \beta(\text{Medium Risk Depression})$
Estimate = $-.0300316$; SE = $.0379565$; Pr > |z| = 0.429
$Financial\ Future\ Bias: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = $-.0300316$; SE = $.0379565$; Pr > |z| = 0.429
$Financial\ Impatience: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = $.1567164$; SE = $.1930404$; Pr > |z| = 0.132
$Present\ Bias\ in\ Eating: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = $-.0300316$; SE = $.0379565$; Pr > |z| = 0.429
$Present\ Bias\ in\ Sleep: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = $-.0218898$; SE = $.0364317$; Pr > |z| = 0.548
$Present\ Bias\ in\ Exercise: \beta(High\ Risk\ Depression) - \beta(Medium\ Risk\ Depression)$
Estimate = $-.0673932$; SE = $.0381821$; Pr > = 0.078

Mechanisms of Comorbid Depression and Unhealthful Behaviors

We fitted conducted a series of multiple-group path analyses with robust standard errors to examine whether financial present bias explained the association between depression and present bias in healthful behaviors at each level of risks for depression (Mackinnon et al., 2007), The candidate model for this mediation constitutes three simultaneous equations, as illustrated by sleep as an outcome example.

$$PresentBias\_Sleep = i_1 + c\ CESD + \epsilon_1 \qquad 1$$

$$PresentBias\_Sleep = i_2 + c'CESD + b\ PresentBias\_Finance + \epsilon_2 \qquad 2$$

$$PresentBias\_Finance = i_3 + a\ CESD + \epsilon_3 \qquad 3$$

In this model, i_1, i_2, i_3 were intercepts and $\epsilon_1, \epsilon_2, \epsilon_3$were the error terms for the respective simultaneous equations. *c* was the coefficient relating the predictor and outcome variables through a direct path, *c′* was the coefficient relating the predictor and the outcome variable adjusted for the mediator, *b* was the coefficient relating the mediator to the outcome adjusted for the exposure variable, *a* was the coefficient relating the predictor variable to the mediator. The mediated effect of depression on present bias in health behaviors was a*b, (SE =$\sqrt{a^2 s_b^2 + b^2 s_a^2}$).

Direct and Indirect Effects of Depression on Present Bias in Health Behaviors

Adjusted for present bias in financial decisions, CESD-R score was positively associated with present bias in eating, exercise, and sleep respectively among those who were at low risks for depression [Exercise: c' =1.1, p<0.01; Eating: c' = 0.8, p<0.01; Sleep: c' = 0.9, p<0.01], CESD-R score was positively associated with eating and sleep respectively, but not with exercising among those who were at medium risks for depression [Exercise: c' =0.0, p=0.7; Eating: c' =0.2, p<0.01; Sleep: c' =0.2, p<0.01]. Among those who were at high risks for depression, CESD-R score was associated with present bias in sleep, but not in eating or exercising, adjusting for present bias in financial decisions [Exercise: c' = 0.2, p = 0.3; Eating: c' = 0.0, p=0.9; Sleep: c' = 0.6, p<0.01] (Table 3.2). The indirect effect of depression on present bias in health behaviors (a*b) were negligible, whereby changes in financial present bias was unlikely to lead to changes in present bias in health behaviors (Table 3.2). Path coefficients on the indirect paths indicated that present bias in financial choices were negatively correlated with present bias in eating and exercise, but not in sleep among those who were at low risks for depression. In contrast, present bias in financial choices was only negatively correlated with present bias in eating, but not in sleep or exercise, among those who were at medium risks for depression. Among those who were at medium risks for depression, present bias in financial choices was not significantly associated with present bias in health behaviors.

Table 3.2. Multiple-group Path Analyses on Depression, Financial Present Bias, and Present Bias in Health Behaviors

		Exercise	Eat	Sleep
Financial Present bias <-CESD-R				
	Low risk	0.0074466	0.0074466	0.0074466
		(-0.113063)	(-0.113063)	(-0.113063)
	Medium risk	0.1368445	0.1368445	0.1368445
		(0.0948214)	(0.0948214)	(0.0948214)
	High risk	-0.0838513	-0.0838513	-0.0838513
		(0.1476296)	(0.1476296)	(0.1476296)
Constant				
	Low risk	6.681652***	6.681652***	6.681652***
		(0.8536406)	(0.8536406)	(0.8536406)
	Medium risk	4.383149*	4.383149*	4.383149*
		(2.489022)	(2.489022)	(2.489022)
	High risk	10.94098*	10.94098*	10.94098*
		(6.021216)	(6.021216)	(6.021216)
Present Bias in Health Behavior <- Financial Present Bias	Low risk	-0.1029045**	-0.0791159***	-0.0552131
		(0.0418418)	(0.0274047)	(0.0443142)
	Medium risk	-0.0754427	-0.0803506	-0.0234071
		(0.0653621)	(0.0524924)	(0.0596102)
	High risk	0.1112597	-0.2392548**	-0.0025006
		(0.1133288)	(0.1183601)	(0.1214439)
CESD-R				
	Low risk	1.081166***	0.7945909***	0.8802175***
		(0.1185364)	(0.0884006)	(0.1138089)
	Medium risk	0.0352209	0.2052088**	0.2050172**
		(0.1093168)	(0.0902844)	(0.0993404)
	High risk	0.1892715	0.0288843	0.5945842***
		(0.1705014)	(0.1611009)	(0.150068)
Constant				
	Low risk	14.61771***	7.899968***	11.82202***
		(0.9961306)	(0.6935346)	(0.8493757)
	Medium risk	29.01311***	15.43158***	20.86563***
		(3.023293)	(2.522227)	(2.84458)
	High risk	21.06476***	24.35417***	5.335826
		(6.808193)	(6.720493)	(6.306943)

Robust disturbance terms in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Effect of Health Message Priming on Uptake of Commitment Devices

We fitted logistic regressions to test the effect of health message that contains personalized information on depression status on their likelihood of self-report interests on commitment devices and on their likelihood to click on a hyperlink to get more information about commitment devices respectively. We replicated the analyses among those who were present biased financially only, and among those who were present biased in health behaviors (Table 3.3a and 3.4a).

Among those who had a CESD-R score of 16 and above, individuals who were primed with their depression status (i.e., "According to your survey response, you have been experiencing symptoms of depression for more than a few days.") were not more likely to report interest in commitment devices or to click on the hyperlink that contains more information on commitment devices. Among individuals who had CESD-R score below 16, individuals who were primed with their healthy status (i.e., "According to your survey response, depression is not a problem for you right now.") did not report interest in commitment devices differently but were approximately half as likely to click on the commitment device as compared to those who were not primed ($p<0.001$).

We adjusted for level of risks for depression which was found to be associated with present bias differently (Table 3.1). We also adjusted for self-report of current psychiatric medication, because we expected that individuals who learned about their depression status for the first time to behave differently from those who were already aware of their psychiatric conditions. Individuals who were on psychiatric medication were 1.7 times more likely to be interested in commitment devices (Full Sample: $OR=1.7$ $p<0.001$; Among Financially Present-biased: $OR=2.2$, $p<0.001$; Among Behaviorally Present-biased: $OR=1.7$, $p<0.001$) but were not more likely to click on the hyperlink for commitment devices (Full Sample: OR=1.7, $p=0.430$; Among Financially Present-biased: OR=0.9, $p=0.717$; Among Behaviorally Present-biased: OR=10.9, $p=0.5$).

Table 3.3a Logistic Regressions of Health Message on Self-Report Interests in Commitment Devices

	Full Sample				Financially Present-Biased				Behaviorally Present-Biased			
VARIABLES	3a-1	3a-2	3a-3	3a-4	3a-5	3a-6	3a-7	3a-8	3a-9	3a-10	3b-11	3b-12
Depressed	0.522***	0.564***	0.678	0.639	0.741	0.852	0.934	3.041	0.547***	0.589***	1.291	1.458
	(0.0983)	(0.108)	(0.854)	(0.866)	(0.246)	(0.294)	(1.510)	(4.609)	(0.104)	(0.114)	(1.865)	(2.109)
Primed	1.289	1.286	1.294	1.290	1.667	1.672	0.542	1.730	1.240	1.235	1.251	1.245
	(0.234)	(0.235)	(0.235)	(0.237)	(0.560)	(0.578)	(0.339)	(0.605)	(0.230)	(0.231)	(0.232)	(0.234)
Depressed* Primed	0.800	0.848	0.796	0.846	0.437*	0.485	-0.847*	0.471	0.824	0.874	0.816	0.866
	(0.216)	(0.230)	(0.215)	(0.230)	(0.209)	(0.235)	(0.483)	(0.230)	(0.225)	(0.240)	(0.223)	(0.238)
Medium Risk			0.797	0.918			-1.270	0.277			0.441	0.424
			(1.000)	(1.241)			(1.499)	(0.416)			(0.636)	(0.611)
High Risk			0.688	0.776			-1.130	0.291			0.373	0.350
			(0.847)	(1.033)			(1.439)	(0.419)			(0.530)	(0.497)
Medication		1.679***		1.683***		2.178***		2.187***		1.681***		1.692***
		(0.275)		(0.277)		(0.616)		(0.622)		(0.277)		(0.280)
Constant	2.247***	0.850	2.247***	0.847	1.800***	0.419	0.588***	0.416	2.143***	0.811	2.143***	0.802
	(0.280)	(0.280)	(0.280)	(0.280)	(0.411)	(0.242)	(0.228)	(0.242)	(0.272)	(0.269)	(0.272)	(0.266)
Observations	1,009	1,009	1,009	1,009	311	311	311	311	966	966	966	966

Robust Standard Error eform in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Test of combinations of coefficients:
$3a-1: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.031354 ; SE = .2063909 ; Pr > |z| = 0.877
$3a-2: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.090889 ; SE = .2183598; Pr > |z| = 0.664
$3a-3: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.030809 ; SE = .2063846; Pr > |z| = 0.880
$3a-4: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.090423 ; SE = .2183771; Pr > |z| = 0.666
$3a-5: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = .7285714 ; SE = .2488813; Pr > |z| = 0.354
$3a-6: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = .8117722 ; SE = .2773244; Pr > |z| = 0.542
$3a-7: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = .7368847 ; SE = .2527471; Pr > |z| = 0.373
$3a-8: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$

$\text{Estimate} = .8153522$; $\text{SE} = .2794353$; $\Pr > |z| = 0.551$

$3a - 9: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$

$\text{Estimate} = 1.021978$; $\text{SE} = .2047322$; $\Pr > |z| = 0.914$

$3a - 10: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$

$\text{Estimate} = 1.079205$; $\text{SE} = .2161129$; $\Pr > |z| = 0.703$

$3a - 11: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$

$\text{Estimate} = 1.020701$; $\text{SE} = .2046122$; $\Pr > |z| = 0.919$

$3a - 12: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$

$\text{Estimate} = 1.078323$; $\text{SE} = .2161066$; $\Pr > |z| = 0.707$

Table 3.3b. Linear Probability Models of Health Message on Self-Report Interests in Commitment Devices

VARIABLES	Full Sample				Financially Present-Biased				Behaviorally Present-Biased			
	3b-1	3b-2	3b-3	3b-4	3b-5	3b-6	3b-7	3b-8	3b-9	3b-10	3b-11	3b-12
Depressed	-0.152***	-0.133***	-0.103	-0.115	-0.0714	-0.0377	0.210	0.249	-0.142***	-0.124***	0.0544	0.0833
	(0.0441)	(0.0446)	(0.281)	(0.299)	(0.0795)	(0.0807)	(0.377)	(0.377)	(0.0447)	(0.0452)	(0.361)	(0.362)
Primed	0.0514	0.0505	0.0521	0.0510	0.107	0.106	0.113	0.112	0.0448	0.0435	0.0464	0.0452
	(0.0366)	(0.0368)	(0.0367)	(0.0369)	(0.0702)	(0.0713)	(0.0705)	(0.0716)	(0.0385)	(0.0387)	(0.0385)	(0.0388)
Depressed* Primed	-0.0437	-0.0299	-0.0446	-0.0305	-0.186*	-0.157	-0.189*	-0.162	-0.0394	-0.0254	-0.0414	-0.0273
	(0.0617)	(0.0613)	(0.0618)	(0.0614)	(0.110)	(0.109)	(0.111)	(0.110)	(0.0629)	(0.0625)	(0.0630)	(0.0626)
Medium Risk			-0.0407	-0.00877			-0.290	-0.290			-0.186	-0.195
			(0.280)	(0.298)			(0.375)	(0.375)			(0.360)	(0.361)
High Risk			-0.0775	-0.0497			-0.256	-0.278			-0.228	-0.242
			(0.274)	(0.293)			(0.360)	(0.361)			(0.356)	(0.356)
Medication		0.122***		0.123***		0.186***		0.187***		0.124***		0.125***
		(0.0394)		(0.0395)		(0.0686)		(0.0690)		(0.0400)		(0.0400)
Constant	0.692***	0.462***	0.692***	0.461***	0.643***	0.293**	0.643***	0.292**	0.682***	0.450***	0.682***	0.447***
	(0.0266)	(0.0791)	(0.0266)	(0.0794)	(0.0526)	(0.140)	(0.0528)	(0.141)	(0.0276)	(0.0802)	(0.0276)	(0.0803)
Observations	1,009	1,009	1,009	1,009	311	311	311	311	966	966	966	966
R-squared	0.034	0.043	0.034	0.044	0.038	0.062	0.041	0.064	0.029	0.039	0.030	0.040

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Test of combinations of coefficients:
$3b-1: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = $.0076597$; SE = $.0497225$; Pr > |z| = 0.878
$3b-2: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = $.0205797$; SE = $.0490242$; Pr > |z| = 0.675
$3b-3: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = $.0075211$; SE = $.0497472$; Pr > |z| = 0.880
$3b-4: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = $.0204745$; SE = $.0490425$; Pr > |z| = 0.676
$3b-5: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = $-.0786749$; SE = $.0849338$; Pr > |z| = 0.355
$3b-6: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = $-.0508885$; SE = $.0825337$; Pr > |z| = 0.538
$3b-7: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = $-.0758109$; SE = $.0855644$; Pr > |z| = 0.376

$3b - 8: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
$\text{Estimate} = -.0497985 ; \text{SE} = .0830293; \Pr > |z| = 0.549$
$3b - 9: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
$\text{Estimate} = .005396 ; \text{SE} = .0497996; \Pr > |z| = 0.914$
$3b - 10: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
$\text{Estimate} = .0180928 ; \text{SE} = .0490708; \Pr > |z| = 0.712$
$3b - 11: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
$\text{Estimate} = .0050793 ; \text{SE} = .0498208; \Pr > |z| = 0.919$
$3b - 12: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
$\text{Estimate} = .0178743 ; \text{SE} = .0490803; \Pr > |z| = 0.716$

Table 3.4a. Logistic Regressions of Health Message on Clicking of Commitment Devices Hyperlink

	Full Sample				Financially Present-Biased				Behaviorally Present-Biased			
VARIABLES	4a-1	4a-2	4a-3	4a-4	4a-5	4a-6	4a-7	4a-8	4a-9	4a-10	4b-11	4b-12
Depressed	0.779	0.758	0.167	0.170	0.327**	0.318**	0.0278**	0.0270**	0.728	0.711	0.0871*	0.0840*
	(0.191)	(0.187)	(0.214)	(0.222)	(0.177)	(0.169)	(0.0472)	(0.0455)	(0.179)	(0.175)	(0.128)	(0.123)
Primed	0.541***	0.542***	0.529***	0.530***	0.607	0.608	0.559	0.559	0.560**	0.561**	0.546**	0.546**
	(0.127)	(0.127)	(0.125)	(0.125)	(0.259)	(0.259)	(0.244)	(0.245)	(0.132)	(0.132)	(0.130)	(0.130)
Depressed* Primed	2.453**	2.407**	2.508***	2.462**	3.629*	3.545*	3.795*	3.716*	2.387**	2.346**	2.447**	2.404**
	(0.867)	(0.853)	(0.889)	(0.876)	(2.605)	(2.591)	(2.749)	(2.739)	(0.846)	(0.834)	(0.870)	(0.858)
Medium Risk			4.859	4.658			13.23	13.22			8.691	8.784
			(6.215)	(6.073)			(21.95)	(21.94)			(12.71)	(12.84)
High Risk			4.061	3.917			7.600	7.739			7.364	7.497
			(5.032)	(4.956)			(11.07)	(11.28)			(10.51)	(10.70)
Medication		0.845		0.853		0.857		0.862		0.859		0.859
		(0.181)		(0.183)		(0.364)		(0.372)		(0.184)		(0.184)
Constant	0.233***	0.320***	0.233***	0.313***	0.235***	0.314	0.235***	0.311	0.249***	0.331***	0.249***	0.331***
	(0.0342)	(0.135)	(0.0342)	(0.133)	(0.0655)	(0.263)	(0.0655)	(0.265)	(0.0369)	(0.139)	(0.0369)	(0.140)
Observations	1,009	1,009	1,009	1,009	311	311	311	311	966	966	966	966

Robust Standard Error eform in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Test of combinations of coefficients:
4a − 1: β(Primed) + β(Depressed ∗ Primed)
Estimate = .0405645 ; SE = .0405645 ; Pr > |z| = 0.283
4a − 2: β(Primed) + β(Depressed ∗ Primed)
Estimate = .038044 ; SE = .0378627; Pr > |z| = 0.315
4a − 3: β(Primed) + β(Depressed ∗ Primed)
Estimate = .0404707 ; SE = .037821; Pr > |z| = 0.285
4a − 4: β(Primed) + β(Depressed ∗ Primed)
Estimate = .0381018 ; SE = .0379035; Pr > |z| = 0.315
4a − 5: β(Primed) + β(Depressed ∗ Primed)
Estimate = .073499 ; SE = .0527187; Pr > |z| = 0.164
4a − 6: β(Primed) + β(Depressed ∗ Primed)
Estimate = .0709253 ; SE = .054579; Pr > |z| = 0.195
4a − 7: β(Primed) + β(Depressed ∗ Primed)
Estimate = .0698357 ; SE = .0526867; Pr > |z| = 0.186
4a − 8: β(Primed) + β(Depressed ∗ Primed)
Estimate = .0415347; SE = .0378675; Pr > |z| = 0.273

$4a - 9: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = .005396 ; SE = .0497996; $Pr > |z| = 0.914$
$4a - 10: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = .0392932 ; SE = .0379477; $Pr > |z| = 0.301$
$4a - 11: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = .04136 ; SE = .0379468; $Pr > |z| = 0.276$
$4a - 12: \beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = .0391114 ; SE = .0380148 ; $Pr > |z| = 0.304$

Table 3.4b Linear Probability Models of Health Message on Clicking of Commitment Devices Hyperlink

VARIABLES	Full Sample				Financially Present-Biased				Behaviorally Present-Biased			
	4b-1	4b-2	4b-3	4b-4	4b-5	4b-6	4b-7	4b-8	4b-9	4b-10	4b-11	4b-12
Depressed	-0.0353	-0.0390	-0.278	-0.276	-0.119**	-0.122**	-0.535	-0.539	-0.0458	-0.0491	-0.444	-0.449
	(0.0340)	(0.0341)	(0.277)	(0.280)	(0.0531)	(0.0526)	(0.365)	(0.365)	(0.0347)	(0.0348)	(0.358)	(0.358)
Primed	-0.0769***	-0.0767***	-0.0791***	-0.0789***	-0.0655	-0.0654	-0.0742	-0.0742	-0.0770**	-0.0768**	-0.0797***	-0.0795***
	(0.0289)	(0.0290)	(0.0289)	(0.0289)	(0.0558)	(0.0559)	(0.0556)	(0.0557)	(0.0308)	(0.0308)	(0.0307)	(0.0308)
Depressed* Primed	0.117**	0.115**	0.120**	0.117**	0.139*	0.136*	0.144*	0.142*	0.119**	0.116**	0.121**	0.119**
	(0.0476)	(0.0477)	(0.0476)	(0.0477)	(0.0768)	(0.0781)	(0.0766)	(0.0779)	(0.0488)	(0.0489)	(0.0488)	(0.0490)
Medium Risk			0.249	0.243			0.428	0.428			0.403	0.405
			(0.277)	(0.280)			(0.363)	(0.364)			(0.358)	(0.358)
High Risk			0.224	0.219			0.384	0.386			0.380	0.383
			(0.274)	(0.277)			(0.359)	(0.359)			(0.355)	(0.355)
Medication		-0.0238		-0.0224		-0.0172		-0.0166		-0.0218		-0.0220
		(0.0311)		(0.0312)		(0.0491)		(0.0496)		(0.0316)		(0.0316)
Constant	0.189***	0.234***	0.189***	0.231***	0.190***	0.223**	0.190***	0.222**	0.199***	0.240***	0.199***	0.241***
	(0.0226)	(0.0625)	(0.0226)	(0.0627)	(0.0431)	(0.102)	(0.0433)	(0.103)	(0.0237)	(0.0635)	(0.0237)	(0.0635)
Observations	1,009	1,009	1,009	1,009	311	311	311	311	966	966	966	966
R-squared	0.009	0.009	0.010	0.011	0.015	0.016	0.024	0.025	0.008	0.008	0.010	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Test of combinations of coefficients:
$4b-1$: $\beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.327957; SE = .3513174 ; Pr > |z| = 0.284
$4b-2$: $\beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.304314 ; SE = .346217; Pr > |z| = 0.317
$4b-3$: $\beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.327384 ; SE = .3513072 ; Pr > |z| = 0.285
$4b-4$: $\beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 1.304578 ; SE = .3466266; Pr > |z| = 0.317
$4b-5$: $\beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 2.20339 ; SE = 1.272266; Pr > |z| = 0.171
$4b-6$: $\beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 2.153561 ; SE = 1.279719; Pr > |z| = 0.197
$4b-7$: $\beta(\text{Primed}) + \beta(\text{Depressed} * \text{Primed})$
Estimate = 2.122176 ; SE = 1.225942; Pr > |z| = 0.193

$4\mathrm{b}-8$: $\beta(\mathrm{Primed}) + \beta(\mathrm{Depressed} * \mathrm{Primed})$

Estimate = 2.078289 ; SE = 1.234877 ; $\Pr > |z| = 0.218$

$4\mathrm{b}-9$: $\beta(\mathrm{Primed}) + \beta(\mathrm{Depressed} * \mathrm{Primed})$

Estimate = 1.336205 ; SE = .3536042; $\Pr > |z| = 0.273$

$4\mathrm{b}-10$: $\beta(\mathrm{Primed}) + \beta(\mathrm{Depressed} * \mathrm{Primed})$

Estimate = 1.315504 ; SE = .3490971; $\Pr > |z| = 0.301$

$4\mathrm{b}-11$: $\beta(\mathrm{Primed}) + \beta(\mathrm{Depressed} * \mathrm{Primed})$

Estimate = 1.334837 ; SE = .3536269 ; $\Pr > |z| = 0.276$

$4\mathrm{b}-12$: $\beta(\mathrm{Primed}) + \beta(\mathrm{Depressed} * \mathrm{Primed})$

Estimate = 1.313479 ; SE = .3491541; $\Pr > |z| = 0.305$

Discussion

As compared to lab experiments, online experiments using Turk Prime was much more cost-effective ($6/hour vs. $20/hour) and time-efficient (100 participants per hour online) for research in judgment and decision making. MTurk participants tend to be more demographically diverse than typical American college samples (Buhrmester et al., 2011), but have similar attitudes about money as compared to traditional student samples (Goodman et al., 2012). In general, mTurk workers have an incentive to produce work of reliable quality given that their payment is contingent upon mTurk employers' approval. In addition, such approval is then translated to an approval rate that would impact the workers' eligibility for jobs posted on mTurk. A recent review has shown that mTurk participants tend to show decision biases, such as present bias, loss aversion and certainty effect, similar to those in community and student samples (Goodman et al., 2012). Moreover, there is a growing number of studies using mTurk to study clinical populations (Shapiro et al., 2013; Schütz et al., 2013; Lund et al., 2015; Morris et al., 2015; Henshaw, et al., 2014, Boden et al., 2015). Mental health measures, such as Beck Depression Inventory, Beck Anxiety Index, CAGE-AID, have demonstrated internal reliability, test-retest reliability and criterion validity among mTurk participants. In addition, mTurk workers reported that they prefer an online format to an in-person interview that involves disclosure of clinical information (Shapiro et al., 2013). On the contrary, mTurk workers' willingness to produce work in exchange for a $0.10 per minute might indicative of strong present bias for an extremely small reward "now". In other words, selection bias might occur, if participation in the study was a common effect of depression and financial present bias. To minimize selection bias, we did not mention depression or sadness in any recruitment materials. Another limitation of online survey is the inability to collect data on biologic or cognitive vulnerability that would impact depression status, health behaviors and present bias thus led to unmeasured confounding. Lastly, this study primarily relied on self-reports which might have introduced measurement error and recall bias. Future study could consider using sophisticated tracking devices to obtain behavioral data to avoid recall bias.

The mechanisms linking depression and the respective health behaviors are complex, leading to numerous potential causal models including reversed causation and unmeasured confounding of depression and present bias in health behaviors. In this cross-sectional design that evaluated the relationship between time preference and depression, the directionality of the causation remained unclear. We posited that depression led to present bias in health and finances, because of the sadness-induced reward-seeking tendency. For instance, to remedy the feeling of loss caused by sadness, people might have a harder time going to bed on time by watching an extra episode of TV or playing an extra hour of video game to experience pleasure. However, it is also possible that present bias in health behaviors leads to poorer mental health and worsening depression. For instance, someone who is present bias in sleep, ends up experiencing chronic sleep deprivation which eventually leads to depression. On the other hand, a person who has a sensation seeking disposition would be more risk loving and hence more willing to engage in risky health behaviors such as substance use for leisure and for self-medication to treat depression as well as sleep problems (Zuckerman, 2007, Brower et al., 2014). Furthermore, lack of information on biologic or cognitive vulnerability that would impact depression status, health behaviors and present bias may lead to unmeasured confounding. Future study should consider collecting longitudinal data and adjusting for baseline depression to get a better understanding of the directionality between time preference and depression.

The survey items on present bias in health behaviors were self-referential. The current study was not able to tease apart failure to achieve a healthy level of expected behaviors or unrealistic expectations. Given depressive symptoms such as guilt and worthlessness, individuals who were at risks for depression might be more self-critical and perceive greater level of failure in achieving an intended level of health behaviors independent of their actual level of health behaviors. In order to accommodate the small budget and short duration of the study, we had limited our number of survey items. Future studies should consider collecting information on both actual and expected level of health behaviors. Further development in time preference measurements are also needed in order to better understand present bias specific to health behaviors.

As for the current experimental design, we expected that individuals who learned about their depression status for the first time to behave differently from those who were already aware of their psychiatric conditions. Future research should consider collecting information of clinical diagnosis they have received at the end of the survey, to tease apart the effect of awareness vs. reminder of depression. Aim 3 is currently underpowered to ascertain the effect of knowing one's depression status on the uptake of commitment device, given the low prevalence of both commitment device uptake and major depressive episode.

Conclusions

We evaluated the relationships among present bias in financial choices, and in health behaviors at various risk levels for depression using an online survey response. The relationship between depression and time preference differed by their levels of risks for depression and by the nature of time preference. Consistent with our hypotheses, findings of the financial choice tasks showed that medium risks for depression was associated with choices consistent with present-biased preferences, while high risks for depression was not associated with choices consistent with present-bias preferences, as compared to people who were at low risks for depression. Interestingly, present bias was more pronounced in health behaviors (nutrition, sleep, and physical activity) than in financial choices among those who were at medium risks for depression. Participants who were at high risks for depression were also three times more likely to go to bed more than an hour later than intended in the past week but were not more likely to eat more than intended or wish to be more physically active in the past week. In contrast, individuals were at high risks for depression were half as likely to wish that they had been more physically active in the past week, as compared to those who were at medium risks for depression. As for impatience, individuals at medium risks for depression were not more impatient than healthy control, whereas individuals who were at high risks for depression were 90% less likely to be impatient than health controls. The pattern of financial time preference among those at medium risks for depression was similar to the patterns found in health individuals who were primed with sadness in Lerner, Li, & Weber (2013). The pattern of time preference was the opposite among those at high risks for depression, suggesting that decision biases in the presence of additional depressive symptoms exceeded biases due to sadness alone. The results in individuals who were at high risks for depression were consistent with findings from a clinical study that found less myopic decisions about their future among the depressed (Lempert et al., 2010). The tendency to be patient among those who were at high risks for depression could be due to inability to experience pleasure at present or expectations for better mood in the future. We speculate that depressive symptoms, such as the lack of energy, psychomotor retardation, change in appetite, led to reduced motivation to exercise and to eat, thus reduced the likelihood of present bias in eating and in physical activity among those who were at high risks for depression. In Aim 1, we found some evidence of domain-specific present bias, which was bolstered by the findings in Aim 2. Results from path analyses suggested that changes in financial present bias was unlikely to lead to changes in present bias in health behaviors in the context of depression. Lastly, we tested experimentally if the priming of a health message that contains personalized depression status would change the uptake of commitment devices, and found that knowledge alone was insufficient to change either self-report interest in commitment devices or clicking of the hyperlink to obtain more information on commitment devices.

References

Aish, A.-M., & Wasserman, D. (2001). Does Beck's hopelessness scale really measure several components? Psychological Medicine, 31, 367–372.

Allgöwer, A., Wardle, J., & Steptoe, A. (2001). Depressive symptoms, social support, and personal health behaviors in young men and women. Health Psychology: official journal of the Division of Health Psychology, American Psychological Association, 20, 223–227.

American Psychiatric Association. (2013). Diagnostic and Statistical Manual of Mental Disorders (DSM-5®). American Psychiatric Pub.

Babyak, M., Blumenthal, J. A., Herman, S., Khatri, P., Doraiswamy, M., Moore, K., ... & Krishnan, K. R. (2000). Exercise treatment for major depression: maintenance of therapeutic benefit at 10 months. Psychosomatic medicine,62(5), 633-638.

Baglioni, C., Battagliese, G., Feige, B., Spiegelhalder, K., Nissen, C., Voderholzer, U., ... & Riemann, D. (2011). Insomnia as a predictor of depression: a meta-analytic evaluation of longitudinal epidemiological studies. Journal of affective disorders, 135(1), 10-19.

Baker, F., Johnson, M. W., & Bickel, W. K. (2003). Delay discounting in current and never-before cigarette smokers: similarities and differences across commodity, sign, and magnitude. Journal of abnormal psychology, 112(3), 382.

Berns, G. S., Laibson, D., & Loewenstein, G. (2007). Intertemporal choice–toward an integrative framework. Trends in cognitive sciences, 11(11), 482-488.

Beck, A. T. (1964). Thinking and depression: II. Theory and therapy. Archives of general psychiatry, 10(6), 561-571.

Blumenthal, J. A., Babyak, M. A., Moore, K. A., Craighead, W. E., Herman, S., Khatri, P., ... & Krishnan, K. R. (1999). Effects of exercise training on older patients with major depression. Archives of internal medicine, 159(19), 2349-2356.

Brown, F. C., Buboltz Jr, W. C., & Soper, B. (2002). Relationship of sleep hygiene awareness, sleep hygiene practices, and sleep quality in university students. Behavioral medicine, 28(1), 33-38.

Breslau, N., Kilbey, M. M., & Andreski, P. (1991). Nicotine dependence, major depression, and anxiety in young adults. Archives of general psychiatry, 48(12), 1069-1074.

Boden, M. T., & Thompson, R. J. (2015). Facets of emotional awareness and associations with emotion regulation and depression. Emotion, 15(3), 399.

Booth, M. L., Ainsworth, B. E., Pratt, M. I. C. H. A. E. L., Ekelund, U., Yngve, A. G. N. E. T. A., Sallis, J. F., & Oja, P. E. K. K. A. (2003). International physical activity questionnaire: 12-country reliability and validity. Med sci sports Exerc, 195(9131/03), 3508-1381.

Buysse, D. J., Reynolds, 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.

Brower, K. J., Aldrich, M. S., Robinson, E. A., Zucker, R. A., & Greden, J. F. (2014). Insomnia, self-medication, and relapse to alcoholism. *American Journal of Psychiatry*.

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), 220-231.

Chabris, Christopher F., David I. Laibson and Jonathon P. Schuldt. (2008a) "intertemporal choice." The New Palgrave Dictionary of Economics. Second Edition. Eds. Steven N. Durlauf and Lawrence E. Blume. Palgrave Macmillan.

Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., & Taubinsky, D. (2008b). Individual laboratory-measured discount rates predict field behavior. Journal of Risk and Uncertainty, 37(2-3), 237-269.

Chabris, C., Laibson, D., & Schuldt, J. (2006). Intertemporal choice. The new Palgrave dictionary of economics, 2.

Chivers, L. L., & Higgins, S. T. (2012). Some observations from behavioral economics for consideration in promoting money management among those with substance use disorders. The American journal of drug and alcohol abuse, 38(1), 8-19.

Cohen, S. (1988). Perceived stress in a probability sample of the United States.

Cryder, C. E., Lerner, J. S., Gross, J. J., & Dahl, R. E. (2008). Misery is not miserly sad and self-focused individuals spend more. Psychological Science,19(6), 525-530.

Dahal, A., & Fertig, A. (2013). An econometric assessment of the effect of mental illness on household spending behavior. Journal of Economic Psychology, 37, 18-33.

Dennis, M. L., Chan, Y. F., & Funk, R. R. (2006). Development and validation of the GAIN Short Screener (GSS) for internalizing, externalizing and substance use disorders and crime/violence problems among adolescents and adults. American Journal on Addictions, 15(sup1), 80-91.

Dierker, L. C., Avenevoli, S., Stolar, M., & Merikangas, K. R. (2002). Smoking and depression: an examination of mechanisms of comorbidity. Am J Psychiatry, 159(6):947-53.

Dimidjian, S., Hollon, S. D., Dobson, K. S., Schmaling, K. B., Kohlenberg, R. J., Addis, M. E., … & Jacobson, N. S. (2006). Randomized trial of behavioral activation, cognitive therapy, and antidepressant medication in the acute treatment of adults with major depression. Journal of consulting and clinical psychology, 74(4), 658.

Doyle, F., Rohde, D., Rutkowska, A., Morgan, K., Cousins, G., & McGee, H. (2014). Systematic

Review and Meta-Analysis of the Impact of Depression on Subsequent Smoking Cessation in Patients With Coronary Heart Disease: 1990 to 2013. Psychosomatic medicine, 76(1), 44-57.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economic Association, 9(3), 522-550.

Dunn, A. L., Trivedi, M. H., Kampert, J. B., Clark, C. G., & Chambliss, H. O. (2005). Exercise treatment for depression: efficacy and dose response.American journal of preventive medicine, 28(1), 1-8.

Etter, J. F., Le Houezec, J., & Perneger, T. V. (2003). A self-administered questionnaire to measure dependence on cigarettes: the cigarette dependence scale. Neuropsychopharmacology, 28(2), 359-370.

Everson, S. A., Maty, S. C., Lynch, J. W., & Kaplan, G. A. (2002). Epidemiologic evidence for the relation between socioeconomic status and depression, obesity, and diabetes. Journal of psychosomatic research, 53(4), 891-895. – SES being the common cause of depression and lack of healthy food options

Faith, M. S., Butryn, M., Wadden, T. A., Fabricatore, A., Nguyen, A. M., & Heymsfield, S. B. (2011). Evidence for prospective associations among depression and obesity in population- based studies. Obesity Reviews, 12(5), e438-e453.

Ferrari, A. J., Charlson, F. J., Norman, R. E., Patten, S. B., Freedman, G., Murray, C. J., … & Whiteford, H. A. (2013). Burden of depressive disorders by country, sex, age, and year: findings from the global burden of disease study 2010. PLoS medicine, 10(11), e1001547.

Ford, D. E., & Kamerow, D. B. (1989). Epidemiologic study of sleep disturbances and psychiatric disorders: an opportunity for prevention?. Jama,262(11), 1479-1484.

Fuchs, V. R. (1980). Time preference and health: an exploratory study.

Glassman, A. H., Helzer, J. E., Covey, L. S., Cottler, L. B., Stetner, F., Tipp, J. E., & Johnson, J. (1990). Smoking, smoking cessation, and major depression. Jama, 264(12), 1546-1549.

Grant, B. F. (1995). Comorbidity between DSM-IV drug use disorders and major depression: results of a national survey of adults. Journal of substance abuse, 7(4), 481-497.

Hankin, B. L., & Abramson, L. Y. (2001). Development of gender differences in depression: An elaborated cognitive vulnerability–transactional stress theory. Psychological bulletin, 127(6), 773.

Henshaw, E. J. (2014). Too Sick, Not Sick Enough?: Effects of Treatment Type and Timing on Depression Stigma. The Journal of nervous and mental disease, 202(4), 292-299.

Heymsfield, S. B. (2011). Evidence for prospective associations among depression and obesity in population- based studies. Obesity Reviews, 12(5), e438-e453.

Horton, J. J., & Chilton, L. B. (2010). The labor economics of paid crowdsourcing. In Proceedings from EC ’10: The 11th ACM Conference on Electronic Commerce (pp. 209–218). New York, NY: ACM. doi:10.1145/1807342.1807376

Jackson, J. S., Knight, K. M., & Rafferty, J. A. (2010). Race and unhealthy behaviors: chronic stress, the HPA axis, and physical and mental health disparities over the life course. American Journal of Public Health, 100, 933–939. doi:10.2105/AJPH.2008.143446

Jacobson, N. S., Martell, C. R., & Dimidjian, S. (2001). Behavioral activation treatment for depression: Returning to contextual roots. Clinical Psychology: Science and Practice, 8, 255-270.

Karasu, T. B., Gelenberg, A., Merriam, A., & Wang, P. (2000). Treatment of patients with major depressive disorder. American Psychiatric Association Practice Guidelines for the Treatment of Psychiatric Disorders Compendium, 413-495.

Kendler, K. S., Neale, M. C., MacLean, C. J., Heath, A. C., Eaves, L. J., & Kessler, R. C. (1993). Smoking and major depression: a causal analysis. *Archives of general psychiatry*, *50*(1), 36-43.

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Koretz, D., Merikangas, K. R., … & Wang, P. S. (2003). The epidemiology of major depressive disorder: results from the National Comorbidity Survey Replication (NCS-R). Jama, 289(23), 3095-3105.

Kessler, R. C., & Bromet, E. J. (2013). The epidemiology of depression across cultures. Annual review of public health, 34, 119.

Kohn, R., Saxena, S., Levav, I., & Saraceno, B. (2004). The treatment gap in mental health care. Bulletin of the World health Organization, 82(11), 858-866.

Konttinen, H., Männistö, S., Sarlio-Lähteenkorva, S., Silventoinen, K., & Haukkala, A. (2010). Emotional eating, depressive symptoms and self-reported food consumption. A population-based study. Appetite, 54(3), 473-479.

Kroenke, K., Spitzer, R. L., & Williams, J. B. (2002). The PHQ-15: validity of a new measure for evaluating the severity of somatic symptoms. Psychosomatic medicine, 64(2), 258-266.

Lejuez, C. W., Hopko, D. R., Acierno, R., Daughters, S. B., & Pagoto, S. L. (2011). Ten year revision of the brief behavioral activation treatment for depression: revised treatment manual. Behavior modification, 35(2), 111-161.

Lejoyeux, Michel, & Weinstein, Aviv (2010). Compulsive buying. American Journal of Drug and Alcohol Abuse, 36, 248–253.

Lewinsohn, P. M. (1974). A behavioral approach to depression. In R. J. Friedman & Katz, M. (Eds.), The psychology of depression: Contemporary theory and research (pp. 157–178). Oxford, England: Wiley. Bandura, 1971

Lewinsohn, P. M., Solomon, A., Seeley, J. R., & Zeiss, A. (2000). Clinical implications of" subthreshold" depressive symptoms. *Journal of abnormal psychology*, *109*(2), 345.

Lund, E. M., Nadorff, M. R., & Seader, K. (2015). Relationship Between Suicidality and Disability When Accounting for Depressive Symptomology. Rehabilitation Counseling Bulletin, 0034355215586388.

MacKinnon, D. P. (2008). Mediation analysis. The Encyclopedia of Clinical Psychology.

Martinsen, E. W. (2008). Physical activity in the prevention and treatment of anxiety and depression. Nordic journal of psychiatry, 62(sup47), 25-29.

Meier, S., & Sprenger, C. (2010). Present-biased preferences and credit card borrowing. American Economic Journal: Applied Economics, 193-210.

Murphy, J. M., Burke, J. D., Monson, R. R., Horton, N. J., Laird, N. M., Lesage, A., … Leighton, A. H. (2008). Mortality associated with depression: a forty-year perspective from the Stirling County Study. Social Psychiatry and Psychiatric Epidemiology, 43, 594–601. doi:10.1007/s00127-008-0323-3

Mokdad, A. H., Marks, J. S., Stroup, D. F., & Gerberding, J. L. (2004). Actual causes of death in the United States, 2000. Jama, 291(10), 1238-1245.

Oppenheimer, D., Meyvis T., & Davidenko N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. Journal of Experimental Social Psychology, 45, 867–872.

Mokdad, A. H., Marks, J. S., Stroup, D. F., & Gerberding, J. L. (2004). Actual causes of death in the United States, 2000. Jama, 291(10), 1238-1245.

Morris, R. R., Schueller, S. M., & Picard, R. W. (2015). Efficacy of a Web-Based, Crowdsourced Peer-To-Peer Cognitive Reappraisal Platform for Depression: Randomized Controlled Trial. Journal of medical Internet research, 17(3).

Oliver, G., Wardle, J., & Gibson, E. L. (2000). Stress and food choice: a laboratory study. Psychosomatic medicine, 62(6), 853-865.

Pate, R. R., Pratt, M., Blair, S. N., Haskell, W. L., Macera, C. A., Bouchard, C., ... & Wilmore, J. H. (1995). Physical activity and public health: a recommendation from the Centers for Disease Control and Prevention and the American College of Sports Medicine. Jama, 273(5), 402-407.

R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Regier, D. A., Farmer, M. E., Rae, D. S., Locke, B. Z., Keith, S. J., Judd, L. L., & Goodwin, F. K. (1990). Comorbidity of mental disorders with alcohol and other drug abuse: Results from the Epidemiologic Catchment Area (ECA) study. Jama, 264(19), 2511-2518.

Riemann, D., Berger, M., & Voderholzer, U. (2001). Sleep and depression—results from psychobiological studies: an overview. Biological psychology,57(1), 67-103.

Rogers, T., Milkman, K. L., & Volpp, K. G. (2014). Commitment devices: using initiatives to change behavior. JAMA, 311(20), 2065-2066.

Schütz, E., Sailer, U., Al Nima, A., Rosenberg, P., Arntén, A. C. A., Archer, T., & Garcia, D. (2013). The affective profiles in the USA: happiness, depression, life satisfaction, and happiness-increasing strategies. PeerJ, 1, e156.

Strawbridge, W. J., Deleger, S., Roberts, R. E., & Kaplan, G. A. (2002). Physical activity reduces the risk of subsequent depression for older adults.American journal of epidemiology, 156(4), 328-334.

Strine, T. W., Mokdad, A. H., Balluz, L. S., Gonzalez, O., Crider, R., Berry, J. T., & Kroenke, K. (2008). Depression and anxiety in the United States: findings from the 2006 behavioral risk factor surveillance system. Psychiatric Services,59(12), 1383-1390.

Spitzer, R. L., Kroenke, K., Williams, J. B., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: the GAD-7. Archives of internal medicine, 166(10), 1092-1097.

Swendsen, J. D., & Merikangas, K. R. (2000). The comorbidity of depression and substance use disorders. Clinical psychology review, 20(2), 173-189.

Teychenne, M., Ball, K., & Salmon, J. (2010). Sedentary behavior and depression among adults: a review. International journal of behavioral medicine,17(4), 246-254.

Toussaert, S. (2014). Connecting commitment to self-control: a field experiment with participants in a weight loss challenge.

Wilhelm, K., Mitchell, P., Slade, T., Brownhill, S., & Andrews, G. (2003). Prevalence and correlates of DSM-IV major depression in an Australian national survey. Journal of affective disorders, 75(2), 155-162.

Winterstein, B. P., Silvia, P. J., Kwapil, T. R., Kaufman, J. C., Reiter-Palmon, R., & Wigert, B. (2011). Brief assessment of schizotypy: Developing short forms of the Wisconsin Schizotypy Scales. Personality and Individual Differences, 51(8), 920-924.

Vallance, J. K., Winkler, E. A., Gardiner, P. A., Healy, G. N., Lynch, B. M., & Owen, N. (2011). Associations of objectively-assessed physical activity and sedentary time with depression:

NHANES (2005–2006). Preventive medicine,53(4), 284-288.

Veale, D. (2008). Behavioural activation for depression. Advances in Psychiatric Treatment, 14(1), 29-36.

Ziedonis, D., Hitsman, B., Beckham, J. C., Zvolensky, M., Adler, L. E., Audrain-McGovern, J., … Williams, J. (2008). Tobacco use and cessation in psychiatric disorders: National Institute of Mental Health report. Nicotine & Tobacco Research: official journal of the Society for Research on Nicotine and Tobacco, 10, 1691–1715.

Zuckerman, M. (2007). *Sensation Seeking and Risk*. American Psychological Association.