Emotion Expression on Social Networking Sites: Exploring Mood Profiles and Depression

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Table of Contents

List of Tables

List of Figures

Chapter 5: Do people feel what they Tweet? A case-series exploration of daily mood ratings and the emotions expressed on Twitter

Chapter 6: General Discussion

Copyright notices

Abstract

This thesis explores the use of emotion language on social media and its relationship with depression. Previous research has shown that depression is visible on social media through the language used in status updates. Typically, using negative emotion words over time is thought to reflect depression symptoms such as persistent low mood. While the detection of depression from social media language generally performs well, the predictive performance of language models seeking to identify depressed individuals range from .30 to around .80 accuracy, suggesting that both sensitivity and specificity of depression identification from these models could be improved. In addition, the research to date has primarily utilized depression assessed at a single time-point to infer depression status of individuals, with little verification that the content of social media posts is reflective of how an individual is feeling in real time. Considering the time-sensitive data available from social media, it is likely that the dynamic patterns of negative emotion words across status updates will provide more sensitive identification and earlier prediction of mental health status as a reflection of underlying emotion processes.

The research reported in this thesis aimed to address two primary questions:

(1) What emotion dynamic features in the mood profiles generated across status updates are associated with depression severity?

and;

(2) Do the emotions expressed on social media through language accurately reflect subjective daily mood?

A systematic review of the literature was conducted to explore the intersections between mental health and social media use which identified several behaviors, including language use, that were consistently linked to poorer mental health outcomes. This review also indicated the need for a data collection method that better integrated social media data with the psychological information of participants. *MoodPrism,* a smartphone experience sampling app collecting psychological, contextual, social media, and daily mood data was developed and utilized to meet this methodological need.

Examination of the patterns of emotion word use across status updates revealed that negative affect instability was visible on the social media platform Facebook and that it was associated with greater depression severity. On Twitter, greater variability of negative emotion word use was predictive of lesser depression symptom severity. A further detailed exploration of daily mood and social media language was conducted with five participants through case studies revealing that the emotion words used on Twitter do not correspond well with subjective daily mood, indicating that language may not reliably sample experienced mood over time. This thesis demonstrates the need to move beyond static measure of language alone in identifying individuals at risk of depression on social media. It shows that by considering indices of variability and instability more sensitive depression prediction can be achieved. It also highlights the need to take into account factors other than language in collecting reliable and valid data for depression. The practical extensions for language-based depression detection discussed in this thesis may improve the specificity of the automated monitoring of depression risk on social media. Integrating accurate and automated language-models with tailored advertising and push notifications on social media will greatly improve the speed with which support, and resources can be delivered to at risk individuals in the community.

General Declaration

Publications during enrolment

Rickard, N., Arjmand, H.-A., Bakker, D., & Seabrook, E. (2016). Development of a mobile phone app to support self-monitoring of emotional well-being: A mental health digital innovation. *JMIR Mental Health*, *3*(4), e49. doi: 10.2196/mental.6202

Seabrook, E. M., Kern, M. L., & Rickard, N. S. (2016). Social networking sites, depression, and anxiety: A systematic review. *JMIR Mental Health*, *3*(4), e50. doi: 10.2196/mental.5842

Seabrook, E. M., Kern, M. L., Fulcher, B. D., & Rickard, N. S. (2018). Predicting depression from language-based emotion dynamics: Longitudinal analysis of Facebook and Twitter status updates. *JMIR (forthcoming).* doi:10.2196/jmir.9267

Seabrook, E. M., Kern, M. L., Fulcher, B. D., & Rickard, N. S. (2018). *Do people Tweet what they feel? A case-series exploration of daily mood ratings and the emotions expressed on Twitter* Submitted for publication.

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

This thesis includes *two* original papers published in peer reviewed journals and *one* submitted publication. The core theme of the thesis is emotion expression on social media and depression. The ideas, development and writing up of all the papers in the thesis were the principal responsibility of myself, the student, working within the School of Psychological Sciences, Monash University under the supervision of Adjunct Associate Professor Nikki Rickard, Dr Peggy Kern, and Dr Ben Fulcher.

The inclusion of co-authors reflects the fact that the work came from active collaboration between researchers and acknowledges input into team-based research.

In the case of chapters 2, 4, and 5 my contribution to the work involved the following:

Thesis Chapter	**Publication Title**	**Status**	**Nature and % of student contribution**	**Co-author name(s) Nature and % of Co-author's contribution***
Chapter 2	Social networking sites, depression, and anxiety: A systematic review	Published	70% Conceptualisation, investigation and data collection, writing-original draft, writing-review and editing.	1) Nikki Rickard 15% 2) Peggy Kern 15% Supervisory guidance, framing, inter-rater relatibility, and editing.
Chapter 4	Predicting depression from language-based emotion dynamics: Longitudinal analysis of Facebook and Twitter status updates	Published	70% Conceptualisation, investigation and data collection, methodology, data curation, data analysis, writing-original draft, writing-review and editing.	1) Nikki Rickard 10% 2) Peggy Kern 10% 3) Ben Fulcher 10% Supervisory guidance, project oversight, contributions to data analysis, manuscript editing.

Thesis Chapter	Publication Title	Status	Nature and % of student contribution	Co-author name(s) Nature and % of Co-author's contribution*
Chapter 5	Do people feel what they Tweet? A case-series exploration of daily mood ratings and the emotions expressed on Twitter	Submitted	70% Conceptualisation, investigation and data collection, methodology, data curation, data analysis, writing-original draft, writing-review and editing.	1) Nikki Rickard 10% 2) Peggy Kern 10% 3) Ben Fulcher 10% Supervisory guidance, project oversight, conceptualisation, contributions to methodology, manuscript editing.

I have not renumbered sections of submitted or published papers to generate a consistent presentation within the thesis.

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-authors' contributions to this work. In instances where I am not the responsible author I have consulted with the responsible author to agree on the respective contributions of the authors.

Student signature: [redacted] **Date: 28/01/2018**

Main Supervisor signature: [redacted] **Date: 28/01/2018**

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Chapter 1

General Introduction

1.0 Overview and Contribution

This thesis provides a novel exploration of the way emotion language is expressed on social media over time and how patterns of emotion expression are associated with depression. The major contributions of this research to the field of mental health include: the development and application of an integrated experience sampling approach to collecting social media and daily mood data; an improved understanding of the way social media behaviours may signal depression risk; and the application of emotion dynamic features to the language data from social media to predict depression status. In this General Introduction, the research rationale is developed, and the thesis structure is provided.

1.1 Introduction

The use of social media is intertwined with mental health. Social media platforms, like Facebook, Twitter, and Weibo, are used worldwide and are a common component of many people's daily lives. Psychological well-being can be bolstered through the creation and maintenance of friendships, positive online social interactions, and the availability of social support (Best, Manktelow, & Taylor, 2014; Davila et al., 2012a; Ellison, Vitak, Gray, & Lampe, 2014; Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017). However, negative online social interactions and addictive social media use may perpetuate or contribute to psychopathology such as depression (Koc & Gulyagci, 2013; Landoll, La Greca, Lai, Chan, & Herge, 2015; Radovic, Gmelin, Stein, & Miller, 2017; Shensa et al., 2017).

Social media is, in part, defined by the user-generated content individuals produce and consume (boyd & Ellison, 2007; Ellison & boyd, 2013). As such, observable behaviours such as the content produced in status updates, have been shown to be useful in detecting the depression status of social media users (Bazarova, Choi, Whitlock, Cosley, & Sosik, 2017; Guntuku, Yaden, Kern, Ungar, & Eichstaedt, 2017; Moreno et al., 2012). Emotion language, specifically, the frequent use of negative emotion words, has emerged as one of the key features in status updates that can provide insight into the presence of depression (De Choudhury, Gamon, Counts, & Horvitz, 2013; Settanni & Marengo, 2015). However, emotion language expressed on social media has predominantly been utilised as a static (trait) construct for depression prediction; little has been reported on how patterns of emotion language across status updates may indicate changes relevant to the evolution of depression in an individual. As emotion dysregulation is a predisposing factor for depression (Gotlib & Joormann, 2010), uncovering patterns of emotion language and how well these patterns might act as an indicator of emotion experiences is critical to utilising the naturally occurring behavioural traces from social media for the early detection of depression.

1.1.1 Depression and emotion dysregulation.

Major depressive disorder (MDD) and dysthymia impact on mood, with major symptoms including persistent sadness or depressed mood, and loss of interest or pleasure (American Psychiatric Association, 2013; World Health Organization, 2017). Depression is a leading cause of disability worldwide and recent estimates suggest the global prevalence to be 4.4% (World Health Organization, 2017). Further, depression is underreported and underdiagnosed (Cepoiu et al., 2008; Collins, Westra, Dozois, & Burns, 2004). There are multiple factors that determine help-seeking behaviour, and at an individual level this may be hampered by viewing depression symptoms as temporary or a lack of insight into their severity (Collins et al., 2004; Magaard, Seeralan, Schulz, & Brütt, 2017). The challenge of identifying and delivering resources to at-risk individuals who may not be visible to mental health providers prioritises the need for development of early detection strategies for depression that do not require professional assessment. Behavioural markers that indicate early risk factors, without the need for an individual to seek help or self-report their mood, may be useful in this regard.

Emotion dysregulation is a key risk factor for depression that is visible prior to depression onset and persists through remission (Gotlib & Joormann, 2010; Wichers, 2014). Recent work has suggested that depression can be reliably predicted by the way emotion changes over time, or by dynamic emotion features (Houben, Van Den Noortgate, & Kuppens, 2015; Koval, Pe, Meers, & Kuppens, 2013; Wichers, 2014). Kuppens and Verduyn (2017) suggest that emotion change is governed by four intrinsic processes: (1) that emotions occur in response to internal or external events (principle of contingency), (2) emotions are resistant to change and 'carry over' from moment to moment (principle of inertia), (3) emotions are regulated to reach an optimal fit for a given context (principle of regulation), and (4) emotions interact with each other over time (principle of interaction). When these processes interact in a maladaptive way for extended periods of time, the risk of macro-level psychopathology like depression is increased (Kuppens & Verduyn, 2017; Wichers, 2014).

Cognitive theories of depression argue that biased cognitive processing and emotion dysregulation interact to constitute the vulnerability factors for depression (Beck, 1974; Gotlib & Joormann, 2010). For example, cognitive biases such as rumination – a persistent negative self-focus – contribute to prolonged experiences of negative affect, suggesting that the negative emotions experienced in depression are resistant to change over time (Gotlib & Joormann, 2010; Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008). Depression is also associated with a reduced ability to inhibit negative stimuli (Joormann & Gotlib, 2010) and increased exposure to stressful life events (Connolly, Eberhart, Hammen, & Brennan, 2010). Ineffective emotion regulation in these contexts may contribute to more unstable daily experiences of negative emotion (Thompson et al., 2012).

Over different time periods and in response to different stimuli, depression manifests observable dynamic emotion patterns, which include stability (i.e., persistent or sustained periods of negative affect), and large fluctuations (i.e., frequent and intense experiences of negative affect in response to stressors; Koval et al., 2013; Thompson et al., 2012). The ability to monitor emotion dynamic processes at a large scale may be instrumental in developing approaches for the early detection of depression. However, sampling emotion data is challenging, particularly where active individual input is required. With over 2 billion Facebook users alone, social media is a rich data source for passively sampling momentary data where expressions of emotion occur frequently (Kramer, 2012; Manago, Taylor, & Greenfield, 2012; Nowak, 2017).

1.1.2 Monitoring depression: Social media for passive data collection.

Language sits at the intersection of cognition and emotion, playing a role in the way emotion is experienced, interpreted, and regulated (Lindquist, Gendron, & Satpute, in press). Depression has been associated with unique linguistic markers that manifest in both verbal and written communication (Pennebaker, Mehl, & Niederhoffer, 2003; Pulverman, Lorenz, & Meston, 2015; Rude, Gortner, & Pennebaker, 2004; Segrin & Flora, 1998). In this way, social media is uniquely positioned as a medium through which rich psychologically relevant language data may be sampled in a non-invasive, ongoing, and temporally sensitive manner (Kern et al., 2016; Schwartz et al., 2013).

Numerous studies have indicated that depression can be reliably predicted by the language used in status updates (Guntuku et al., 2017). Depressive symptoms are disclosed in status updates more frequently by those with more severe depression symptoms (Moreno et al., 2012), and the frequent use of negative emotion words has emerged across many language prediction models as a key language feature associated with depression status (Guntuku et al., 2017). While at a population level, diurnal and seasonal variation in depression severity has been observed in social media language (De Choudhury et al., 2013; Schwartz et al., 2014), the individual path of emotion expression over time as a potential indicator of emotion dysregulation has not been explored.

1.1.2.1 The caveats.

It is also important to note here, some prominent caveats to the use of social media language for depression prediction. First, there are social media specific contexts that may influence the way people express themselves online. For example, status updates are broadcast publicly to an individual's social network (Ellison & boyd, 2013). Audience composition (close or weak ties) may influence the likelihood to disclose emotion and the valence expressed (Lin, Tov, & Qiu, 2014). The norms and expectations of interactions between social media platforms also differ and may have an impact on language use (Waterloo, Baumgartner, Peter, & Valkenburg, 2017). Second, individual characteristics, like personality, are related to emotion traits (e.g., neuroticism and frequent negative emotional experiences), posting behaviours on social media (e.g. conscientiousness inhibiting impulsive disclosures), and to the use of emotion language (e.g., extraversion is association with the use of positive emotion words; Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011; Park et al., 2015; Seidman, 2013; Verduyn & Brans, 2012). Together, these confounding factors influence a person's idiolect (their specific way of using language; Dittmar, 1996) on social media which may obscure the detection of depression for some individuals. This has implications for both the patterns of emotion expressed on social media, and the reliability with which social media posts can serve as a proxy for self-reported or experienced emotion.

1.1.3 Research rationale.

The language expressed on social media is likely to reflect some of the cognitive and affective processes involved in depression. While emotion language can differentiate between depressed and non-depressed social media users, little is known about the emotion dynamics expressed through language and if, over status updates, they signal depression risk. As emotion dynamic features often precede depression onset, detecting these processes through language may signal depression risk earlier than looking at the average emotion language used in status updates alone. Further, no clear link has been established between the emotion expressed on social media and the subjective emotional experience of the individual. Understanding how reliably emotion language taps into the emotional experience of social media users is critical for developing a clear understanding of when negative emotion words signal depression symptoms or when other drivers of language use (e.g., personality, gender, age) may be prominent. Taken together, it is important to examine how, at the individual level, the emotion visible on social media unfolds over time to reveal patterns of change that signal depression status or onset.

1.2 Research Questions

This thesis has the broad aim of investigating the link between depression and the emotion expressed on social media. To achieve this aim, it focuses on exploring the positive and negative mood profiles of social media users across their status updates and advances a methodology that integrates social media data collection with a complementary experience sampling method delivered via smartphone. Specifically, this work addresses two major research questions:

(1) What emotion dynamic features in the mood profiles generated across status updates are associated with depression severity?

and;

(2) Do the emotions expressed on social media through language accurately reflect subjective daily mood?

Methodologically, the research reported in this thesis involved the development and testing of the social media data capabilities of the experience sampling smartphone application (app), *MoodPrism* (introduced in Chapter 3), and aimed to demonstrate the feasibility of this method through its practical application in this research.

1.3 Structure of the Thesis

This thesis comprises six chapters, including this introduction. Chapter 2 presents a systematic review of the literature considering social networking site use and its association with depression and anxiety. It includes discussion of potential moderators and mediators to these relationships and, additionally, highlights the research that has included well-being variables as a part of its investigation. This chapter provides a broad context for the work presented here and was instrumental in the development of the research questions addressed in the empirical papers presented in this thesis and the rationale for the methodology introduced in Chapter 3.

Chapter 3 provides a detailed description of the research methodology and links the gaps in the literature identified in Chapter 2 to the development of the data collection method used in this research, a smartphone app – *MoodPrism. MoodPrism* integrates the capacity to collect social media data and deliver a self-report experience sampling method for collecting daily mood, mental health, and well-being data. Specific focus is given to the social media data components of this research with further detail on the *MoodPrism* app presented in Appendix A *"Development of a mobile phone app to support self-monitoring of emotional well-being: A mental health digital innovation"* (Rickard, Arjmand, Bakker, & Seabrook, 2016). Brief discussion is also provided on the ethical considerations of conducting social media research and how these considerations were addressed by the approach taken here.

Chapter 4 presents the first empirical paper that has been submitted for publication. This paper introduces the observation of temporal patterns in the expression of emotion across Facebook and Twitter status updates as potential indicators of depression. This chapter also presents cross-platform comparisons of the emotion patterns in language, and supplementary materials explore differences in individual characteristics between platforms that may impact on emotion expression and depression prediction.

Chapter 5 presents the second empirical paper that has been submitted for publication. This paper provides a detailed account of emotion language expressed on Twitter and its similarity and dissimilarities to self-reported daily mood. In this case-series analysis, mood profile features (the average, variability, instability, and probability of acute change) are compared between Twitter and self-report, and this is discussed with reference to the impact this may have on detecting depression status through language.

The final chapter (Chapter 6) consists of an overall integrated discussion, bringing together the findings from Chapters 2, 4, and 5. This chapter provides a brief overview of the findings, then discusses implications, directions for future research, and a conclusion.

Chapter 2

Social Networking Sites, Depression, and Anxiety: A Systematic Review

2.1 Preamble to the Systematic Review

This chapter presents a systematic review titled "Social Networking Sites, Depression, and Anxiety: A Systematic Review". This paper reviews the literature from 2005 to 2016, providing an up-to-date account of the research investigating social media use and depression or anxiety. Recommendations for future research are provided and limitations of the literature are discussed. Importantly, this paper provides the context for the development of the research questions introduced in Chapter 1 and the empirical investigation conducted in Chapters 4 and 5.

The following paper was published in the peer-reviewed journal, the *Journal of Medical Internet Research – Mental Health* in November 2016 and is formatted in accordance with the journal requirements. References are provided in the style of the *American Medical Association* (10^{th} edition).

Review

Social Networking Sites, Depression, and Anxiety: A Systematic Review

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Abstract

Background: Social networking sites (SNSs) have become a pervasive part of modern culture, which may also affect mental health.

Objective: The aim of this systematic review was to identify and summarize research examining depression and anxiety in the context of SNSs. It also aimed to identify studies that complement the assessment of mental illness with measures of well-being and examine moderators and mediators that add to the complexity of this environment.

Methods: A multidatabase search was performed. Papers published between January 2005 and June 2016 relevant to mental illness (depression and anxiety only) were extracted and reviewed.

Results: Positive interactions, social support, and social connectedness on SNSs were consistently related to lower levels of depression and anxiety, whereas negative interaction and social comparisons on SNSs were related to higher levels of depression and anxiety. SNS use related to less loneliness and greater self-esteem and life satisfaction. Findings were mixed for frequency of SNS use and number of SNS friends. Different patterns in the way individuals with depression and individuals with social anxiety engage with SNSs are beginning to emerge.

Conclusions: The systematic review revealed many mixed findings between depression, anxiety, and SNS use. Methodology has predominantly focused on self-report cross-sectional approaches; future research will benefit from leveraging real-time SNS data over time. The evidence suggests that SNS use correlates with mental illness and well-being; however, whether this effect is beneficial or detrimental depends at least partly on the quality of social factors in the SNS environment. Understanding these relationships will lead to better utilization of SNSs in their potential to positively influence mental health.

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KEYWORDS
depression; anxiety; social media; social networking; review, systematic; mental health; well-being

Introduction

Background

Social networking sites (SNSs) are Web-based platforms on which individuals connect with other users to generate and maintain social connections [1]. Considerable disagreement exists as to associations that SNS use may have with depression and anxiety [2,3]. On the one hand, SNSs may protect from mental illness, as they support and enable social interaction and connection [1,4], and allow users to reflect aspects of their identity and express emotion that may be relevant to their lived experience [5]. On the other hand, there are many opportunities for miscommunications and mismanaged expectations, and maladaptive tendencies can be exaggerated, leaving individuals feeling a greater sense of isolation [2,6]. As a whole, the SNS environment may be just as complex as face-to-face interactions. As SNS membership continues to rise [7], it is becoming increasingly important to address the possible benefits and detriments the use of SNSs may have on mental health.

Affective disorders such as depression and anxiety have been shown to have bidirectional interactions with the social environment that influence the path of illness onset and maintenance [8]. Depression and anxiety have an approximate prevalence of 4.7% and 7.3%, respectively, in the global population [9,10]. These disorders have high levels of comorbidity [11] and impact the quality of social relationships [12,13]. Depression and anxiety may be implicated in determining the size and structure of an individual's social network [12], the quality of interactions within these networks, and how effectively social capital may be leveraged or developed to provide an individual with social support [8,14].

The social characteristics (both qualitative and structural) affected by depression or anxiety are also relevant to one's sense of well-being. Current mental health theories suggest that the presence of well-being is not the same as the absence of mental illness; a complete model of mental health requires not just the absence of psychopathology, but also a focus on positive indices of functioning such as subjective well-being [15]. This is particularly pertinent when exploring how the social environment may affect an individual, as such environments may simultaneously confer a number of benefits to the individual and exaggerate deficits [16-18].

Social aspects of the Internet have been argued to augment social relationships and support mental health. SNSs in particular connect us to friends, family, colleagues, strangers, and celebrities and can help users to maintain and make new friendships, express thoughts and feelings, and express identity [1,4,19]. The primary social functions that SNSs perform may augment the benefits of engaging in face-to-face interaction by extending the reach and accessibility of our social networks [20]. Indeed, SNS use is associated with lower levels of loneliness and greater feelings of belonging (social connectedness), social capital, and actual and perceived access to social support and is generally associated with higher levels of life satisfaction and self-esteem [6,21-26].

As a whole, the positive social components of SNS use suggest a protective role against depression and anxiety. For instance, higher levels of self-esteem and life satisfaction may aid in attenuating depressive symptoms [27]. Kraut et al [28] found that frequent general Internet use did not increase depression over time, and, in a second study, communication activities on the Internet were shown to be associated with lower levels of depressive symptoms [29]. Computer-mediated communication (CMC; eg, email, instant messaging) allows users to express and interpret emotion in a similar way to face-to-face interaction [17]. CMC may therefore be beneficial for emotion regulation as has been demonstrated for offline forms of written emotional expression [30,31].

However, for individuals with depression or anxiety, the interpretation and frequent exposure to this emotion may have a negative impact [13]. SNS use may increase an individual's exposure to negative social interactions (eg, cyberbullying), which may negatively impact mood and mental health [2]. For example, negative interaction quality was associated with decreases in self-esteem and life satisfaction [32]. Even passive exposure to the language used in SNS posts has been shown to influence the emotive language subsequently expressed by the receiving SNS user, where positive or negative emotions are argued to transfer via contagion [33-35]. As SNSs explicitly support a number of social features, the relationships and interactions between the user, their emotional experience, and Web-based technology are likely to be complex and may even accentuate differences between those who are doing well in life and those who are struggling.

Cognitive and social factors frequently emerge as both moderators and mediators of the relationships between offline social interactions or events and depression [36-38] and might also occur in Web-based environments. For instance, self-esteem mediates the pathway between relationship interactions and depressive symptoms [39], but it might also moderate how a person uses and is affected by the SNS. Rumination, a response style where an individual maintains a passive and repetitive focus on their distress [40], is one mechanism linking stressful life events and the development or maintenance of depression [41], and the SNS environment provides opportunity for a person to both internally ruminate on bad events and have an entire social network further accentuate shortcomings. Social support has additionally been shown to moderate relationships between stress and depression, with greater levels of social support acting as a buffer to depressive symptoms [42]. This is pertinent to SNSs as they present a potential intervention opportunity for developing and strengthening supportive social networks for vulnerable individuals.

Objective

Since the advent of SNSs, a number of articles have been published examining the relationship between SNS use and depression and anxiety. The interaction between SNSs and our mental health and well-being is clearly varied and complex. The objective of this paper was to provide a systematic review of literature examining SNSs and their relationship with depression and anxiety. It also considers links with well-being, as well as potential mediators and moderators to these relationships.

Methods

Search Strategy

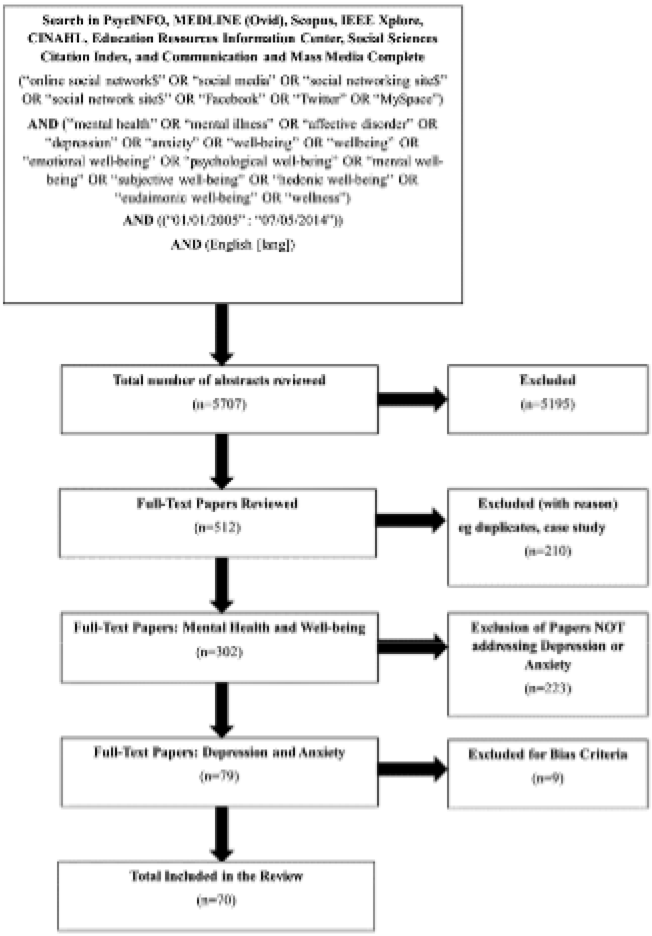
Figure 1 summarizes the search strategy and article selection. A multidatabase search identified studies conducted between January 2005 and June 2016. The databases included were PsycINFO, MEDLINE (Ovid), Scopus, IEEE Xplore, CINAHL (Cumulative Index to Nursing and Allied Health Literature), Education Resources Information Center, Social Sciences Citation Index, and Communication and Mass Media Complete. The inclusion of conference papers accessed through IEEE Xplore was intended to capture the research within the computer sciences and engineering fields that may have been relevant to the psychological literature.

Search terms were selected in order to comprehensively capture the various ways mental health, mental illness, subjective well-being, and SNSs have been defined and explored in the existing literature.

SNSs were defined as conceptualized by Ellison and Boyd [1] as sites that are a Web-based communication platform with 3 distinct characteristics: (1) user profiles are unique and created through user-provided content and content provided by other users, (2) the network connections between individuals are visible and can be navigated through by other users, and (3) individuals can broadcast content and consume and interact with content contributed by others in a continuous stream of information. Prototypical examples of SNSs include Facebook, Twitter, Myspace, and Instagram.

For mental health, search terms specifically focused on depression and anxiety, as well as overall well-being (eg, subjective well-being, psychological well-being, wellness; see Figure 1 for full list of search terms).

Figure 1. Overview of search strategy and selection process for the systematic review.



Inclusion and Exclusion Criteria

Studies were included if they had a primary focus on SNS use as a behavior. As such, studies that referred to SNSs as a recruitment method only or used SNSs as a means for intervention delivery were excluded.

Articles were included if they provided results addressing anxiety or depression directly and were excluded if they were only referred to in the context of general psychological distress (or similar). As the primary focus of the review was on depression and anxiety, not the broader well-being construct, articles addressing well-being were only included if they also included specific reference to anxiety or depression.

The search was limited to articles published after 2005 to capture research on the prototypical examples of SNSs that include the basic features of modern networks. Studies that had a primary focus on the Internet, chat rooms, or online support forums were also excluded; although they may contain some of the features of SNSs, differences in the function they perform for users may exist [19].

Additionally, articles were restricted to English language, peer-reviewed journal or conference proceedings, and quantitative or mixed methodologies. Gray literature, commentary and editorial, qualitative research, literature reviews, and descriptive case studies were excluded.

Data Extraction and Data Synthesis

Two raters (the first author and a trained research assistant) reviewed all abstracts returned from the literature search and selected abstracts for full-text reading based on the inclusion and exclusion criteria. All articles that included measurement of depression, anxiety, or well-being were retained. The selected full-text articles were downloaded and reviewed by the first and third authors.

To provide some preliminary evaluation of the strength of the research, three risk of bias indicators were adapted from the Cochrane bias tool (*Cochrane Handbook for Systematic Reviews of Interventions* [43]), which classifies methodology that may limit replicability or generalizability. Studies were rated to indicate whether the study (1) included psychometrically reliable and valid measures, (2) used an external measurement criterion for mental health, and (3) provided description of the sample demographics including some SNS activity statistics (eg, number of friends and/or use frequency). These were rated by the first and third authors from "0=No bias," "1=Unclear risk of bias," and "2=High risk of bias" and were summed to create a final score between 0 and 6. A linear weighted kappa statistic for interrater reliability (.78, SE=.06) indicated that there was very good agreement in applying the bias criteria. Consensus was reached on all ratings. Articles with a rating of 3 or above were excluded [44-52], resulting in the final set of 70 studies, as presented in Multimedia Appendix 1.

From each article, the year of study, population of interest, type of SNS, and variables used (anxiety, depression, well-being) were noted, along with whether or not any formal mediators or moderators of these relationships were indicated. Information was then qualitatively synthesized to identify common themes.

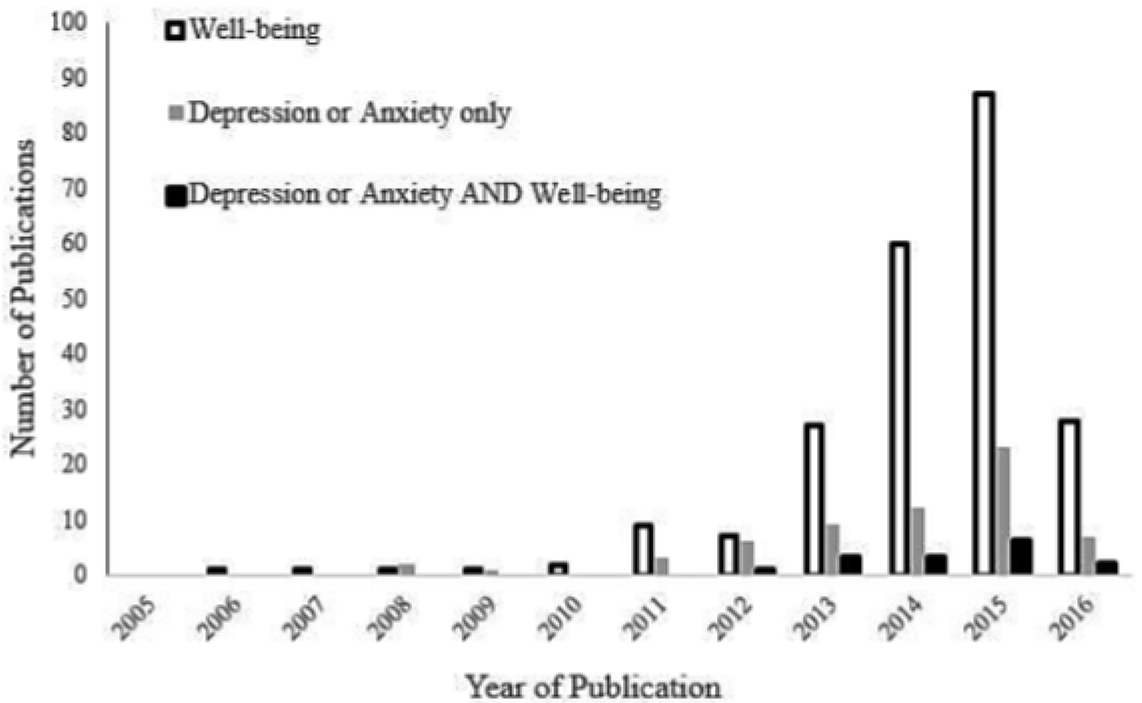
Results

Description of Studies

Figure 2 indicates the number of articles addressing SNSs, depression and anxiety, and well-being from 2005 through 2016, based on the 302 full-text articles initially reviewed. There were considerably more articles addressing well-being alone than articles only addressing depression and anxiety. Only 15 articles included both positive and negative aspects of mental health. This review includes the 70 articles that include depression or anxiety only or depression or anxiety and well-being.

A total of 22 studies addressed potential moderators or mediators in SNSs' relationship with depression or anxiety (see Multimedia Appendix 1). Most articles obtained a bias rating of 0 to 1. Ratings of 1 or above were primarily due to the limited focus on reporting SNS activity statistics, such as the number of friends or average frequency of use, which help characterize the average SNS user in each sample. Facebook was the most commonly explored SNS followed by the measurement of SNS use as a general category (ie, no specific platform explored). The majority of studies examined young adults (late teens or early 20s).

Figure 2. Publication frequency of research into well-being, depression or anxiety only, and depression or anxiety with well-being from 2005 to June 2016, based on the initial 302 full text articles reviewed, which included quantitative findings. Case studies, editorials, literature reviews, and gray literature were excluded.



Depression, Anxiety, and Social Networking Sites: Summary of Findings

Across the 70 articles, several general themes were apparent: frequency of use, size and structure of the SNS, language features and observable SNS activities, self-disclosure and expression, quality of interactions, social support, social connectivity, social comparison, addictive and problematic behaviors, and physiological associations. Findings are summarized in Multimedia Appendix 2 and are described below, with particular attention to moderators and possible mechanisms involved in the associations. As some articles were relevant to multiple themes, these articles appear in multiple sections. Studies that included well-being are also highlighted.

Frequency of Social Networking Site Use

Overall, total frequency or time spent on SNSs had mixed associations with depression and anxiety. Of the 30 studies examining these variables (see Multimedia Appendix 2) [53-81], 8 studies found a direct positive association with depression and 16 found a nonsignificant association. For anxiety (and social anxiety), 3 studies found direct positive associations and 7 found nonsignificant associations. With the exception of 1 study showing a significant negative association between Facebook-specific social anxiety and the frequency of SNS use [80], no studies supported an association between the frequent use of SNSs and a lower level of anxiety or depressive symptoms.

Several moderators appeared. In one study, the number of strangers followed moderated frequent Instagram use and greater depressive symptoms, where a significant relationship only occurred for those with high proportions of strangers in their social networks [68]. Similarly, time spent on Facebook was only a predictor of depression and anxiety for those individuals who have higher motives to use the site for social connection [73].

Associations may be affected by the study design. Studies utilizing an experience sampling method (ESM) to collect SNS use frequency over 1 to 2 weeks found no significant associations between SNS use frequency and depressive symptoms over time [61,63,77]. Indeed, across 2 studies, while Steers et al [77] found a positive association between the time spent on Facebook and depression when using a retrospective survey, this effect was nonsignificant when participants completed daily ESM diaries. In addition, 2 studies [54,56] conducted a 3-week follow-up and demonstrated no change in depressive or anxiety symptoms over time as a function of SNS use frequency.

Tendencies toward depressive rumination and corumination did not moderate associations, suggesting that the frequency of SNS use may not be a significant risk factor for depression even across varying cognitive styles [54]. Kross et al [63] additionally included depression as a moderator of the relationship between the frequency of daily SNS use and affective well-being (ratings of negative affect) and cognitive well-being (life satisfaction). Although more frequent SNS use was associated with more negative affect and lower life satisfaction across a 2-week period, depression did not moderate these associations.

A number of studies have made a more nuanced consideration of SNS use frequency by looking at the different functions of use of SNSs [54,56,69,74-76,78]. Table 1 presents how these broad functions have been defined in the literature and presents some example behaviors. It also provides the Cronbach alphas that have been reported for the measures of each function. The table shows a distinction between passive and active use (broad-level functions). Active use may further be divided into content production and interactive communication functions. The table also shows where behaviors may be enacted in public (entire SNS friend network audience) or in private (dyads or small selected audience).

Table 1. Broad functions of social networking site use and example behaviors.

	Passive use (alpha=.77-.88)[a] [75,78]	Active social use (alpha=.83-.86)[a] [69,76]	
		Content production (public) (alpha=.52)[a] [75]	Interactive communication (alpha=.80)[a] [75]
Example behaviors	Checking or reading friends' profiles or posts	Status updates	Chatting in messages (private)
	Browsing the newsfeed	Updating profile pictures	Posting on friends' walls (public)
		Image management (maintaining profile information)	Posting comments on statuses (public)

[a]Cronbach alphas indicating the internal consistency of measures defining functions of social networking site use as defined in the reviewed literature.

In general, passive uses of SNSs was not directly related to depression and anxiety, but there may be differential behavioral patterns for individuals high in depression or social anxiety [75,78]. Higher levels of social anxiety were significantly related to passive uses of Facebook but not to content production uses of Facebook [75]. Brooding, or anxious rumination, emerged as a mediator of the relationship between passive Facebook use and social anxiety and may be a cognitive risk factor for increasing social anxiety symptoms where passive Facebook use is frequent. Tandoc et al [78] found that Facebook envy mediated frequent passive Facebook use and depression, where lower levels of Facebook envy resulted in a direct effect of passive Facebook use reducing depressive symptoms and higher levels of envy led to greater depressive symptoms.

Active uses of SNSs demonstrate a more complex relationship. Shaw et al [75] found that depressive symptoms positively correlated with more frequent content production and interactive communications. McCord et al [69] showed that the frequency of social Facebook use did not predict social anxiety in the entire sample but was positively correlated with anxiety for a high anxiety group only.

Simoncic et al [76] suggested that personality and gender moderate the association of frequent active uses of Facebook (content production and interactive communication) and depression and may be protective. The study found a three-way interaction between gender, Facebook active uses, and neuroticism, such that lower depressive symptoms occurred in females who were high in neuroticism and actively used Facebook.

Size and Structure of Social Network on Social Networking Sites

The size of the SNS friendship network and its association with depression and anxiety has similarly yielded mixed findings. Fernandez et al [57] and Weidmann and Levinson [82] found significant negative relationships between social anxiety and the number of friends, and Park et al [83], Park et al [84], Rae and Lonborg [73], and Rosen et al [74] found this same relationship direction when examining depression. Rae and Lonborg [73] found that a greater number of friends on Facebook was associated with higher general positive affect and life satisfaction, when use of the site was motivated by maintaining friendships. The remaining studies demonstrated no significant relationship between the number of SNS friends, depression, or anxiety [53,57,64,67,71,73,78,79,85,86].

Specific friend categories have also been examined. Tsai et al [87] found that users accepting the friend request of an ex-partner tend to have higher levels of trait anxiety and depression severity than those who reject the request. Mota-Pereira [88] demonstrated that for individuals with treatment-resistant major depressive disorder (MDD) also currently taking antidepressants, the use of Facebook over a 3-month period significantly reduced depressive symptoms, compared with a no-Facebook control, and the addition of a "psychiatrist as a friend" showed significantly faster improvement in depressive symptoms. Such findings suggest a broad beneficial impact of SNS use when treatment is augmented by friends from a user's network.

The structure of the network itself may make a difference. For instance, Homan et al [89] revealed significant differences in the network structures of individuals with depression and those without on an LGBTQ (lesbian, gay, bisexual, transgender, and queer) support SNS, TrevorSpace. Individuals without depression had significantly more integrated friendship networks on the SNS compared with depressed individuals, with their friends being more likely to know each other and also having a higher proportion of friends who do not know each other. For the depressed group this could indicate they have less diverse social networks. Peer-selected groups have the potential to offer social support to depressed individuals, whereas groups over which the user had less control may contribute further exposure to psychological distress [90].

Language Features and Observable Social Networking Site Activity

A number of articles have examined the language features in SNS posts, with the potential for identifying individuals with depression. SNS users with depression differ from users without depression in that they express negative affect more frequently, use more personal pronouns, and generally have lower frequencies of interaction with others in their SNS network [91,92]. Park et al [93] have shown that individuals with a diagnosis of MDD more frequently post negative sentiment than those who are not depressed, and Moreno and colleagues [85,94] demonstrated that depression could be identified in the language used in the Facebook posts of college students based on the *Diagnostic and Statistical Manual of Mental Disorders* (Fourth Edition) criteria for MDD.

Settani and Marengo [95] directly examined the expressed emotion in participant status updates and generated an automated word count from the emotion dictionaries of the Italian version of *Linguistic Inquiry and Word Count* (*LIWC*), which was also supplemented with emoticons. Providing face validity, the frequency of word use from the negative emotion and sadness *LIWC* subscales positively correlated with depression, while the anger subscale positively correlated with anxiety. Positive emotion was unrelated to depression or anxiety scores. Interestingly, only the relationship between the sadness subscale and anxiety remained statistically significant when examining individuals older than 25 years.

In addition to language features, the time of posting, relative volume of posts, and reciprocity (likes and comments, tweets and retweets) may also aid in describing individuals with and without depression, with depression correlating with more night activity and less volume and reciprocity than nondepressed peers [84,91,96]. Over multiple weeks, there may also be subtle variation across time [96]. Park et al [84] provided evidence indicating that, for individuals experiencing acute depression (or a relative increase in their symptom severity), there is an increase in their posting frequency over a 6-month period. This is consistent with Shaw and colleagues' [75] findings indicating those with higher depressive symptoms engage in content production features on Facebook frequently.

The number of identity items on SNS users' profile page have also been associated with both depression and social anxiety scores [57,82,97]. For example, listing a "Single" relationship status relates to higher levels of social anxiety [82]. This related to the quantity of information provided in specific areas of a user's profile information (eg, TV, Books, Quotes, Music; [57]). Although some of the specific findings are mixed [57,82,98], studies generally suggest that social anxiety may be visible on SNSs through compensatory behaviors (increases in information disclosure) or through relative inactivity or social withdrawal [57,82].

Social Networking Sites for Self-Disclosure and Expression

At a broad level, it has been suggested that users of Facebook have lower levels of social anxiety than nonusers, suggesting that there might be a selection effect, such that SNS activities are unattractive to individuals high in social anxiety [99]. However, this depends on the social media platform. Baker and Moore [100] showed that, for new Myspace users, those who intended to use the site for blogging had higher mean depression and anxiety ratings than those who did not intend to blog. These individuals were also more likely than nonbloggers to feel dissatisfaction with their social networks and had a greater likelihood to use self-blame and venting coping strategies. Average levels of depression and anxiety among the bloggers were maintained across a 2-month period, although there was a trend in some symptoms being reduced and a significant increase in feelings of social integration and satisfaction with online and offline friendships [101]. Similarly, große Deters and Mehl [102] found that depressive symptoms remained stable through an intervention, although loneliness decreased via feelings of social connectedness.

Social anxiety is associated with an increased preference for SNS-mediated communication [103] and relates to differences in the depth of self-disclosure via public (status updates) or private (eg, messages) communication on SNSs. For individuals with higher levels of social anxiety, greater importance is placed on the need for reduced social cues and increased controllability of communication [59,104]. This leads to greater disinhibition and Facebook self-disclosure for private SNS communication only and not for public SNS communication [59]. Green et al [59] suggest that this may be related to the trust, audience size, and privacy differences between private and public communication on SNSs, which may position private SNS communication as more attractive and accessible for individuals high in social anxiety. Similarly, Baker and Jeske [80] suggested that assertiveness on Facebook (the ease with which an individual offers opinion or interacts with others) is lower for individuals high in social anxiety compared with those low in social anxiety.

A potential explanation for the self-disclosure activities of individuals with high social anxiety on SNSs may be related to motivations or perceived pressure to present an idealized self-image or to avoid presenting a negative image on SNSs [86,105,106]. Motivations to avoid presenting a negative self-image have been found to be a greater concern for individuals who had experienced high social anxiety the previous day and does not vary according to levels of perceived social competence [105]. Similarly, frequent impression management (including updating profile information) on SNSs is positively related with depression [74].

Frequently expressing positive or negative affect (emotional valence) in SNS status updates has also been shown to relate to depression and may be mediated by rumination [67]. In contrast, positive and negative expression appears to be unrelated to social anxiety [98]. Positive and negative self-disclosures may, instead, impact the quantity of social reciprocity an individual with social anxiety receives [98]. For example, when individuals higher in social anxiety post positive status updates, this generates more pronounced increase in social feedback (likes) than when positive posts are made by those low in social anxiety or when posts have low positive content [98].

Quality of Interactions

Considerable evidence suggests a link between the quality of interactions on SNSs and mental health. Studies have operationalized SNS interaction quality as either the perceived (when self-rated) or observed (when coded by experimenters) valence of interactions between friends and the user on SNSs. Items often refer to a global estimate of "How positive [or negative] are your interactions with people on Facebook" [54] or, where coded, the frequency of positive or negative sentiment expressed in comments on posts [103]. This differs from the frequency of social or interactive communication on SNSs, discussed above, which refers to the estimated frequency or total time spent engaging in these activities.

Depression is generally associated with fewer positive interactions and more negative interactions on SNSs [54,56,103,107,108]. Social and global anxiety similarly relate to the perception of negative quality interactions on SNSs [56,107]. Depressed individuals may use SNSs in a more problematic manner than do anxious individuals [56], thus creating negative interactions. For instance, symptoms recorded at the age of 13 years significantly predicted a reduced likelihood of receiving comments that contained deviancy talk from SNS peers at the age of 20 years; however, symptoms at the age of 20 years predicted a greater instance of verbally abusive comments from peers [103]. The findings of Frison et al [81] also suggest that depressive symptoms are a risk factor for peer victimization on Facebook. Moberg and Anestis [108] have additionally shown that, when controlling for the influence of depressive symptoms on perceived negative interactions on SNSs, greater ratings of negative interactions predict feelings of thwarted belongingness (disconnection), a potential risk factor for suicidal desire.

Depressive rumination and corumination may moderate associations between the perception of SNS interaction quality and depression. In 2 studies, Davila et al [54] showed that those with higher levels of depressive rumination exhibited a stronger relationship between the frequency of perceived negative interactions on SNSs and greater depressive symptoms. Although corumination (ie, "excessive discussion of problems within friendships"; [54] p73) did not emerge as a significant moderator, it did yield a number of relationships with other variables, notably, feeling down or depressed after interactions on SNSs and a greater frequency of SNS use. The quality of use also relates to intentions for continued SNS use. Belief that online communities are dangerous, including concerns about privacy and the potential to encounter hostile or negative interactions, has been shown to be a potential antecedent of online and general social anxiety and their link to reduced continuance intention of using Facebook for social communication [109].

Associations may depend in part on the methodologies used. When researchers have directly observed and coded the language of comments made to an SNS user by their friends, it has been shown that a greater level of social anxiety at age 20 years was a significant predictor of more positive supportive comments from SNS friends and fewer negative peer interactions [103]. This is in contrast with the research utilizing self-report survey methods that show more frequent reporting of negative interactions for those with high levels of depression and anxiety symptoms [54,56,107]. This discrepancy suggests there may be a role for perceptual bias in a participant's interpretation of the quality of interactions to which they are exposed on SNSs. In this light, individuals with higher levels of depression and anxiety may be more inclined to interpret or perceive SNS interaction as more negative regardless of the communication content exchanged between users. The potential for such a perceptual bias in interpreting SNS interactions has also been suggested in reference to social support perceptions and is further discussed below (see Park et al [93]).

Social Support

Social support plays a mixed and varied role within the SNS environment. Studies suggest that individuals with higher depressive symptoms perceive their SNS friend networks as providing them with less social support than they actually receive [93] and that SNS social support seeking may exacerbate depressed mood for some individuals [110]. Perception of support appears to be more important than actual support. Across 2 studies, Park et al [93] showed that in the general population greater depressive symptoms were associated with more *actual* social support on status updates that contained negative emotion. In contrast, *perceived* support was negatively associated with depression, and higher depressive symptoms were associated with a greater discrepancy between actual and perceived social support. Frison and Eggermont [110] similarly found that depressed mood increased in adolescents when social support was sought on Facebook but perceived to not occur. Other research has also demonstrated the protective role of perceived social support in ameliorating the impact of SNS peer victimization on depression [81].

For anxiety, social support provided on SNSs may play a protective role. Indian and Grieve [111] found that perceptions of Facebook social support were only predictive of subjective well-being for individuals with high levels of social anxiety and not for those reporting low levels of social anxiety. Furthermore, in the high social anxiety group, perceived Facebook social support was the only significant predictor of subjective well-being, suggesting that SNS social support may provide unique benefits to individuals with high levels of social anxiety.

The nature of seeking social support on SNSs may differ from traditional face-to-face approaches [110,112]. Some evidence suggests that emotional support provided by Facebook can increase depressive symptoms and decrease quality of life [112]. It may depend in part on the characteristics of the user. For example, SNS users' perceived communication competence—an overall evaluation of communication skills and behaviors—plays a role in determining the level of satisfaction they feel is generated from their SNS social support. Wright et al [79] demonstrated that better perceived communication competence predicted higher ratings of both face-to-face social support and Facebook social support satisfaction, which in turn were significantly negatively related to depression.

Social Connectedness

Facebook social connectedness encompasses subjective feelings of belonging and closeness to an individual's social network [113]. Grieve et al [113] demonstrated that higher levels of Facebook social connectedness were related to lower levels of depression and anxiety and higher levels of subjective well-being (life satisfaction). Feelings of social connectedness may mediate the impact an increase in posting behavior has on decreasing loneliness [102].

Social Comparison

Social comparison on SNSs, where individuals compare themselves as having more positive (downward comparison) or negative (upward comparison) qualities than others, is a significant risk factor for depression and anxiety [68,77,114,115]. Several studies found that Facebook envy, a hostile evaluation of others from their social information on SNSs, is associated with higher ratings of depressive symptoms [78,116]. Lee [114] found that depression and anxiety were positively related to the frequency of social comparison on Facebook. Feinstein et al [115] extended these findings by revealing rumination as a mediator in the relationship between negative (upward) social comparison on Facebook and depressive symptoms. This relationship changed over time; at a 3-week follow up, more frequent negative social comparison on Facebook was associated with increases in rumination and a subsequent increase of depressive symptoms.

Appel et al [116] examined how depression may influence an SNS user's interpretation of the profile information of other users. Individuals with depression were more likely to rate themselves as being unhappier (or inferior) in comparison with profiles of any type (attractive or unattractive) than those without depression. Individuals with depression also experienced greater envy than those without depression in response to viewing the unattractive profile, with this difference being greater after viewing the attractive profile.

Social comparison of any direction (upward, nondirectional, or downward) may also indirectly mediate the association between the time spent on Facebook and depression. Across 2 studies, as individuals spend more time on Facebook they engage in more frequent negative (upward) and nondirectional social comparison and less positive (downward) social comparison, which in turn relates to more depressive symptoms [77].

Envy potentially plays a destructive role in passive Facebook use (eg, viewing or browsing profiles; see Table 1). Where Facebook envy is high, greater frequency of passive Facebook use is associated with greater depressive symptoms, and where Facebook envy is low (or not present), passive Facebook use is associated with reduced depressive symptoms [78]. Indeed, research into Instagram (a photo-sharing SNS) [68] has shown that more positive (downward) social comparisons are associated with decreased depressive symptoms. Social network composition, additionally, may moderate the relationship between frequent Instagram use and increases in depressive symptoms via social comparison [68].

Addictive or Problematic Social Networking Site Use

"SNS addiction" and "problematic SNS use" are linked with depression and anxiety [58,60,62,65,104,106,117-121], although associations most likely are bidirectional in nature. It has been suggested that such maladaptive SNS use is only present for a small subset of users [62,106], although one study suggested that 41.9% of adolescents had a Facebook addiction [119]. While depression and social anxiety explain much of the variance in problematic SNS use or SNS addiction, other variables (younger age, male, and more frequent SNS or general Internet use) have also emerged as significant predictors [58,62,118]. Through cluster analysis, Moreau et al [120] showed that problematic Facebook use is most prevalent in individuals high in borderline personality traits and depressive and social anxiety symptoms compared with groups low in those symptoms or high in sensation seeking (but low in psychopathology). Their findings may indicate considerable comorbidity between psychopathological symptoms and SNS addiction.

Wegmann et al [121] suggested that depressive symptoms and social anxiety have both a significant direct relationship with SNS-specific addiction and a partially mediated pathway to SNS-specific addiction via 2 cognitive styles: self-regulation and Internet use expectancies. In these pathways, higher levels of depression and anxiety are related to lower levels of self-regulation, which are in turn related to higher SNS-specific addiction scores. Internet use expectancies, the perception that the Internet can aid in increasing pleasure and decreasing negativity, were greater for those with higher depression or anxiety symptoms, which again lead to greater vulnerability for SNS-specific addiction. They suggest that depression and social anxiety may predispose SNS users to these cognitive styles.

In contrast, Andreassen et al [117] found that while social anxiety was positively related to addictive SNS use, depression was negatively related to addictive SNS use. This was interpreted as reflecting social withdrawal characteristics of depression and CMC's social compensation for individuals with social anxiety [117]. Indeed, addiction and the compensatory uses of SNSs have been demonstrated to be related to higher levels of social anxiety [106]. Some evidence suggests that the addictive use of SNSs arises from the need to compensate for the social functions affected by social anxiety symptoms. Casale and Fioravanti [104], for example, show that addressing unmet face-to-face social needs, such as the need to belong, to be perceived as socially competent, and to be assertive in communication, may drive problematic SNS use. However, associations may depend on gender. For males and females, a direct association between social anxiety and problematic SNS use has been demonstrated; however, a significant mediator (motivations for competent self-presentation) in this relationship only emerged for males [104]. Lee-Won et al [65] suggested that when the need for social reassurance (ie, motivations to seek social interactions and feelings of belonging) is high or moderate, the relationship between social anxiety and problematic SNS use is strengthened. Thus, social anxiety may only be a risk factor for problematic use of SNSs where the need for social connection is also high.

Physiology and Facebook

Finally, one study examined the impact of Facebook or face-to-face exposure as a primer for physiological arousal [122]. Arousal was greater for individuals when observing someone face-to-face after browsing their Facebook profile than for individuals exposed to a face-to-face encounter followed by the Facebook condition. Social anxiety was a significant moderator, with a more pronounced increase in arousal for those high in social anxiety, particularly in the Facebook than face-to-face exposure. The authors suggested that for the high social anxiety group, the initial exposure to Facebook may prime social comparison and self-presentation concerns for the subsequent face-to-face meeting. However, as emotional valence was not measured, it is unclear if the arousal experienced by participants was perceived as a positive or negative event.

Discussion

Principal Findings

This systematic review examined associations between SNS use and anxiety and depression. Across 70 studies reviewed, a number of positive and negative correlates have been suggested, as well as moderators and mechanisms of these associations. On the basis of this review, it is likely that there are differing engagement and interactional styles on SNSs for users high in social anxiety and depression. These may be driven or defined by both symptoms and motives to compensate for needs that are not met face-to-face. Negative interactions, frequent social comparison, and SNS addiction or problematic use are related to higher levels of depression and anxiety. Furthermore, cognitive response styles such as rumination or brooding may exacerbate the negative interactions between SNS use, depression, or anxiety for some individuals.

While these potential risks exist for mental health, it is also clear that SNSs can provide considerable benefits to their users. Positive quality interactions, social support, and social connectedness most consistently related to lower levels of depression and anxiety. Social support and connectedness derived from SNS use may be uniquely beneficial to individuals with social anxiety who are unable to access these resources face-to-face. However, especially for those with depression, some evidence suggests that there is a discrepancy between the perceptions of interaction quality and social support and the actual content of their SNS communications, which may attenuate the potential positive impacts of SNS use.

Across a number of studies, observable SNS features such as language use and expressions of identity on user profiles have been demonstrated to provide insight into the depression and anxiety status of the SNS user. With continuing research these characteristics may be a useful tool for monitoring mental health. The content and quality of interactions on SNSs may provide the clearest candidates for monitoring depression and anxiety and may be potential intervention targets for improving mental health and well-being through engaging with SNSs.

Social Aspects of Social Networking Sites

Across studies, social aspects, including feelings of social support, social connectedness, and positive interaction quality, emerged as protective factors for SNS users. The SNS network structure itself may play an important role in supporting mental health, in that some platforms may better provide social resources to individuals with depression. Indeed, more integrated social networks on SNSs were associated with lower levels of depression [89]. Studies suggest that social support and social connectedness derived from SNSs are constructs distinct from general social support or connectedness [111,113]. SNSs may therefore be contributing additional benefit to their users by creating another domain in which individuals can access, or have greater perceived access to, social support, especially with individuals for whom face-to-face interaction is difficult

[123-125]. The broad and visibly articulated social context on SNSs may contribute to the feeling of social connectedness derived from SNSs and its association with better mental health outcomes [126]. As such, SNSs may provide an environment where those already high in social skills and resources are benefiting from their cumulative sources of social support ("rich-get-richer"; see [28]) as well as augmenting social support access for those who have difficulties engaging face-to-face [111,123-125].

Consistent with offline research, the perception of social support appears to be more important than actual support [126-128]. Findings demonstrated that perceived social support was greater in those with lower depression scores and that perceived communication competence may contribute to this relationship [79,93]. Greater perceived positive interaction quality and greater reciprocity in interactions are also indicative of lower depression and anxiety. Similarly, Valkenburg et al [32] demonstrated higher levels of life satisfaction and self-esteem for those who frequently reported positive peer experiences on SNSs. However, aspects of the individual that drive depressive feelings and social anxiety, greater use of negative language, and cognitive aspects such as social comparison and rumination, can prevent the user from perceiving support that is actually there [93], further contributing to depressive or anxious symptoms.

Emotional Aspects of Social Networking Sites

The valence of posts on SNSs may both reflect and impact depression and anxiety. Individuals scoring higher on depression scales in the reviewed studies generally expressed more negative affect on SNSs and were more likely to perceive negative interactions. The way individuals interpret emotional and social content on SNSs may place depression as antecedent to maladaptive SNS use, which may, in turn, maintain depressive symptoms. For individuals who are already depressed, ambiguous interactions are often interpreted as negative [13,129], which may attenuate the potential benefits available through SNS use.

Evidence suggests that frequent positive expressions are associated with better mental health, and frequent negative expressions are associated with depression and poorer life satisfaction [67,91,96]. While therapeutic writing can provide some benefits in reducing distress and improving well-being [30,31], online writing may serve a different function, with Web-based expressions reflecting the lived experience of the individual (eg, [91,130-132]), rather than providing a therapeutic outlet. Indeed, relative increases in posting frequency were shown to be associated with greater depressive symptoms [84]. For others, the presence of social anxiety may hinder the use of posting functions for emotional disclosure on SNSs [59], which may decrease access to potential social interaction [98]. As emotional content can be effectively communicated on the Web [133], SNSs represent another space in which positive and negative interactions can be enacted and may provide key behavioral insights into the mental health and well-being of a SNS user. Alternatively, increases in self-expression on SNSs may be more beneficial to well-being domains (such as connectedness, social support, and life satisfaction) but may not have an impact on depression or anxiety. A direct comparison of these relationships has not been conducted, and might be an area to investigate in the future.

Cognitive Aspects as Mechanisms and Moderators

The prominent risk factors for depression and anxiety that emerged from this review included frequent SNS social comparison, negative perceived interaction quality, addictive or problematic SNS use, and rumination (or brooding). These factors represent cognitive and interactional styles that have well-established associations with depression and anxiety but may be enhanced by the enduring nature of social content on SNSs. Although the total frequency of SNS use does not appear to be directly related to either depression or anxiety, there are different moderating and mediating factors [68,73,77,78] and patterns in the functions of SNS use by individuals with higher depression or anxiety that may contribute to or exacerbate symptoms [69,74-76,78].

One of the risk factors for depression and an individual's interaction with SNSs was rumination. Greater rumination is frequently associated with higher ratings of depression and also impacts well-being by maintaining a focus on negative affect [134,135]. Rumination is a likely mechanism for the relationship between negative interactions with SNSs and depression based on its role in SNS negative emotional expression [67] and social comparison [115]. There is considerable potential for SNSs to amplify and assist ruminative processes by exposing SNS users to a constant stream of rich social information that can be selectively reflected on as permanent content on a user's profile [54,115].

Similar to depression, the cognitive risk factors for social anxiety include social comparison (via brooding) and the perception of frequent negative interactions. However, the pathway to and importance of these risk factors may differ from depression. In contrast to those with depression, those high in social anxiety mainly use SNSs for passive browsing and private communication, not for content production [75]. The passive uses of SNSs may place individuals at greater risk of more frequent social comparison, which may have negative mental health effects [114]. This differs from the relative benefit of content production on SNSs for an individual with social anxiety, as posts are often rated as being more appreciated by friends in the network [98], which may have a flow-on effect to the perception of SNS-derived social support [111] and may even reflect more positive interactions with peers [103].

The reduced social cues on SNSs may be attractive to individuals with social anxiety, as has previously been suggested in the general Internet literature [124]. However, the need to compensate for a lack of belonging and social reassurance in face-to-face interactions, in conjunction with lower self-regulation, may drive problematic SNS use for individuals with social anxiety [65,104,106,117]. Similarly, these motives may also contribute to individuals with social anxiety generating more content on their profile pages than others [57], and for those highest in social anxiety it may contribute to a higher frequency of SNS use [69]. On the whole, there appear to be a number of well-being benefits to using SNSs for individuals high in social anxiety that cannot be gained in face-to-face interactions; however, the pattern of SNS use may negatively affect other domains.

Mixed Results and Nonpredictors

The frequency of SNS use as a whole suggested no clear association with depression and anxiety. Longitudinal research suggests that depression and anxiety remain stable in the context of how frequently a user engages with SNSs [54,56,61,63,77] and the function of use holds clearer associations with depression and anxiety [75]. This is consistent with the literature examining general Internet use where total frequency of use is often not a predictor of depression, particularly when examining the social features of the Internet [28,125]. For example, when examining different functions on the Internet, Morgan and Cotten [29] showed that more hours spent using the Internet for social activities (IM'ing, chat rooms) are associated with decreased levels of depression and that informational uses and gaming are associated with increases in depression.

While total SNS use may not affect psychopathology, it may be related to subjective well-being. This was illustrated in the study by Kross et al [63], in which more frequent SNS use was related to experiencing more negative affect and reducing life satisfaction. As frequent experience of negative affect may contribute to the onset and maintenance of depression, it is likely that a pathway to poorer mental health outcomes exists via the impact SNS use has on the frequency of experiencing positive and negative emotions [54,63,67]. Additionally, other SNS features and cognitive processes (eg, network size, structure, and composition, tendency to ruminate, frequent social comparison) may be more informative in describing the impact frequent SNS use has on mental health.

In contrast with the literature examining social network size and structure offline [12,136], SNS friendship network size, on the whole, was not associated with depression or anxiety. However, some evidence has shown distinct network structure differences between individuals with depression and those without in terms of the interconnection between friends within a network [84]. Individuals with depression or anxiety have previously been shown to have more impoverished social networks, and changes in mental health are often associated with changes in an individual's social network [12,137]. Impoverished social networks are often a risk factor for depression and anxiety by reducing access to "buffering" social support and increasing feelings of isolation [138-140]. They may also result from poor-quality social interactions, often typical of depression and anxiety [137].

The absence of a clear association between depression or anxiety and the number of friends on SNSs may be explained by one of the major differences between the offline and online social networks; that is, the way friendships are maintained over time. As SNSs do not necessitate direct social interaction to maintain the status of "friendship," many users may not actively redefine their networks [141]. It is likely that the social pruning and the dissolution of social ties associated with mental illnesses such as depression and anxiety may not be visible on SNSs. Social pruning does occur for many SNS users (eg, 63% of American SNS users endorsed that they had removed friends from the "friends" list; [141]), but how comprehensively this behavior is performed remains unknown. Therefore, change in mental health status for SNS users may not be as accurately detected by a decreased social network size online as it may be when observing offline networks. Other metrics, such as communication output and reciprocity, may be more informative in describing the social network changes associated with depression and anxiety. For instance, De Choudhury et al [91] demonstrated that the volume of tweets and the associated replies were reduced in Twitter users with depression compared with those without.

Strengths and Limitations

As with any study, there are both strengths and limitations of this review. We included a basic criterion for bias that focused on evaluating the methodology of studies, which considered whether papers included (1) the use of psychometrically reliable and valid measures; (2) an external measurement criterion for mental health; and (3) description of sample demographics that included basic SNS user activity statistics. Only 9 studies were excluded for bias, suggesting that there is relative strength in defining the variables of interest in this field. However, a greater focus on defining the SNS characteristics of the sample is required.

The review attempted to characterize the research in terms of the populations and specific SNSs that have been studied. Studies have focused rather narrowly on the young adult population. While these individuals tend to represent the highest membership category of SNSs, recent estimates have suggested that SNS use is becoming more evenly represented across the life span, with more than 50% of older Internet users (65+ years) now also using SNSs [7]. This is an important consideration for future research as the social connection that may be gained through SNSs may provide more benefit for older users as quality of the interactions, particularly through language use, may vary significantly over the life span [142].

Despite the systematic approach to this review, the identified themes are not exhaustive. Other themes such as the differences between SNS users and nonusers and SNS use motives may have been extracted and more explicitly discussed. The discussion of results was limited to the depression or anxiety context and did not discuss findings outside this scope. Well-being, which clearly is becoming a growing area of interest (Figure 1), was only included if there was also a focus on depression or anxiety. Future studies might extend to other aspects of mental illness and wellness.

Finally, although we identified some moderating characteristics, few studies have considered individual differences such as gender and personality and their interaction with SNS variables. Future studies might give greater attention to how characteristics of users impact the identified factors.

Implications and Future Directions

The results of this systematic review have revealed considerable support for the importance of examining the content and quality of the interactions a user has with SNSs. As such, the language used in interactions on SNSs could become a target of interest, particularly as it has been shown to be sensitive in identifying individuals with depression [91,92,94,143]. Further research should also focus on the interplay between the network structure components and dynamic interactions observable on SNSs. The SNS friend structure could be instrumental in defining the type and efficiency with which social resources may be accessed on SNSs. Examining network structure in concert with the quality of interactions, characteristics such as perceived social support, and mental health could provide rich explanations for why some people benefit from SNS use and others are placed at risk, echoing the detailed social network research that has occurred offline (eg, [12]).

Only a few studies in this review utilized SNS-derived data to answer their research questions. The majority focused on the use of self-report survey and relied on participant estimates of their SNS behaviors, which may have introduced considerable retrospective bias. This bias was addressed to some extent by including ESMs that more accurately sample a participant's lived experience [144]. The studies directly observing SNS behaviors indicate that the mental health status of SNS users may be at least partly derived from their patterns of use, language expression, and profile information. These findings provide more weight to the potential of using computational science techniques within psychological research, particularly in characterizing well-being in large community samples [33-35,145,146], as well as predicting personality [147]; see also [148]. In reference to depression and anxiety, SNS data hold huge potential for early identification and time-sensitive monitoring of symptoms [143]. SNS data should be leveraged in future research as a part of ESMs to provide real-time, unobtrusive accounts of social behavior in a natural setting.

Conclusions

This systematic review examined the recent research on associations between SNSs and depression and anxiety. It examined findings in association with the suggested mediators and moderators and the links made with well-being. With more than 50% of adults using multiple SNSs [7], they permeate many aspects of daily life. For many, SNSs represent a way to socially connect with others. However, for others, SNSs may encourage and perpetuate maladaptive tendencies. SNSs maintain and reflect the complexities of the offline social environment and the risks and benefits it may pose to mental health. SNSs represent a novel, unobtrusive, real-time way to observe and leverage mental health and well-being information in a natural setting, with the ultimate potential to positively influence mental health.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Summary of studies included in the systematic review.

[PDF File (Adobe PDF File), 321KB - mental_v3i4e50_app1.pdf]

Multimedia Appendix 2

Main results table: associations between depression, anxiety, and social networking site outcomes across the 70 reviewed studies.

[PDF File (Adobe PDF File), 106KB - mental_v3i4e50_app2.pdf]

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Abbreviations

CMC: computer-mediated communication
ESM: experience sampling method
LIWC: Linguistic Inquiry and Word Count
MDD: major depressive disorder
SNS: social networking site

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Multimedia Appendix 1

Table 2.2 Summary of studies included in the systematic review.

Study	Population	SNS	Sample Size	Bias Rating	Well-being	Mediators/ moderators
Andreassen et al. [117]	General	General	23533	1		
Appel et al. [116]	General	Facebook	89	1	✓	
Baker & Jeske [80]	General	Facebook	184	0	✓	
Baker & Moore [100]	General	MySpace	134	1		
Baker & Moore [101]	General	MySpace	58	1		
Banjanin et al. [53]	Adolescents	Facebook	336	0		
Blachnio et al. [118]	General	Facebook	672	1		
Bodroža & Jovanović [106]	General	Facebook	804	0		
Burke & Ruppel [105]	Young adults	Facebook	152	1		✓
Casale & Fioravanti [104]	Young adults	Facebook	400	1		✓
Davidson & Farquhar [86]	Young adults	Facebook	336	1		
Davila et al. [54]	Young adults	Facebook/MySpace	718	0		✓
De Choudhury et al. [91]	General	Twitter	489	1		
De Choudhury et al. [92]	Other	Facebook	165	0		
große Deters & Mehl [102]	Young adults	Facebook	86	0	✓	✓
große Deters et al. [98]	Young adults	Facebook	362	1		✓
Dumitrache et al. [97]	Adolescents	Facebook	123	2		
Farahani et al. [55]	Young adults	Facebook	265	1		
Feinstein et al. [115]	Young adults	Facebook	268	1		✓
Feinstein et al. [56]	Young adults	Facebook/MySpace	301	0		
Fernandez et al. [57]	Young adults	Facebook	62	0		
Frison & Eggermont [110]	Adolescents	Facebook	910	1	✓	✓
Frison et al. [81]	Adolescents	Facebook	1621	0	✓	✓
Ghosh & Dasgupta [99]	General	Facebook	120	2	✓	
Giota & Kleftaras [58]	Young adults	Facebook	143	1		
Green et al. [59]	General	Facebook	306	0		
Grieve et al. [113]	Young adults	Facebook	618	1	✓	
Hanprathet et al. [119]	Adolescents	Facebook	832	1		
Homan et al. [89]	Young adults	Trevorspace	195	1		
Hong et al. [109]	Young adults	Facebook	230	0		✓

Table 2.2 cont.

Study	Population	SNS	Sample Size	Bias Rating	Well-being	Mediators/ moderators
Hong et al. [60]	Young adults	Facebook	241	1	✓	✓
Indian & Grieve [111]	General	Facebook	299	0	✓	✓
Jelenchick et al. [61]	Young adults	Facebook	190	0		
Koc & Gulyagci [62]	Young adults	Facebook	447	0		
Kross et al. [63]	General	Facebook	82	0	✓	✓
Labrague [64]	Young adults	Facebook	76	0		
Landoll et al. [107]	Young adults	General	430	1		
Lee [114]	Young adults	Facebook	191	2	✓	
Lee-Won et al. [65]	Young adults	Facebook	243	0		✓
Lin et al. [66]	Adults	General	1787	0		
Locatelli et al. [67]	Young adults	Facebook	251	0	✓	✓
Lup et al. [68]	Young adults	Instagram	117	0		✓
McCloskey et al. [112]	Young adults	Facebook	633	1	✓	
McCord et al. [69]	Young adults	Facebook	216	0		
Moberg & Anestis [108]	Young adults	General	305	0		
Mok et al. [70]	General	General	59	2		
Moreau et al. [120]	Adolescents	Facebook	456	1		
Moreno et al. [85]	Young adults	Facebook	200	2		
Moreno et al. [94]	Young adults	Facebook	307	1		
Morin-Major et al. [71]	Adolescents	Facebook	88	0	✓	
Mota-Pereira [88]	Clinical (depression)	Facebook	60	2		
Pantic et al. [72]	Adolescents	General	160	1		
Park et al. [83]	Young adults	Facebook	55	2		
Park et al. [84]	General	Facebook	212	0		
Park et al. [93]	Young adults	Facebook	103	0		
Rae & Lonborg [73]	Young adults	Facebook	119	0	✓	✓
Raunch et al. [122]	Young adults	Facebook	26	1		
Rosen et al. [74]	General	Facebook	1143	1		
Settani & Marengo [95]	Adults	Facebook	201	0		
Shaw et al. [75]	Young adults	Facebook	75	0		✓

Table 2.2 cont.

Study	Population	SNS	Sample Size	Bias Rating	Well-being	Mediators/ moderators
Simoncic et al. [76]	Young adults	Facebook	237	0		✓
Steers et al. [77]	Young adults	Facebook	332	0		✓
Szwedo et al. [103]	Young adults	Facebook/MySpace	138	1		
Takahashi et al. [90]	General	Depression specific SNS (unnamed)	105	1		
Tandoc et al. [78]	Young adults	Facebook	736	0		✓
Tsai et al. [87]	General	Facebook	202	0		
Tsugawa et al. [96]	General	Twitter	209	0		
Wegmann et al. [121]	Young adults	General	334	1		✓
Weidmann & Levinson [82]	Young adults	Facebook	77	0		✓
Wright et al. [79]	Young adults	Facebook	361	0		

Note. SNS = social network site. Check indicates that well-being or mediators/ moderators were included. See main article for references.

Multimedia Appendix 2

Table 2.3 Main results table: associations between depression, anxiety, and social networking site outcomes across the 70 reviewed studies.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Frequency of SNS use					
	Banjanin et al. [53]	Depression	Average time on SNS (timeframe unclear)	NS	
	Davila et al. [54]	Depression	Daily average time on SNS	NS	
	Farahani et al. [55]	Depression	Daily average time on SNS	NS	
	Feinstein et al. [56]	Depression	Daily average time on SNS	NS	
	Frison et al. [81]	Depression	Daily average time on SNS	+	
	Giota & Kleftaras [58]	Depression	Daily average time on SNS	NS	
	Jelenchick et al. [61]	Depression	Daily average time on SNS	NS	
	Labrague [64]	Depression	Daily average time on SNS	+	
	Lin et al. [66]	Depression	Daily average time on SNS	+	
	Locatelli et al. [67]	Depression	Daily average time on SNS	NS	
	Lup et al. [68]	Depression	Daily average time on SNS	+	Moderated by the proportion of strangers in a network and was only significant at the highest level. It became NS at the lower levels of strangers followed.

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Pantic et al. [72]	Depression	Daily average time on SNS	+	
Rae & Lonborg [73]	Depression	Daily average time on SNS	NS	Significant interaction-relationship is positive for those higher in motivations to use Facebook for connection purposes
Simoncic et al. [76]	Depression	Daily average time on SNS	NS	
Steers et al. [77]	Depression	Daily average time on SNS	+ (cross-sectional) NS (ESM diaries)	Social comparison was a mediator
Tandoc et al. [78]	Depression	Daily average time on SNS	NS	
Hong et al. [60]	Depression	Daily average time on SNS (apps, news feed, chat)	NS	
Davila et al. [54]	Depression	Daily average time on SNS interacting with others	NS	
Rosen et al. [74]	Depression	Frequency of SNS use	NS	
Shaw et al. [75]	Depression	Frequency of SNS use	NS	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Shaw et al. [75]	Depression	Frequency of SNS Interactive Communication Use	+	
Shaw et al. [75]	Depression	Frequency of SNS Content Production Use	+	
Shaw et al. [75]	Depression	Frequency of Passive SNS use	NS	
Tandoc et al. [78]	Depression	Frequency of Passive SNS use	NS	Significant negative association with depression when mediated by Facebook envy
Rosen et al. [74]	Depression	Frequency of impression/profile management on SNS	+	
Simoncic et al. [76]	Depression	Frequency of Active SNS use	NS	Active uses of Facebook were associated with lower depression in a three-way interaction also including gender and neuroticism (female, high neuroticism).
Davila et al. [54]	Depression	Number of times checking SNS per day	NS	
Lin et al. [66]	Depression	Number of times checking SNS per week	+	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Koc & Gulyagci [62]	Depression	Weekly average time on SNS	NS	
Mok et al. [70]	Depression	Weekly average time on SNS	*	No inferential statistics are presented
Morin-Major et al. [71	Depression	Weekly average time on SNS	NS	Findings were also NS in reference to the frequency of peer interactions and self-presentation behaviours
Wright et al. [79]	Depression	Weekly average time on SNS	+	
Farahani et al. [55]	Anxiety	Daily average time on SNS	+	
Labrague [64]	Anxiety	Daily average time on SNS	+	
Rae & Lonborg [73]	Anxiety	Daily average time on SNS	NS	Significant interaction-relationship is positive for those higher in motivations to use Facebook for connection purposes
Feinstein et al. [56]	Anxiety	Daily average time on SNS interacting with others	NS	
Koc & Gulyagci [62]	Anxiety	Weekly average time on SNS	NS	
Baker & Jeske [80]	Social Anxiety	Daily average time on SNS	NS	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Baker & Jeske [80]	Social Anxiety (Facebook-specific)	Daily average time on SNS	-	
Green et al. [59]	Social Anxiety	Daily average time on SNS	NS	
Lee-Won et al. [65]	Social Anxiety	Daily average time on SNS	NS	
Feinstein et al. [56]	Social Anxiety	Daily average time on SNS interacting with others	NS	
Fernandez et al. [57]	Social Anxiety	Frequency of SNS use	NS	
Shaw et al. [75]	Social Anxiety	Frequency of SNS use	+	When included in regression with other functions of SNS use this becomes NS
McCord et al. [69]	Social Anxiety	Frequency of Social SNS use	NS	Significant positive association when moderated by the degree of 'Anxiety on Facebook' only for those in the high group.
Shaw et al. [75]	Social Anxiety	Frequency of SNS Interactive Communication	NS	
Shaw et al. [75]	Social Anxiety	Frequency of SNS Content Production	NS	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Shaw et al. [75]	Social Anxiety	Frequency of Passive SNS Use	+	Remains significant when controlling for depression and anxiety symptoms and was mediated by brooding. An alternative mediation model provided support for social anxiety as a mediator of passive Facebook use and brooding.
Burke & Ruppel [105]	Social Anxiety	Weekly average time on SNS	NS	
Frison et al. [81]	*Life Satisfaction*	Daily average time on SNS	-	
Locatelli et al. [67]	*Life Satisfaction*	Daily average time on SNS	NS	
Rae & Lonborg [73]	*Psychological Well-being*	Daily average time on SNS	NS	
Baker & Jeske [80]	*Self-Esteem*	Daily average time on SNS	NS	
Hong et al. [60]	*Self-Esteem*	Daily average time on SNS (apps, news feed, chat)	NS	
Kross et al. [63]	*Life Satisfaction* *Affective well-being*	Frequency of SNS use	-	Depressive symptoms did not moderate these relationships
Morin-Major et al. [71	*Self-Esteem*	Weekly average time on SNS	NS	

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Size and Structure of SNS					
	Banjanin et al. [53]	Depression	Number of Facebook Friends	NS	
	Fernandez et al. [57]	Depression	Number of Facebook Friends	NS	
	Labrague [64]	Depression	Number of Facebook Friends	NS	
	Locatelli et al. [67]	Depression	Number of Facebook Friends	NS	
	Morin-Major et al. [71	Depression	Number of Facebook Friends	NS	
	Park et al. [84]	Depression	Number of Facebook Friends	-	Group Differences: depressed participants had significantly fewer Facebook friends than non-depressed participants
	Park et al. [83]	Depression (BDI)	Number of Facebook Friends	-	NS when depression was measured by the CES-D
	Rae & Lonborg [73]	Depression	Number of Facebook Friends	-	
	Rosen et al. [74]	Depression	Number of Facebook Friends (index)	-	Technology attitudes and anxiety were held constant.
	Tandoc et al. [78]	Depression	Number of Facebook Friends	NS	
	Wright et al. [79]	Depression	Number of Facebook Friends	NS	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Homan et al. [89]	Depression	Network Structure Characteristics	Differ in high and low depression groups	High depression scores have significantly less integrated online social networks
Takahashi et al. [90]	Depression	Network Structure Characteristics		Described network characteristics and connections across different levels of depression severity. Qualitative analysis is also included
Mota-Pereira [88]	Depression	Facebook use with psychiatrist as a "friend"	-	"Facebook Use" group and "Facebook Use with a psychiatrist as a friend" group, depressive symptoms decreased significantly over a 3-month period compared to a control group.
Tsai et al. [87]	Depression	Accepting friend requests from former partners	+	
Tsai et al. [87]	Anxiety	Accepting friend requests from former partners	+	
Labrague [64]	Anxiety	Number of Facebook Friends	NS	
Rae & Lonborg [73]	Anxiety	Number of Facebook Friends	NS	

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
	Davidson & Farquhar [86]	Anxiety (Facebook-specific)	Number of unique groups on Facebook	NS	
	Davidson & Farquhar [86]	Social Anxiety	Number of unique groups on Facebook	NS	
	Fernandez et al. [57]	Social Anxiety	Number of Facebook Friends	-	
	Weidmann & Levinson [82]	Social Anxiety	Number of Facebook Friends	-	
	Locatelli et al. [67]	*Life Satisfaction*	Number of Facebook Friends	NS	
	Rae & Lonborg [73]	*Life Satisfaction*	Number of Facebook Friends	NS	Significant interaction – relationship is positive for those high in friendship motivations for using Facebook
	Rae & Lonborg [73]	*Positive Affect*	Number of Facebook Friends	+	
	Morin-Major et al. [71	*Self-Esteem*	Number of Facebook Friends	NS	
Language Features and Observable SNS Activity					
	De Choudhury et al. [91]	Depression	Twitter Use Data	Predictive language and SNS use features identified	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Tsugawa et al. [96]	Depression	Twitter Use Data	Predictive language and SNS use features identified	
De Choudhury et al. [92]	Postpartum Depression	Facebook Use Data	Predictive language and SNS use features identified	
Dumitrache et al. [97]	Depression	Identity items on profile	+	
Fernandez et al. [57]	Depression	Identity items on profile	+	Depression was associated with a greater amount of profile information posted
Moreno et al. [85]	Depression	Status update content	Predictive language	Depression symptoms can be observed and coded based on the DSM-IV criteria for MDD
Moreno et al. [94]	Depression	Status update content	+	Depression displays in status updates (based on the DSM-IV criteria for MDD) were associated with PHQ-9 scores

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Park et al. [84]	Depression	Inbound comments	NS	Group differences- fewer inbound comments to depressed participants compared to non-depressed participants
Park et al. [84]	Depression	Inbound likes	NS	Group differences- fewer inbound likes to depressed participants compared to non-depressed participants
Park et al. [84]	Depression	Outbound comments	-	Group differences- fewer outbound comments from depressed participants compared to non-depressed participants
Park et al. [84]	Depression	Wall post rate	+	
Park et al. [93]	Depression	Positive disclosure in status updates	NS	Group differences- fewer between those with MDD and those without. MDD participants disclose more negative and less positive content than non-depressed participants.
Park et al. [93]	Depression	Negative disclosure in status updates	NS	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Settani & Marengo [95]	Depression	Positive emotion in status updates	NS	
Settani & Marengo [95]	Depression	Negative emotion in status updates	+	
Settani & Marengo [95]	Anxiety	Positive emotion in status updates	NS	
Settani & Marengo [95]	Anxiety	Negative emotion in status updates	+	
Fernandez et al. [57]	Social Anxiety	Identity items on profile	+	Social interaction anxiety was associated with a greater amount of profile information posted
Fernandez et al. [57]	Social Anxiety	Number of posts by friends	NS	
Fernandez et al. [57]	Social Anxiety	Number of status updates	NS	
große Deters et al. [98]	Social Anxiety	Number of status updates	NS	
große Deters et al. [98]	Social Anxiety	Number of likes on status updates	NS	

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
	Weidmann & Levinson [82]	Social Anxiety	Facebook Profile Inactivity	NS	Group Differences- participants listing a single relationship status compared to a relationship with other people and an absence of status updates compared to profiles with status updates had significantly higher scores of social anxiety.
	Weidmann & Levinson [82]	Social Anxiety	Observer ratings of social anxiety from profile content	+	
SNS for Self-disclosure and expression					
	Baker & Moore [100]	Depression	Intention to blog	+	Group differences- intending bloggers had significantly higher depression scores than non-bloggers
	Baker & Moore [101]	Depression	Blogging on MySpace	NS	Bloggers (and non-bloggers) had no change in depression scores between T0 and T1 (2-month interval)
	große Deters & Mehl [102]	Depression	Increased status posting	NS	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Locatelli et al. [67]	Depression	Frequency of negative status updates	+	Rumination indirectly mediated the association between negative posts and depression
Locatelli et al. [67]	Depression	Frequency of positive status updates	NS	Rumination indirectly mediated the association between positive posts and depression (significant negative association)
Baker & Moore [100]	Anxiety	Intention to blog	+	Group differences- intending bloggers had significantly higher anxiety scores than non-bloggers
Baker & Moore [101]	Anxiety	Blogging on MySpace	NS	Bloggers (and non-bloggers) had no change in anxiety scores between T0 and T1 (2-month interval)
Davidson & Farquhar [86]	Anxiety (Facebook-specific)	Self-presentation (role conflict)	+	
Baker & Jeske [80]	Social Anxiety	Assertiveness on SNS	-	Group differences – Higher social anxiety has lower assertiveness scores than low social anxiety

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Casale & Fioravanti [104]	Social Anxiety	Assertiveness on SNS	+	Both males and females have a positive association between social anxiety and the feelings of assertiveness in SNS communication compared to face-to-face settings.
Bodroža & Jovanović [106]	Social Anxiety	Self-presentation	+	
Burke & Ruppel [105]	Social Anxiety	Self-presentation	+	Higher social anxiety was associated with greater concern of presenting a negative self-image on Facebook
Casale & Fioravanti [104]	Social Anxiety	Self-presentation	+	Both males and females have a positive association between social anxiety and the feeling they have more control over SNS self-presentation compared to face-to-face settings.
Davidson & Farquhar [86]	Social Anxiety	Self-presentation (role conflict)	+	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
große Deters et al. [98]	Social Anxiety	Social Reciprocity and Valence of Status Updates	+ (Study 1) NS (Study 2)	Positive posts elicit a greater number of 'likes', particularly for those high in social anxiety. This was not supported in Study 2
Ghosh & Dasgupta [99]	Social Anxiety	SNS membership	-	Group differences – Facebook users had significantly lower social anxiety scores than non-users. This difference was more pronounced for female non-users compared to males.
Green et al. [59]	Social Anxiety	SNS self-disclosure (public)	NS	
Green et al. [59]	Social Anxiety	SNS self-disclosure (private)	NS	Significant mediated pathway from social anxiety to private Facebook self-disclosure via the characteristics of online communication and disinhibition.
Locatelli et al. [67]	*Life Satisfaction*	Frequency of negative status updates	-	Rumination indirectly mediated the association between negative posts and life satisfaction

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
	Locatelli et al. [67]	*Life Satisfaction*	Frequency of positive status updates	NS	Rumination indirectly mediated the association between positive posts and life satisfaction (significant positive association)
	große Deters & Mehl [102]	*Loneliness*	Increased status posting	+	Loneliness significantly decreased in the experimental group (increased posting) from T1 to T2 (1-week interval) and did not change in the control condition. The decrease in loneliness was mediated by feelings of social connectedness
	Ghosh & Dasgupta [99]	*Self-Esteem*	Facebook membership	+	Group differences – Facebook users had significantly higher self-esteem scores than non-users
	große Deters & Mehl [102]	*Subjective Happiness*	Increased status posting	NS	
Quality of Interactions					
	Davila et al. [54]	Depression	Perceived frequency of negative interactions	+	Greater perceived frequency of negative interactions (T1) predicted increases in depressive symptoms (T2)

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Davila et al. [54]	Depression	Perceived frequency of positive interactions	NS (Study 1) - (Study 2)	Lesser perceived frequency of positive interactions (T1) predicted increases in depressive symptoms (T2)
Feinstein et al. [56]	Depression	Perceived frequency of negative interactions	+	Depressive symptoms at T1 predicted more negative interactions at T2 with close friends and romantic partners
Feinstein et al. [56]	Depression	Perceived frequency of positive interactions	-	Depressive symptoms at T1 predicted less positive interactions at T2 with romantic partners
Frison et al. [81]	Depression	Negative peer experiences on SNSs	+	Cross-lagged analyses suggested a unidirectional relationship between depression (T1) and increases in negative Facebook experiences (T2; 6-month interval)
Landoll et al. [107]	Depression	Negative peer experiences on SNSs	+	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Moberg & Anestis [108]	Depression	SNS interactions (very negative – very positive)	-	When controlling for depression, interaction ratings and thwarted belongingness had a significant negative relationship
Szwedo et al. [103]	Depression	Positive peer relationship quality	NS	
Szwedo et al. [103]	Depression	Negative peer relationship quality	- +	Symptoms at age 13 (T1) predicted less deviancy talk from peers at age 20 (T2) Symptoms at age 20 (T2) predicted more verbally aggressive comments from peers at T2
Feinstein et al. [56]	Anxiety	Perceived frequency of negative interactions	+	Global Anxiety symptoms at T1 did not predict interactions at T2, though cross-sectional associations were observed.
Feinstein et al. [56]	Anxiety	Perceived frequency of positive interactions	-	

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Feinstein et al. [56]	Social Anxiety	Perceived frequency of negative interactions	+	Social Anxiety symptoms at T1 did not predict interactions at T2, though cross-sectional associations were observed
Feinstein et al. [56]	Social Anxiety	Perceived frequency of positive interactions	-	Relationship is NS when only observing interactions with close friends
Hong et al. [109]	Social Anxiety (online)	Facebook continuance intention	-	Belief that virtual communities are dangerous (including the potential to encounter hostile/negative interactions) is positively associated with online and general social anxiety subsequently links to reduced continuance intention for using Facebook
Landoll et al. [107]	Social Anxiety	Negative peer experiences on SNSs	+	
Szwedo et al. [103]	Social Anxiety	Positive Peer Relationship Quality	+	Symptoms at age 20 (T2) predicted more supportive comments from peers at T2

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
	Szwedo et al. [103]	Social Anxiety	Negative Peer Relationship Quality	-	Symptoms at age 13 (T1) predicted fewer verbally aggressive comments from peers at age 20 (T2)
	Frison et al. [81]	*Life Satisfaction*	Negative peer experiences on SNSs	-	Cross-lagged analyses suggested a bidirectional relationship between life satisfaction (T1/T2) and negative Facebook experiences (T1/T2)
Social Support					
	Frison & Eggermont [110]	Depression	Perceived Social Support (via SNS)	-	
	Frison & Eggermont [110]	Depression	Social Support Seeking (via SNS)	+	Social support seeking through Facebook and its association with depressed mood was mediated by perceived social support (greater perceived social support decreased depressed mood).

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Frison et al. [81]	Depression	Perceived Friend Support (via SNS)-moderator *(Negative Facebook experiences)*	-	Moderated by perceived friend support (low, medium, high), the association between negative Facebook experiences (T1) and depressed mood (T2) was significant only for low and medium levels.
McCloskey et al. [112]	Depression	Perceived social support (via SNS)	NS	
McCloskey et al. [112]	Depression	Emotional support (via SNS)	+	
McCloskey et al. [112]	Depression	Negative social support (via SNS)	+	
McCloskey et al. [112]	Depression	Instrumental support (via SNS)	NS	
Park et al. [93]	Depression	Perceived Social Support (via SNS)	-	
Park et al. [93]	Depression	Actual Social Support (via SNS)	NS	Significant positive relationship where the individual was disclosing negative sentiment and they were higher in depressive symptoms.

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Park et al. [93]	Depression	Discrepancy between actual and perceived support	+	Group differences -discrepancy is larger for individuals with MDD compared to non-depressed participants.
Wright et al. [79]	Depression	SNS Social support satisfaction	-	Path from higher CMC competence predicts more Facebook Social Support Satisfaction and subsequently lower depression scores. Motives to use Facebook for social integration and interpersonal communication also contributed to this model
Indian & Grieve [111]	Social Anxiety (high)	Perceived social support (via SNS)	+ (*subjective well-being*)	Controlled for offline social support Group comparisons also revealed no significant differences in perceived Facebook social support between the low and high social anxiety groups
Indian & Grieve [111]	Social Anxiety (low)	Perceived social support (via SNS)	NS (*subjective well-being*)	

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
	Frison et al. [81]	*Life Satisfaction*	Perceived Friend Support (via SNS) - moderator *(Negative Facebook experiences)*	+	Moderated by perceived friend support (low, medium, high), the association between negative Facebook experiences (T1) and life satisfaction (T2) was significant only for low and medium levels.
	McCloskey et al. [112]	*Quality of Life*	Perceived social support (via SNS)	NS	
	McCloskey et al. [112]	*Quality of Life*	Emotional support (via SNS)	-	Direct association only with psychological well-being of the WHOQOL-BREF domains
	McCloskey et al. [112]	*Quality of Life*	Negative social support (via SNS)	-	
	McCloskey et al. [112]	*Quality of Life*	Instrumental support (via SNS)	NS	
Social Connectedness					
	Grieve et al. [113]	Depression	Facebook social connectedness	-	
	Grieve et al. [113]	Anxiety	Facebook social connectedness	-	
	Grieve et al. [113]	*Life Satisfaction*	Facebook social connectedness	+	

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Social Comparison					
	Appel et al. [116]	Depression	Envy	+	Significant interaction – envy was greater in response to viewing an attractive Facebook profile, with it being more so in a depressed group compared to a non-depressed group
	Tandoc et al. [78]	Depression	Envy	+	Facebook envy mediates the association between surveillance uses of Facebook and depression
	Lup et al. [68]	Depression	Downward Social Comparison on SNSs	-	Social comparison was an indirect mediator of the relationship between the frequency of Instagram use and depression. This pathway was additionally moderated by the proportion of strangers followed in the network.
	Steers et al. [77]	Depression	Downward Social Comparison on SNSs	+	Social comparison mediated the relationship between time spent on Facebook and depressive symptoms

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Steers et al. [77]	Depression	Non-directional Social Comparison on SNSs	+	Social comparison mediated the relationship between time spent on Facebook and depressive symptoms
Steers et al. [77]	Depression	Upward Social Comparison on SNSs	+	Social comparison mediated the relationship between time spent on Facebook and depressive symptoms
Feinstein et al. [115]	Depression	Social Comparison on SNSs	+	More negative social comparison on Facebook at T1 was associated with increases in depressive symptoms at T2 via increases in rumination (3-week interval).
Lee [114]	Depression	Social Comparison on SNSs	+	
Lee [114]	Anxiety	Social Comparison Frequency on SNSs	+	
Appel et al. [116]	*Self-Esteem*	Envy	-	
Lee [114]	*Self-Esteem*	Social Comparison on SNSs	-	

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Addictive or Problematic Use					
	Andreassen et al. [117]	Depression	Addictive SNS use	-	Controlled for demographic characteristics, OCD, and ADHD
	Hanprathet et al. [119]	Depression	Addictive SNS use	+	
	Hong et al. [60]	Depression	Addictive SNS use	+	
	Koc & Gulyagci [62]	Depression	Addictive SNS use	+	
	Wegmann et al. [121]	Depression	Addictive SNS Use	+	Internet use expectancies and self-regulation mediate the relationship between SNS addiction and depression/social anxiety
	Blachnio et al. [118]	Depression	Facebook Intrusion (behavioural addiction)	+	
	Giota & Kleftaras [58]	Depression	Problematic SNS use	+	NS when accounting for personality and average daily SNS use

Table 2.3 cont.

Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
Moreau et al. [120]	Depression	Problematic SNS use	+	Cluster analysis indicated that the 'borderline group' which had significantly higher social anxiety and depression scores than two other clusters, also had a higher level of problematic Facebook use
Andreassen et al. [117]	Anxiety	Addictive SNS use	+	Controlled for demographic characteristics, OCD, and ADHD
Hanprathet et al. [119]	Anxiety	Addictive SNS use	+	
Bodroža & Jovanović [106]	Social Anxiety	Addictive SNS use	+	
Wegmann et al. [121]	Social Anxiety	Addictive SNS Use	+	
Casale & Fioravanti [104]	Social Anxiety	Problematic SNS use	+	Males – The relationship between social anxiety and problematic SNS use is indirectly mediated by the *need for self-presentation*

Table 2.3 cont.

	Study	Mental Health Focus	Key SNS Variables	Direct Associations	Additional Notes and Complex Relationships
	Lee-Won et al. [65]	Social Anxiety	Problematic SNS use	+	NSA moderated this relationship with it being more pronounced for those with high and medium NSA, and becoming NS for those low in NSA
	Moreau et al. [120]	Social Anxiety	Problematic SNS use	+	
	Hong et al. [60]	*Self Esteem*	Facebook Addiction	NS	
Physiological Arousal and Facebook					
	Raunch et al. [122]	Social Anxiety	Facebook exposure	+	High social anxiety had greater physiological arousal in a face-to-face encounter after prior exposure to a Facebook profile.

Note: "+" = significant positive relationship reported; "-" = significant negative relationship reported; "NS" = non-significant findings reported; SNS = Social Networking Site; CMC = Computer Mediated Communication; MDD = Major Depressive Disorder; NSA = Need for Social Reassurance; CES-D = Center for Epidemiologic Studies Depression Scale; PHQ-9 = Patient Health Questionnaire – 9; WHOQOL-BREF = WHO Quality of Life-BREF; BDI = Beck Depression Inventory; ESM = Experience Sampling Method; T0 = baseline; T1 = Time 1; T2 = Time 2

Frequency of SNS use refers to studies using a Likert type question with no defined time measurement (e.g. never – very frequently).

2.3 Concluding Remarks

This chapter presented a systematic review of the research exploring depression and anxiety in the context of social networking site use. It identified both risk and protective factors for mental health. Beneficial aspects of social media use for mental health included reducing loneliness, providing an avenue for social support, and positive social interactions. Detrimental aspects of social media for depression and anxiety use included social comparisons, problematic and addictive social media use, and negative social interactions. Further, cognitive and individual characteristics were identified as potential moderators and mediators to the relationship between social media use and depression or anxiety.

Another systematic review was published concurrently with the work presented here by Baker and Algorta (2016). This review also addressed social networking site use and depression, but did not include articles addressing anxiety. The authors reviewed 30 papers and identified similar themes to those identified in this chapter. They also suggested a complex relationship between social media use and depression that is likely moderated and/or mediated by a number of psychological and individual factors like rumination and social comparison. Consistent with the systematic review presented in this chapter, among the limitations in the literature Baker and Algorta (2016) identified sources of bias including the reliance of self-report of social media behaviours, population bias (young, university student aged), and platform bias (predominantly Faccebook research) which may have impacted on the reliability, validity, and generalisability of findings in the literature.

Several other reviews have been published addressing social media use and mental health outcomes since the publication of the paper presented in this chapter, broadly reviewing the same literature and with findings consistent with those presented here. Frost and Rickwood (2017) reviewed the literature of mental health and Facebook use, examining findings related to depression, anxiety, body image and disordered eating, drinking and alcohol use, other mental health problems, and Facebook addiction. In terms of depression they similarly identified lower depressive symptoms being related to perceived social support, and higher depressive symptoms associated with the type of Facebook use (active, or passive), negative content in status updates, and not perceiving social support from online sources. Mixed findings were again found for the time spent on Facebook and depression. To clarify these mixed findings, Huang (2017) conducted a meta-analysis of the research examining the frequency of social networking sites use and its association with well-being (which included depression). Across the studies examining depression (and other negative well-being indices) the correlation with the time spent on social media was weak.

In a practical sense, others have explored the way natural language processing from social media data can be applied to detect mental illness. Guntuku et al. (2017) presented an integrative review of the approaches seeking to detect depression from observable behaviours (including language use) on social media. The features used in these approaches broadly consider demographic variables, lexical features, behavioural features (e.g., time of posting), and social features (e.g., size of a network) (Calvo, Milne, Hussain, & Christensen, 2017; Guntuku et al., 2017). Overall, while approaches to creating prediction models varied, the automated analysis of social media content was revealed to be feasible and the prediction performance of most approaches was considered to outperform unaided clinician assessment (Guntuku et al., 2017).

A limitation of the systematic review presented in this chapter was that it did not include a synthesis of findings using meta-analysis. While it provided a detailed description of the area by narratively synthesising the reviewed papers by theme, it was unable to make clear conclusions about the size or direction of effects. This limitation is most relevant to the discussion of mixed findings in relation to the frequency of SNS use. As above, this has recently been investigated by Huang (2017).

In the next chapter, the general methodology of this thesis is presented, providing rationale for the data collection methods used and additional context for the empirical papers presented in Chapters 4 and 5.

Chapter 3

General Methodology

3.0 Introduction

This chapter provides an overview of the rationale for the research design of the experimental papers (Chapters 4 and 5). It offers an extended methodology (that is, beyond the brief methodologies included in each publication) outlining the development of the data collection method used, an experience sampling smartphone app - *MoodPrism*. This included the development and testing of a word count script capable of reliably collecting language and emoji data for positive and negative emotion categories from Facebook and Twitter. Privacy and ethical considerations are discussed, and the participant selection processes are outlined.

3.1 The Need to Integrate Social Media Data Collection with Other Experience Sampling Methods

The systematic review presented in Chapter 2 highlighted several key themes in social media and mental health research. Across the 70 studies reviewed however, few directly sampled social media data as a part of their study design, while the remainder utilised self-report as a means of estimating the online activity of their participants. The extensive use of self-report methods for accessing social media behaviour may account for some of the mixed findings highlighted in the review, particularly in relation to the frequency of time spent online, and the size of friend networks with depression and anxiety. Recent work has indicated that people are inaccurate when estimating their time spent on sites like Facebook, often overestimating their time spent online by more than 4 times (Araujo, Wonneberger, Neijens, & Vreese, 2017; Junco, 2013). Estimates may also be influenced by cognitive biases, particularly in relation to perceptions of the quality of interactions occurring on social media (e.g., Davila et al., 2012; Szwedo, Mikami, & Allen, 2011). This was highlighted in the study conducted by Park et al. (2016), where individuals with depression self-reported little social support online, but objective examination of social media communications revealed that they had received significantly more social support than they perceived. While self-report does provide important information about subjective experiences of social media use, direct access to social media data would add time-sensitive and more objective assessment of social media behaviour.

There are several advantages to utilising social media data as a behavioural marker of mental health. With close to 2 billion Facebook accounts (Nowak, 2017), the ability to observe social interactions online and in real-time provides researchers with access to previously hidden behaviours on a greater scale than by any other method (Kosinski, Matz, Gosling, Popov, & Stillwell, 2015). The use of social media data provides insight into participants' lives as an unobtrusive and "ongoing experience sampling method" (Park et al., 2015, p. 935) that has qualitative and quantitative properties. Indeed, natural language use on social media has been shown to provide accurate language markers of mental health and well-being that are also sensitive to temporal patterns (Guntuku et al., 2017; Larsen et al., 2015; Hansen Andrew Schwartz et al., 2013).

However, the use of social media data also has inherent biases and limitations. Despite its reach, social media samples are not representative of the general population (Kosinski et al., 2015; Tufekci, 2014). On average, social media users are younger and more technology literate (Blank, 2017; Kosinski et al., 2015). There are also demographic, social, and, geopolitical influences that impact on the type of social media platform used and how individuals engage with it (Correa, 2016; Haight, Quan-Haase, & Corbett, 2014). An example of the geopolitical variation in Facebook use is provided in Figure 1 where the visualisation of (a) Facebook's global social network created by Paul Butler is contrasted with the (b) "UnFacebook World" by Ian Wojtowicz showing the areas of the world that were, and were not connected by friendship ties on Facebook in 2010. The second panel was created by subtracting Facebook's global social network from NASA's *Earth at Night*, thus showing areas of the world connected to electricity (in yellow), but not represented in "Visualising Friendship".

(a) Visualizing Friendship; *Image:* Paul Butler (2010)

(b) UnFacebook World; *Image:* Ian Wojtowicz (2011)

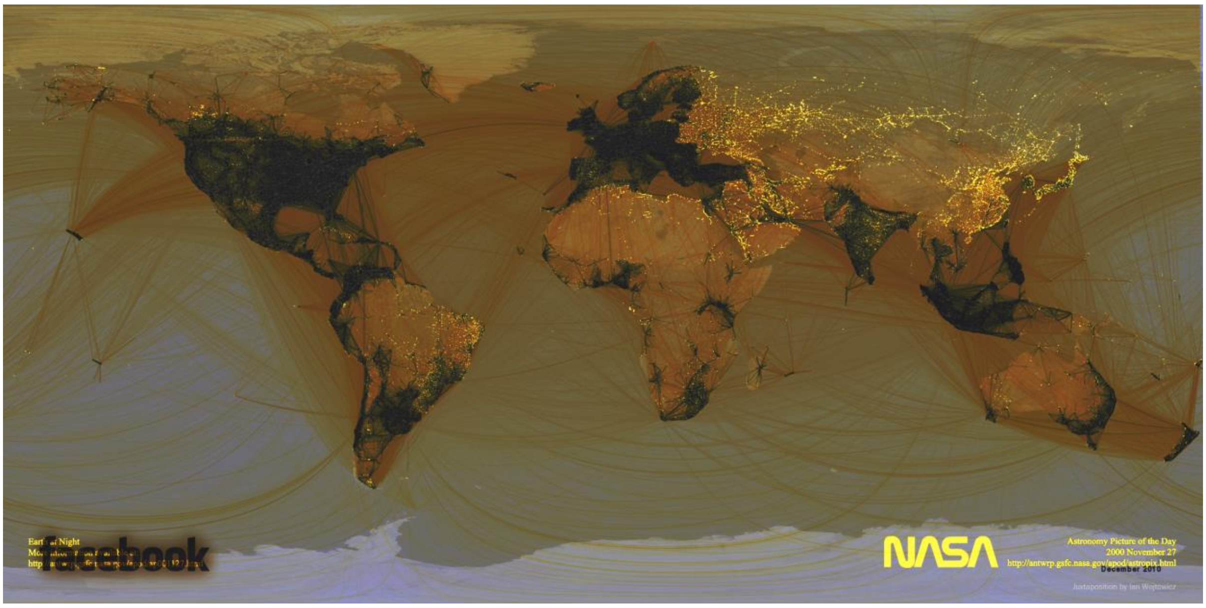


Figure 1. Visualisation of the geopolitical discrepancies between the (a) Facebook and (b) UnFacebook world. These connections have implications for the representativeness and generalisability of social media sample to the population. Image sources:

(a) https://www.facebook.com/notes/facebook-engineering/visualizing-friendships/469716398919/

(b) https://ianwojtowicz.com/UnFacebook%20World/False-Color-Facebook-NASA-Mashup.png

In addition to the factors influencing social media usage generally, not all social media platforms attract the same users or perform the same functions (Phua, Jin, & Kim, 2017; Tufekci, 2014). Phua et al. (2017) discusses this with reference to the Uses and Gratifications Theory (UGT) where individual's selection of social media – as consumers – is guided by how that social media platform can cater to specific needs and wants. They suggest "people may use Facebook to stay in touch with friends, Twitter to follow news and trending topics, Snapchat to instantly share short videos with selected individuals, and Instagram to easily filter and upload visual images" (Phua et al., 2017, p. 414). They found that Snapchat users (compared to Instagram, Twitter, and Facebook) used the platform more for sharing problems, entertainment and passing time. This highlights how the mechanisms of social interaction on different social media platforms may influence the type of content shared between users. This may have implications for prediction of mental health, with data from different platforms potentially providing insight into different underlying behaviours.

Because social media platforms attract different demographic groups, serve different purposes, and have different social mechanisms guiding engagement and interaction (Greenwood, Perrin, & Duggan, 2016; Tufekci, 2014), there is a need to integrate more detailed information about the composition of social media samples. This will better describe who is using social media and account for complexities in the human-technology social environment. It will also provide information about the individual that is not available via social media platforms. For example, depression or anxiety status may not be directly accessible via a status updates. Despite this there are several studies who have used social media data alone to make inferences about mental health (such studies were excluded from analysis in Chapter 2). Without an external criterion of mental health, the validity of conclusions made in such approaches is poor and further highlights the need to incorporate other variables that are not derived from social media data alone (Tufekci, 2014).

Taken together, the methodological considerations discussed above suggest the need for an integrated experience sampling method (ESM) that accesses time-sensitive social media data and supplements this with access to traditional measures that have sound psychometric properties. Such an integrated method is congruent with several practical steps suggested by Tufekci (2014) to increase the strength of research examining social media data. These include the need to (1) sample data from sources external to the social media data set to serve as reliable and valid dependent variables, (2) examine behavioural variation by including qualitative pull-outs, (3) conducting multi-platform analyses and using complementary methods.

3.2 The Development of *MoodPrism*

To address the need for an integrated ESM tool which collects both subjective and objective data relevant to depression from social media and from psychological measures, a new smartphone app, *MoodPrism,* was developed. The requirements of *MoodPrism* for this thesis was that the tool be capable of collecting (1) a valid and reliable measure of depression (external criterion), (2) subjective mood on a daily basis, and (3) social media data from at least two platforms on a daily basis.

MoodPrism was developed for iPhone and Android as a part of a larger project in collaboration with digital product developers *TwoBulls* (Melbourne, VIC). *MoodPrism* delivered an engaging experience sampling method to its users, collected and monitored changes in self-reported emotional well-being over time, collected social media data, and provided its users with colourful and intuitive mood, mental health, and well-being feedback. A detailed account of *MoodPrism*'s development, testing, and procedure is provided in Appendix A "*Development of a mobile phone app to support self-monitoring of emotional well-being: A mental health digital innovation*" (Rickard et al., 2016).

3.2.1 Participants

There were 2,081 downloads of the *MoodPrism* app between April 2016 and May 2017. Participants were recruited through a variety of means which included: targeted Web and Facebook advertising, community engagement and promotion, as well as naturally occurring downloads by individuals seeking a mood tracking app on the Australian Apple and Google Play stores. To be included in the broader *MoodPrism* project participants had to be aged 13 years or older, owned their own smartphone, and were not currently taking psychotropic medication.

Inclusion in the experimental papers (Chapter 4 and 5) of this thesis also required participants:

- to complete the Patient Health Questionnaire- 9 (PHQ-9) from the baseline surveys on *MoodPrism*;
- opt-in to provide either Facebook or Twitter data and;
- to have posted at least 10 status updates over more than 7 days on either Facebook or Twitter within the 12 months prior to completing the PHQ-9;

For the study presented in Chapter 5 the additional inclusion criteria required were:

- completion of at least 70% (21 days) of daily mood reports;
- to have posted at least 10 status updates during the 30 days of *MoodPrism* use.

Figure 2 shows the flow of participant selection for Chapters 4 and 5. It shows from the total downloads 72.4% completed the consent procedures, and from the total sample (N = 1, 518) the opt-in rate for contributing social media data was 14.7%.

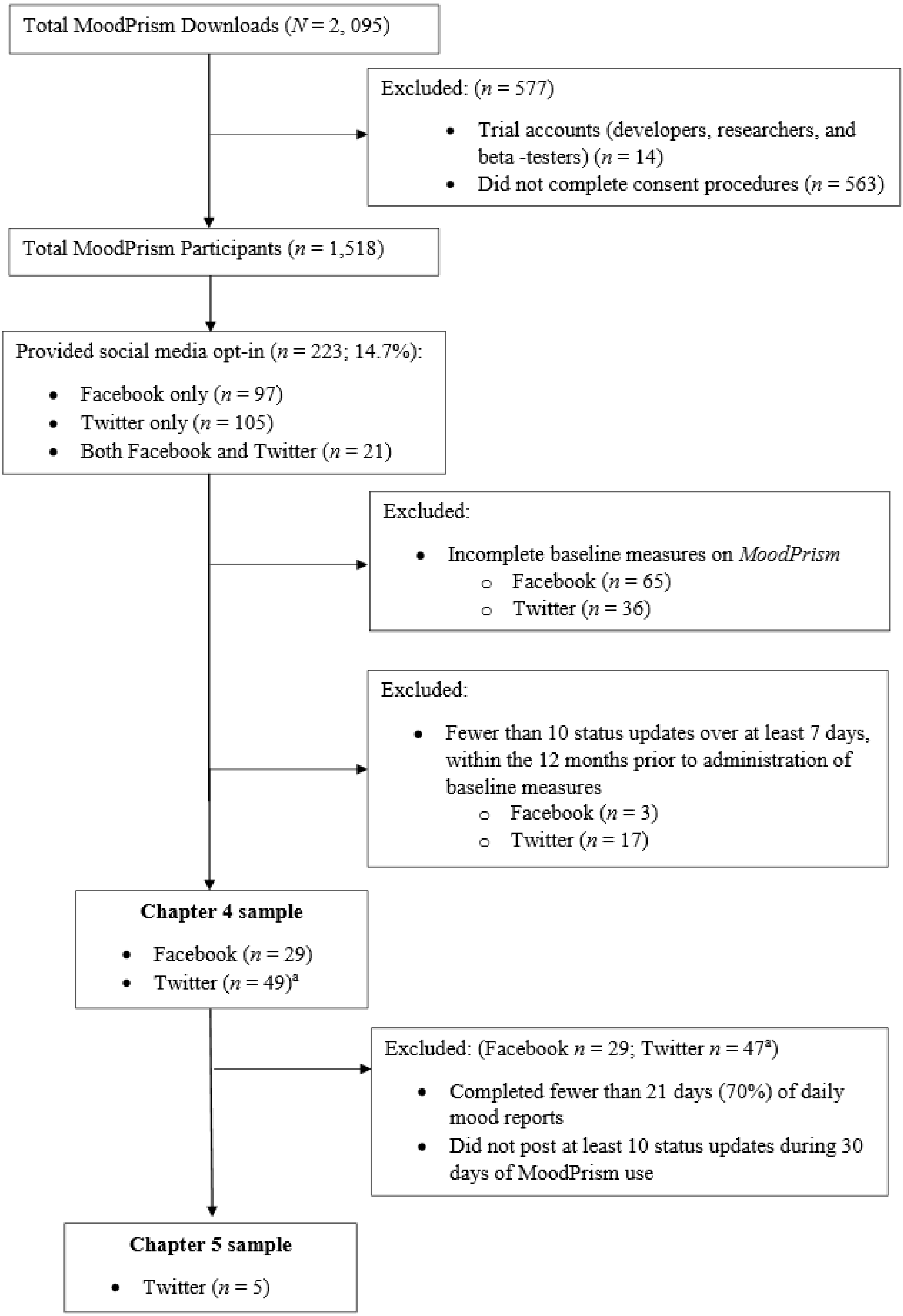


Figure 2. Participant selection flow chart. [a] = To create independent groups for Chapter 4, *n* = 3 who had dual Facebook and Twitter records were allocated to the Facebook group only due to a greater number of language samples. They were then reincluded when assessing suitability for Chapter 5.

Data were available for participants who had opted-in and opted-out to contributing social media data to *MoodPrism*. Table 1 shows the mean scores, standard deviations and frequency counts for individuals in the opt-in and opt-out groups. Sample sizes on each variable differed and these are also indicated in the table. Interestingly, there was a divergence between the self-reported use of social media and the actual use of social media in the opt-in sample. Sixteen participants (1.1%) indicated that they did not use social media in their self-report but also provided social media language samples to the study.

Table 1

Frequency Counts, Means, and Standard Deviations of Participants Who Opted-In and Opted-Out of Contributing Social Media Data to MoodPrism.

Variable	**Opt-in**		**Opt-out**		**Total sample**	
	n	%	*n*	%	*n*	%
Sample	223	14.7	1,295	85.3	1,518	100
Gender (total)	197	13.0	1,164	76.7	1,361	89.7
Male	67	4.4	317	20.9	384	25.3
Female	128	8.4	841	55.4	969	63.8
Other	2	0.1	3	0.2	5	0.3
Don’t want to answer	0	0	3	0.2	3	0.2
Age	154	10.1	918	60.5	1072	70.6
*M(*SD)	33.30 (12.26)		31.86 (13.61)		32.07 (13.43)	
Highest level of education (total)	197	13.0	1161	76.5	1,358	89.5
Primary	5	0.3	12	0.8	17	1.1
Secondary	42	2.8	357	23.5	399	26.3
Tertiary	91	6.0	473	31.2	564	37.2
Post-graduate	58	3.8	302	19.9	360	23.7
Don’t want to answer	1	0.1	17	1.1	18	1.2

Table 1 Continued.

Frequency Counts, Means, and Standard Deviations of Participants Who Opted-In and Opted-Out of Contributing Social Media Data to MoodPrism.

Variable	Opt-in		Opt-out		Total sample	
	n	%	*n*	%	*n*	%
Current study status	196	12.9	1160	76.4	1,356	89.3
Not at all	102	6.7	547	36.0	649	42.8
Part-time	30	2.0	136	9.0	166	10.9
Full-time	64	4.2	477	31.4	541	35.6
Current work status	196	12.9	1157	76.2	1,353	89.1
Not at all, and not seeking work	20	1.3	163	10.7	183	12.1
Not at all, but actively seeking work	18	1.2	123	8.1	141	9.3
Not working due to sick leave	5	0.3	20	1.3	25	1.6
Part-time	79	5.2	445	29.3	524	34.5
Full-time	74	4.9	406	26.7	480	13.6
Social Media Use						
Do you use social media?	159	10.5	975	64.2	1134	74.7
Yes	143	9.4	853	56.2	996	65.6
No	16	1.1	122	8.0	138	9.1
Mental Health						
PHQ-9	196	12.9	1151	75.8	1347	88.7
M (SD)	10.49 (6.64)		10.52 (6.64)		10.52 (6.63)	
GAD-7	196	12.9	1151	78.5	1347	88.7
M (SD)	8.13 (5.42)		8.37 (5.55)		8.33 (5.53)	
WEMWBS	196	12.9	1151	78.5	1347	88.7
M (SD)	41.31 (10.77)		41.13 (9.35)		41.15 (9.56)	

Table 1 Continued.

Frequency Counts, Means, and Standard Deviations of Participants Who Opted-In and Opted-Out of Contributing Social Media Data to MoodPrism.

Variable	**Opt-in**		**Opt-out**		**Total sample**	
	n	%	*n*	%	*n*	%
Personality (mini-IPIP)						
Extraversion	161	10.6	1006	66.3	1167	76.9
M (SD)	9.97 (4.24)		9.70 (4.26)		9.74 (4.26)	
Agreeableness	165	10.9	1038	68.4	1203	79.2
M (SD)	15.18 (3.95)		15.07 (3.96)		15.08 (3.96)	
Conscientiousness	166	10.9	1038	68.4	1204	79.3
M (SD)	12.43 (3.95)		12.30 (4.03)		12.32 (4.01)	
Neuroticism	166	10.9	1030	67.9	1196	78.8
M (SD)	13.14 (4.25)		12.65 (4.04)		12.72 (4.07)	
Openness to Experience	166	10.9	1038	68.4	1204	79.3
M (SD)	12.99 (3.10)		12.38 (3.33)		12.46 (3.30)	
MSPSS	165	10.9	1025	67.5	1190	78.4
Significant Other, *M* (SD)	5.09 (1.57)		5.28 (1.50)		5.25 (1.51)	
Family, *M* (SD)	4.72 (1.49)		4.74 (1.54)		4.73 (1.54)	
Friends, *M* (SD)	4.85 (1.36)		4.91 (1.43)		4.90 (1.42)	
Total, *M* (SD)	4.89 (1.21)		4.97 (1.26)		4.96 (1.25)	
RSES	160	10.5	1001	65.9	1161	76.5
M (SD)	15.24 (2.25)		15.14 (2.05)		15.16 (2.08)	
SDS	189	12.5	1081	71.2	1270	83.7
M (SD)	6.34 (2.78)		6.37 (2.85)		6.36 (2.84)	

Note: PHQ-9 = Patient Health Questionnaire -9; GAD-7 = General Anxiety Disorder -7; WEMWBS = Warwick Edinburgh Mental Well-Being Scale; mini-IPIP = mini International Personality Item Pool; MSPSS = Multidimensional Scale of Perceived Social Support; RSES = Rosenberg Self-Esteem Scale; SDS: Marlowe-Crowne Social Desirability Scale Form-C.

As all distributions were non-normal, Mann-Whitney U tests were used to compare mean rank differences between the opt-in and opt-out groups in age, and on the PHQ-9, General Anxiety Disorder-7 (GAD-7), Warwick Edinburgh Mental Well-Being Scale (WEMWBS), factors on the mini- International Personality Item Pool (mini-IPIP), Multidimensional Scale of Perceived Social Support (MSPSS), Rosenberg Self-Esteem Scale (RSES), and the Marlowe-Crowne Social Desirability Scale Form-C (SDS). This revealed that opt-in participants were older (*Mdn* = 31.00) than the opt-out participants (*Mdn* = 27.00), $U = 62690$, $p = .024$. It also showed that openness to experience was greater in the opt-in (*Mdn* = 14.00) than for the opt-out group (*Mdn* = 13.00), $U = 77304$, $p = .033$).

Relations for the opt-in and opt-out groups on all other variables (gender, highest level of education, current study, and current work status) were explored with Chi-square tests for independence. These revealed that there was a significant association between the opt-in status and the highest level of education achieved (X^2 (4, n = 1,358) = 11.26, p = .024). Standardised residuals showed there was a greater proportion of participants who had completed secondary education in the opt-out compared to the opt-in group.

3.2.2 Privacy and Ethical Considerations.

Ethical approval for the *MoodPrism* project was provided by the Monash University Human Research Ethics Committee (reference number: CF14/968 – 2014000398; Appendix B). Further, permission to promote the *MoodPrism* project to high-school students as a part of the recruitment method was sought and granted by the Victorian Government Department of Education and Training (reference number: 2015_002812; Appendix C). Participant information sheets and the in-app consent screens are provided in Appendix D.

There are currently no universal ethical standards guiding the collection of social media data (Golder, Ahmed, Norman, & Booth, 2017). However, the choice to collect social media data as word counts (aggregate) only and the opt-in process selected for data collection in this thesis was driven by considering the participant's ability to provide informed consent and how to best maintain their privacy. These considerations have been highlighted in recent systematic review exploring the opinions of both researchers and social media users (Golder et al., 2017). While social media research was broadly perceived to be beneficial, the studies reviewed (*n* = 17) illustrated concerns around the use of social media users' data and the implications that had for participant privacy and when/if informed consent should be sought (Golder et al., 2017). Social media users and researchers expressed concerns around the use of verbatim quotes and the risk this posed to anonymity by limiting how effectively participants could be deidentified. There were preferences expressed for the use of aggregate data and transparent research disclosure statements and processes that outline the scope of data access and collection. Seeking informed consent also emerged as a contentious issue that was guided by beliefs around the public or private nature of social media activity. For some researchers and social media users, explicitly gaining the informed consent of public social media users was not seen as necessary, particularly where data was anonymised; while for others informed consent was viewed as a necessary part of ethical practice (Golder et al., 2017).

In the context of the *MoodPrism* app, social media data were collected from both public and private social media sources, from potentially vulnerable groups (e.g. minors), and in combination with extensive demographic, mental health and well-being data. It was therefore important to aggregate and anonymise participant social media data into word counts to reduce the risk of identification and maintain the privacy preferences that may have been implicit in each participant's use of social media.

As we also had direct access to our participants, we elected to include an opt-in process for contributing social media data. From the Beta testing and focus groups conducted prior to the public release of *MoodPrism* however, it became evident that the purpose and scope of the social media data collection was unclear to participants and that trust was an important precursor to opting-in to contribute data (see Appendix A). Clarifying the language and detail leading into the social media opt-in permissions was a crucial improvement to the informed consent processes.

In summary, the following steps were taken as a part of the ethical management of our social media data collection:

(1) Informed consent procedures:

   a. Providing clear explanation of the purpose and scope of the data collected from social media in several formats (within *MoodPrism* leading to the opt-in page; in the explanatory statements; on the website).

   b. Providing participants with an opt-in process for contributing social media data that could be accessed at any time and that was not linked to providing consent to participate in the broader *MoodPrism* study.

(2) Privacy:

   a. Automatically anonymising the participant's social media record upon collection through assigning an alphanumeric code linked to a device ID and not to a user name.

   b. Storing the social media data as aggregate word counts only, thereby reducing the risk of identification.

3.2.3 Measures

3.2.3.1 *Social media data collection by MoodPrism*.

While the development of *MoodPrism* was a collaborative effort between Abdullah Arjmand, David Baker, Nikki Rickard, myself, and *TwoBulls*, the development of the social media data collection scripts and testing was a major component of this thesis and to which I was the primary investigator responsible. This utilised the application programming interfaces (APIs) for Twitter (REST API) and Facebook (Graph API). Documentation is available at https://developer.twitter.com/ and https://developers.facebook.com/. The collection of social media data was broadly completed in three steps:

1) Extraction of raw social media data through API commands;

2) Summary processing of raw data as word counts using custom-developed word count scripts; and,

3) Upload of summary word count data to *MoodPrism* database and deletion of raw social media data from local memory.

Social Media Data Extraction. An API allows software such as *MoodPrism* to communicate with a provider (Facebook or Twitter) using a common programming language to read and retrieve data. The data able to be accessed by *MoodPrism* (as third-party software) is restricted to the functions and permissions granted by both Facebook and Twitter. As outlined above, participants first provided permission by opting-in to have *MoodPrism* extract social media data from their Facebook and/or Twitter accounts. This required participants to log-in with their Facebook or Twitter credentials and consent to providing *MoodPrism* with access to the specific data described in Table 2. This provided *MoodPrism* with a *User Access Token* to query and read data for each participant from the Facebook and Twitter servers. The last 50 status updates on Facebook and/or Twitter for each participant were extracted and any new status update posted over the 30 days of using *MoodPrism* was also called via the API every 24 hours. At this level, the content from status updates was collected; however, it should be noted that this information was never made available to the researchers.

Table 2

Raw Social Media Data Collected by MoodPrism via the Facebook Graph API and Twitter REST API.

Application Programming Interface	Data Called/Retrieved	Description
Facebook Graph API	Status update timestamp	Date and time the status update was posted
	Status update ID	Unique status update identifier
	Status update content	Content of the status update (string data)
	Likes[a]	Number of likes on the status update
	Comments[a]	Number of comments on the status update
	Location[a]	Location status update was posted (if available)
Twitter REST API	Status update timestamp	Date and time the status update was posted
	Status update ID	Unique status update identifier
	Status update content	Content of the status update (string data)
	Number of retweets	The number of times a status update was retweeted. Indicates content has been reposted and was not generated by the *MoodPrism* participant
	Number of favourites	Number of likes on the status update

Note: [a] = errors in calling this information were not resolved during data collection and this data was unavailable for analysis.

***Word count scripts and summary processing*.** After retrieving the data outlined in Table 2, the content of status updates was run through word count scripts developed for the Android and iPhone implementations of *MoodPrism*. The word count scripts processed the raw social media data locally on the participant's smartphone ensuring the content of status updates continued to reside on the user's smartphone only and was never available to the researchers.

The word count scripts for this research were primarily derived from the *Linguistic Inquiry and Word Count 2007* (*LIWC 2007*; Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007). The *LIWC 2007* is a widely used corpus of dictionaries for automated text-analysis. The dictionaries represent 80 language categories that have been used to identify psychological and social information in written and spoken language. Numerous studies have utilised the LIWC 2007 in the examination of individual differences, psychological processes, and for elucidating the language features related to mental health (Tausczik & Pennebaker, 2010). The *LIWC* 2007 was updated during the course of this research to the *LIWC* 2015 (Pennebaker, Boyd, Jordan, & Blackburn, 2015); however, the development costs (time, financial) of updating the dictionaries restricted their inclusion. Despite this, comparison of the 2007 and 2015 versions show very similar performance (Pennebaker Conglomerates, 2015).

A subset of *LIWC* 2007 dictionaries including positive emotion, negative emotion, personal pronoun (first person - singular), and other pronoun (first person plural, second person, third person singular/plural) dictionaries were selected to be included in *MoodPrism*'s word count scripts as they had been shown to be related to mental health outcomes in social media and offline research (De Choudhury et al., 2013; Tausczik & Pennebaker, 2010). Using a subset of target categories (rather than all *LIWC 2007* dictionaries) also reduced the smartphone processing burden. In this research, only the positive and negative emotion dictionaries were included in analyses. The *LIWC 2007* positive and negative emotion dictionaries were supplemented by emojis and internet slang for the emotion categories to better reflect the online environment (Kern et al., 2016). These were generated by conducting an online search to compile a list of emojis and internet slang related to positive and negative emotion. Ambiguous items (unclear emotion or uncommon) and other problematic items (e.g., those that were impractical to implement due to word count script issues) were filtered out to yield the final list (see Appendix E).

The raw word counts from the supplemented *LIWC 2007* dictionaries were operationalised by summing the number of target words in each respective dictionary category used within a language sample (status update) and calculating their proportion relative to the total word count in that language sample. This meant that the relative proportion of all positive, negative, first person personal pronouns, and other pronouns from all words used in each individual Tweet or status update was calculated. This is seen in Equation 1:

$$p(category) = \sum_{word \in category} p(word) = \frac{\sum_{word \in category} count(word)}{N\_words}, \tag{1}$$

where *count(word)* refers to the total number of *LIWC* 2007 dictionary category words contained in a status update or Tweet, and *N_words* is the total number of words in that status update or Tweet.

Practical implementation and testing of word count scripts in Objective C and Java. As *MoodPrism* was developed for both iOS and Android smartphones, the programming language implementations of the word count scripts differed between iOS (Objective C) and Android (Java). To ensure the word count scripts were extracting target words accurately, and consistently across both operating systems, a test set of simulated and real status updates was created that aimed to present simple and complex sentences in order to determine where and if the word count scripts failed at identifying words in the supplemented *LIWC 2007* dictionaries. These test sentences were manually coded for the target words and then automatically processed through *MoodPrism*'s word count script.

Broadly, the steps followed by the word count scripts in both OSs were:

1) *MoodPrism* extracted the content of a status update in a string data format (a series of characters which can consist of alphanumeric, punctuation, and symbols);
2) The string was split into substrings that represented words or emojis;
3) Each substring was run through each of the dictionaries and matches were counted.; and,
4) The word count of matching words within each dictionary was summed and the summary data was uploaded to the *MoodPrism* server.

Testing the first iteration of the word count script through *MoodPrism* revealed both syntax and logic errors. Syntax refers to the rules of language in software and errors occur when symbols are used incorrectly or there are errors in applying the language rules (Youngs, 1974). Logic errors refer to the errors in the performance of the program solution, where the desired outcome of the program is not achieved (Youngs, 1974).

Syntax errors. Firstly, as the word dictionaries had been directly cut and paste from a Microsoft Word (MS Word) document into Objective C and Java, any words containing an apostrophe were not identified as belonging in a dictionary, impacting on contractions, emojis and internet slang. Characters are encoded by a set of universal numeric values called Unicode, providing a common language across programs (Unicode Inc., 2017). In Microsoft Word, apostrophes are automatically converted into curved 'smart quotes' which indicate open and closed apostrophes and quotation marks (Unicode: U+2018 and U+2019), whereas the status update strings retrieved by *MoodPrism* represented apostrophes in their straight format (Unicode: ASCII U+0027). This syntax discrepancy resulted in the word count script incorrectly rejecting all words with straight apostrophes. The error was resolved by replacing all curved MS Word apostrophes with straight apostrophes in the dictionaries.

Secondly, escape commands had not been included on symbols that represent functions (operators) in Objective C and Java, primarily impacting on the ability of the word count script to identify emojis. Part of the syntax in Objective C and Java includes the use of symbols to perform specific functions. For example, brackets “( )” are often used to group a set of statements and symbols such as < operate on other symbols in a statement. These symbols are common characters in emojis, for example. :) and <3. Escape functions (often a backslash; \ ) specify that components in a string are to be read literally (as a character) and not as a function or operator. The syntax error where emojis were not being read literally as substrings was resolved by preceding all Objective C and Java operators present in the dictionaries with an escape function.

Logic errors. Testing also revealed logic errors between the Objective C and Java versions of the word count script. The logic error occurred in Step 2 (above) in how the stings were split into substrings (words). The Objective C implementation defined substrings as consecutive characters that were separated by whitespace (any alphanumeric or symbol characters separated by a ‘space’). The Java implementation in comparison defined substrings as consecutive letters or numbers that were split by non A-Z and 0-9 characters. This had different implications for how the iOS and Android versions of *MoodPrism* identified and counted dictionary words within a status update. Neither solution performed in a way that consistently identified both words (in a context that included punctuation) and emojis:

1) In Objective C, splitting by whitespace resulted in dictionary words attached to punctuation script (e.g. excited!) not to be identified by the word count.
2) In Java, splitting by non-A-Z, 0-9 broke all emojis into their individual characters and none were identified by the word count script.

Final implementation. Beyond making the splitting logic consistent in both Objective C and Java, the inclusion of emojis presented a significant practical challenge and required an amended search and matching strategy for the word count scripts to follow. Punctuation symbols were the consistent problematic factor in both versions of the splitting logic. To address this, the final implementation separated the positive and negative emotion word dictionaries of the *LIWC* 2007 from the positive and negative emojis and internet slang (which had previously been combined in master positive and negative emotion dictionaries). The word count script then followed a two-step search and matching strategy:

1) From the full-text input of a status update, emojis and internet slang were matched and counted with their respective dictionaries without splitting the string into parts. This results in positive and negative emoji and internet slang word counts; and,
2) Then, splitting the string on non A-Z (or apostrophe) substrings representing words are created (letters only). These substrings are then matched and counted for the corresponding positive or negative emotion dictionary of the *LIWC 2007*.

Following the two-step search and matching strategy the word counts from each step are summed to create overall positive and negative emotion word counts.

While this solution allowed for consistency across both OS and resolved the major logic error introduced by punctuation, there are specific cases where a false positive word count occurs. For example in the sentence "Here is a list of colours:Purple, green, and blue", the positive emoji ":P" would be identified in step 1 of the word count where a typographical error had occurred. While we could not assess how often these false positive occurred in the data set as we did not have access to the content of status updates, the rare occurrence of false-positives was considered preferable to the frequent occurrence of false-negatives in the original iteration of the code.

3.2.3.2 *Psychological Measures and Daily Mood Report Items from MoodPrism.*

MoodPrism delivered psychological questionnaires and surveys at baseline, baseline and follow-up (after 30 days of *MoodPrism* use), and at follow-up only. Further, daily mood reports consisting of 16-items were delivered every-day for 30 days after the baseline measures were completed. Tables 3 and 4 provide a summary of the psychological questionnaires delivered by *MoodPrism* at baseline and follow-up. Table 5 describes the items in the daily mood report. These tables have been adapted from Multimedia Appendix 1 in Rickard et al. (2016).

Table 3

Measures Delivered at Baseline Only by MoodPrism.

Measure/Domain	**Brief Description**	**Source**
Demographics [a]	Consisted of custom items asking participants gender, age, highest education, current work and study status.	
mini-International Personality Item Pool [a]	Measure of personality based on the Five-Factor Model: extraversion, neuroticism, conscientiousness, agreeableness, openness to experience. Consists of 20 items rated from "1- Very inaccurate" to "5- Very accurate" and are summed within personality factors (range 4-20).	Donnellan et al. (2006)
Marlow-Crowne Social Desirability Scale Form-C [a]	Measures the tendency to present a desirable social image to other. Consists of 13 dichotomous items rated as "True" or "False". After reverse scoring of relevant items, scores are summed with higher scores indicating higher social desirability.	Reynolds (2006)
Rosenberg Self-Esteem Scale [a]	Measure of self-esteem. Consists of 10 items rated from "0- Strongly disagree" to "3- Strongly agree". These are summed after reverse scoring negatively worded items (range 0-30). Higher scores indicate greater self-esteem.	Rosenberg (1965)
Multidimensional Scale of Perceived Social Support	Measure of perceived social support with subscales for significant others, family, and friends. Consists of 12 items rated from "1- Very strongly disagree" to "7- Very strongly agree". Scores are summed within sub-scales and an average over items obtained. Higher averages indicate stronger perceptions of social support.	Zimet et al. (1988)
Barcelona Musical Reward Questionnaire	Measure of music rewards across five facets: musical seeking, emotional evocation, mood regulation, sensory-motor, and social reward. Consists of 20 items rated from "1- Completely disagree" to "5- Completely agree". Sub-scale score and a total score of musical reward can be derived.	Mas-Herrero et al. (2013)
Technology Use Survey	A custom developed survey addressing patterns of technology use.	

Note: [a] = measure included in analyses presented in this thesis (Chapters 4 and 5).

Table 4

Measures Delivered at Baseline and Follow-Up by MoodPrism.

Measure/Domain	Brief Description	Source
Patient Health Questionnaire-9 [a]	Measure of depression symptom severity over previous 2-weeks. Consists of 9 items rated from “0- Not at all” to “3- Nearly every day” which are summed (range 0-27). Higher scores indicate greater severity.	Kroenke et al. (2001)
General Anxiety Disorder-7	Measure of anxiety symptom severity over previous 2-weeks. Consists of 7 items rated from “0- Not at all” to “3- Nearly every day” which are summed (range 0-21). Higher scores indicate greater severity.	Spitzer et al. (2006)
Warwick Edinburgh Mental Well-Being Scale	Measure of mental well-being addressing positive functioning, positive affect, and interpersonal relationships. Consists of 14 items rated from “1- None of the time” to “5- All of the time” which are summed (range 14-70). Higher scores indicate greater well-being.	Tennant et al. (2007)
Emotional Self-Awareness Scale	Measures emotional self-awareness with sub-scales: recognition, identification, communication, contextualisation, and decision-making. Consists of 33-items rated from “0- Never, to “4- A lot”. Higher scores indicate greater levels of emotional self-awareness.	Kauer et al. (2012)
Coping Self-Efficacy Scale	Measure of perceived self-efficacy to cope with challenges. Consists of 26 items rated from “0- Cannot do at all” to “10- Certain can do”. Items are summed, and higher scores indicate greater coping self-efficacy.	Chesney et al. (2006)
Brief Resilience Scales	Measure of resiliency. Consists of 6 items rated from “1- Strongly disagree” to “5- Strongly agree”. Relevant items are reverse scored, and the items summed. Higher scores indicate greater resiliency to stressors.	Smith et al. (2008)
Mental Health Literacy Questionnaire	Measure of mental health literacy through responses to vignettes.	Adapted from Reavley et al. (2014)

Note: [a] = measure included in analyses presented in this thesis (Chapters 4 and 5).

Table 5

Items in the Daily Mood Reports Delivered by MoodPrism.

Measure/Domain	**Brief Description**	**Source**
Patient Health Questionnaire-2	Adapted to measure daily depression symptoms. Consists of: 1. "Little interest or pleasure in doing things", 2. "Feeling down, depressed or hopeless". Rated from "0- Not at all" to "4- extremely".	Kroenke et al. (2009)
General Anxiety Disorder-2	Adapted to measure daily anxiety symptoms. Consists of: 1. "Feeling nervous, anxious, or on edge", 2. "Not being able to stop or control worrying". Rated from "0- Not at all" to "4- extremely".	Kroenke et al. (2009)
Mood [a]	Consist of 3 items based on the circumplex model of emotion. 1. "Active or alert" 2. "Positive or pleasant" [a] 3. "Negative or unpleasant. [a] Rated from "0- Not at all" to "4- extremely".	Adapted from Russell (1980)
Well-being	Custom developed 5 items addressing daily feelings of control, social connection, motivation, life meaning, and self-esteem. 1. "In control of what I'm doing" 2. "Socially connected and supported" 3. "Motivated, engaged, and interested" 4. "Life is meaningful and with purpose" 5. "Feeling good about myself" Rated from "0- Not at all" to "4- extremely".	Adapted from Bech et al. (2003) and Keyes (2005)
Daily Events	Two items addressed positive and negative daily events. If a positive or negative event was endorsed, a further rating items was triggered where participants rated how positive or negative it was from "0- Not at all" to "4- extremely".	Categories are available in Rickard et al. (2016).
Context	Two items addressed context at the time of completing a daily mood report. 1. Where are you? 2. Who are you with?	Categories are available in Rickard et al. (2016).

Note: [a] = measure included in analyses presented in this thesis (Chapters 4 and 5).

In addition to the measures presented in Tables 3, 4, and 5, a feedback questionnaire was presented at follow-up. This was custom developed and was based on the Mobile Application Rating Scale (Stoyanov et al., 2015). Further detail can be found in Appendix A.

Only the daily mood report items addressing mood ("positive or pleasant", "negative or unpleasant") and the PHQ-9 were included in the main analyses of this research. The mini-IPIP, Marlowe-Crowne Social Desirability Scale Form-C, and Rosenberg Self-Esteem Scale were included in supplementary analyses presented in Chapter 4. To reduce potential repetition, detail on the content and psychometric properties of these measures are provided within Chapters 4 and 5.

3.2.4 General procedure.

Figure 3 shows chronological screenshot examples of the *MoodPrism* user experience and general research procedure. Participants of the *MoodPrism* study downloaded the app onto their smartphone from the Apple or Google Play stores. Upon opening the app participants landed on a welcome page (Figure 3a) and were introduced to the purpose of the study (Figure 3b). Access to a downloadable explanatory statement (pdf. format) was presented on the app before digital consent to participate in the study was provided by the participants (Figure 3c). Permissions were also sought to access social media data from Facebook and Twitter as a part of an opt-in process (Figure 3d). Social media permissions could be provided or revoked at any time by accessing the *Permissions* page from the drop-down menu in *MoodPrism* (Figure 3e).

Participants then completed a battery of baseline surveys which included measures addressing mental health, well-being, personality, self-esteem, and technology use previously outlined in Measures. These were organised into blocks on a dashboard (Figure 3f) and each of these blocks needed to be completed before unlocking access to feedback from the experience sampling component of *MoodPrism* (daily mood reports). While each block of questionnaires needed to be accessed and each questionnaire submitted, completion of items within each questionnaire were optional. After completing the baseline surveys participants selected the timeframe within which they wished to be notified by *MoodPrism* to complete a daily mood report

(Figure 3g). Participants were randomly notified by push-notification on their smartphone of an available daily mood report within this self-defined timeframe every day for 30 days.

The daily mood reports were accessed from the mood feedback overview page and began with the prompt screen provided in Figure 3h. The prompt was followed by 16-items that addressed mood (positive and negative affect, arousal), mental health, eudaimonic well-being, significant daily life events (positive and negative), environmental and social context. At the end of 30 days, participants were also asked to complete a battery of follow-up surveys which consisted of a subset of surveys presented at onboarding. Feedback was provided to participants following each daily mood report showing the number of surveys required to unlock more app content (Figure 3i). It was also presented in a colourful calendar format (Figure 3j), in a weekly view (Figure 3k), and in a detailed daily view (Figure 3l).

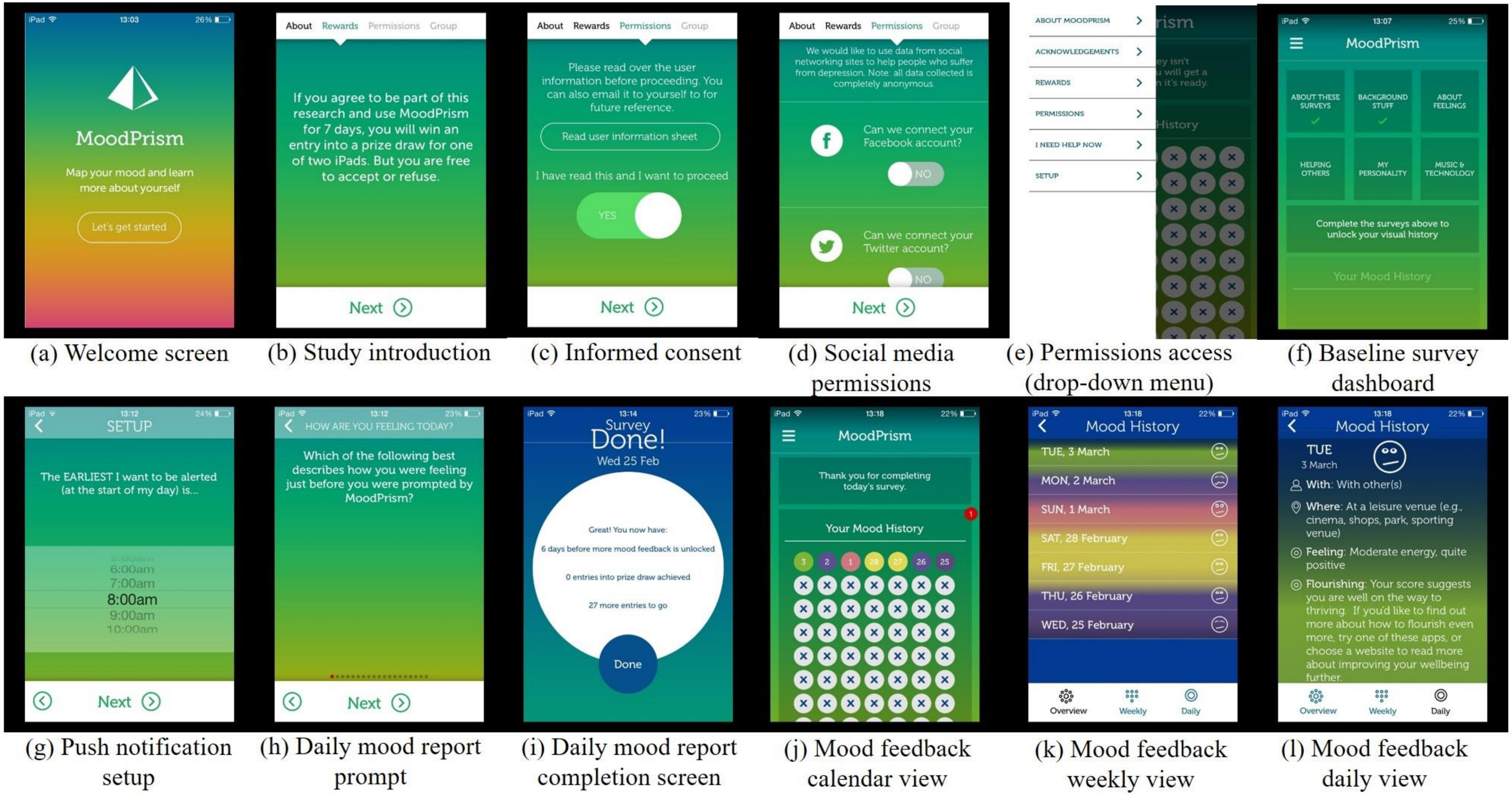


Figure 3. *MoodPrism* screenshots showing the participant's experience through the general research procedure. Captions describe the content of the example screenshots.

3.3 Concluding Remarks

This chapter outlined the need for directly collecting social media data in conjunction with other ESM methods to better sample the individual and contextual factors surrounding social media use. It briefly described the development of the smartphone app *MoodPrism* and introduced the participant selection method and sample characteristics for the social media users included in Chapters 4 and 5. It is clear from the social media opt-in rates and final sample sizes that barriers to contributing social media data may have existed for the majority of participants. As social media data was to be collected within the comprehensive *MoodPrism* ESM, it is likely that concerns around privacy and the breadth of personal information being sampled inhibited the choice to opt-in. To improve opt-in rates in future research, researchers should create opportunities for the user to develop trust in the app before requesting social media data and, as implemented in this research, create detailed social media specific informed consent processes to aid participant understanding of the nature of data they are contributing. The final part of this chapter described the social media data collection method utilised by *MoodPrism,* the development and testing of the word count scripts, and the general research procedure.

Chapter 4

Predicting Depression from Language-Based Emotion Dynamics: Longitudinal Analysis of Facebook and Twitter Status Updates

4.1 Preamble to Empirical Paper 1

This chapter presents the first empirical paper of this thesis titled “Predicting Depression from Language-Based Emotion Dynamics: Longitudinal Analysis of Facebook and Twitter Status Updates”. From the introduction of this thesis and the discussion presented in Chapter 2, it is evident that there has been limited focus on the temporal specificity of observations obtained from social media data and the way these unfold overtime to reveal processes that may be relevant to depression. In this chapter, behavioural (time of posting) and lexical (emotion words) features are combined to tap into the emotion patterns expressed across status updates as a means of providing insight into the depression status of Facebook and Twitter users. Notably, this chapter presents the first application of emotion dynamic indices to social media language data. It also addresses some of the limitations of the research approaches previously taken in the literature identified by Tufekci (2014) and in Chapter 2 by drawing a sample from the general population, using a complementary data collection method for psychological data, providing a cross-platform comparison, and directly sampling social media data rather than relying on self-report alone.

This paper has been published in the *Journal of Medical Internet Research*. As such, the paper is formatted in accordance with the journal requirements. References are provided in the style of the *American Medical Association* (10^{th} edition)

4.2 Predicting Depression from Language-Based Emotion Dynamics: Longitudinal Analysis of Facebook and Twitter Status Updates

Abstract

Background: Frequent expression of negative emotion words on social media has been linked to depression. However, metrics have relied on average values, not dynamic measures of emotional volatility.

Objective: This study reports on the associations between depression severity and the variability (time-unstructured) and instability (time-structured) in emotion word expression on Facebook and Twitter across status updates.

Method: Status updates and depression severity ratings of 29 Facebook users and 49 Twitter users were collected through the app *MoodPrism.* The average proportion of positive and negative emotion words used, within-person variability, and instability were computed.

Results: Negative emotion word instability was a significant predictor of greater depression severity on Facebook ($r_s(29) = .44$, $p = .017$, 95% CI [.09, .69]), even after controlling for the average proportion of negative emotion words used (partial $r_s(26) = .51$, p = .006) and within-person variability (partial $r_s(26) = .49$, p = .009). A different pattern emerged on Twitter where greater negative emotion word variability indicated lower depression severity ($r_s(49) = -.34$, $p = .011$, 95% CI [-.58, .09]). Differences between Facebook and Twitter users in their emotion word patterns and psychological characteristics were also explored.

Conclusions: The findings suggest that negative emotion word instability may be a simple yet sensitive measure of time-structured variability useful when screening for depression through social media, though its usefulness may depend on the social media platform.

Keywords: Automated text analysis, depression, Facebook, Twitter, emotion, variability, instability.

Introduction

"With as much as we have learned about emotions, it is as if we have been taking still photos of a dance." **[**1].

Social media is used in different ways by different people, but for many individuals, status updates provide snapshots of their lived experience. Studies to date have primarily considered how the relative frequency of words indicating positive and negative emotion relate to other characteristics such as mental health status, or which words (or set of words) best predict different outcomes. Such studies indicate that the frequent expression of negative emotion words in status updates can accurately identify individuals experiencing symptoms of depression [2–6]. However, an individual's mental health is reflected by more than just the average frequency or the type of words used; variability in emotional expression over time might also provide significant insights. In the current research, fluctuations in emotional expression over time is explored as another window of insight into the psychological health of social media users.

Depression in Status Updates on Social Media

Depression, including major depressive disorder (MDD) and dysphoria, are characterized by persistent low mood (including sadness or emptiness) or anhedonia (inability to experience pleasure from activities that are usually enjoyable) [7]. At a broad level, the frequent expression of negative affect within social media status updates has been associated with higher levels of depression symptoms [2,3,5,8–11]. Frequently expressing positive affect, on the other hand, tends to be associated with lower levels of depression and greater levels of well-being [9,12,13]. The link between expressed emotion in status updates and mental health is unsurprising considering that expressing current emotion and venting frustration have been reported to be a primary purpose for many users posting on Facebook [14]. Indeed, negative and positive emotional language has been observed to occur in approximately 34% and 55% of status updates on Facebook, respectively [15]. Adding to this, depressed individuals have also been shown to post content more frequently than non-depressed persons [16], and changes in depression severity may be signalled by increases in posting behaviour on social media [17]. Combined, the time-structured features and emotional features of status updates may provide insights into the depression status of social media users.

Several studies have sought to code the content of social media posts for depression disclosures [6]. For instance, Moreno et al. [3] demonstrated that status updates on Facebook with references to depression symptoms such as hopelessness were positively correlated with self-reported depression symptoms. Others extended this by describing the linguistic characteristics of depression in posts and developing coding-schemes to identify depression-indicative Tweets or status updates [2,4,8,18]. While specific topics, keywords, and linguistic features (especially negative emotions) are able to identify depression-indicative posts with high accuracy, many of these features may also be present in posts that are non-indicative of depression (low specificity). For example, Mowery et al. [18] found considerable signal discrepancies - over 70% of tweets identified in their sample containing words related to depression were not actually indicative of depression. Thus, although negative emotion words correlate with the presence of depressive symptoms, it is a noisy and imprecise metric.

This highlights the need to move beyond the frequency of emotional language alone towards other online behavioural indices that may better differentiate depressed and non-depressed individuals. Due to the time-sensitive nature of social media data, examining the dynamic movement of emotion across status updates may provide an additional avenue to tap into the nuanced cognitive-emotional processes underlying depression and may provide a more specific index of maladaptive emotional functioning.

The Emotion Dynamics of Depression

A major change in functioning associated with the onset of depression is the ability to effectively regulate emotion. While the capacity for emotion to vary over time is adaptive and may contribute to psychological well-being, higher levels of emotion variability, especially of negative emotion, have been linked to depression [1,19]. For example, individuals who experience intense negative affect reactivity in response to daily stressors are at greater risk of developing depression

[20–22]. This experience is supported by young people's qualitative accounts of depression, where depression is reported to "[take] over during times of vulnerability such as stress or fatigue" (p. 386) [23]. Negative cognitive biases also contribute to emotion variability in depression. Excessive focus on personal distress (rumination) may lead to persistent experiences of severe negative affect and difficultly regulating mood away from negative rumination [24, 25]. The combination of cognitive-emotional processes result in emergent emotion patterns that can manifest at inappropriate times and in inappropriate ways in response to internal and external events. Maladaptive patterns of emotion build over time to place the individual at an increased risk for depression onset and maintenance [19,26–28].

The emotion variability in depression described above has predominantly been operationalised in two ways. Firstly, variability may be operationalised as within-individual variability as *iSD*, an individual's standard deviation of emotion expression. Like the mean, variability may best be viewed as a "trait-like" measure of emotion expression, as it provides a single number that summarizes the overall variability in affect for an individual across their recording period, but ignores time-structured information [29].

A second operationalisation of variability describes emotional instability and uses the mean squared successive difference statistic, MSSD [30], which quantifies differences between consecutive observations of emotion [1]. This time-structured measure of variability uses the temporal ordering of measurements to quantify the magnitude of incremental changes in emotion [30–32]. Crucially, unlike *iSD* where the same result would be obtained if the same set of emotion expression observations are shuffled through time, the MSSD is sensitive to the time-ordering of observations. For example, for the same distribution of negative emotion values (and thus the same *iSD*), negative emotion increasing in small incremental steps from mild to severe would result in a small MSSD value, whereas negative emotion alternating (or swinging) between mild to severe would result in a large MSSD value. In this way, MSSD captures the temporal instability of positive or negative affect.

Negative affect instability, as measured by the MSSD, has been linked to more severe depression symptoms across several studies and has been identified as a concomitant and early indicator of depression [25,31,33–36]. It has been shown to be a significant risk factor for more frequent and severe suicidal ideation [35] and may be a unique underlying emotion pattern in depression. Negative affect instability has been shown to continue to predict depression when average negative affect and the frequency of negative event exposure are held constant [25,36]. In addition, reductions in negative affect have been shown to be greater for depressed individuals in response to positive events when compared to those who are not depressed, further contributing to potential moment-to-moment variability [37].

Bowen et al. [33] recently aggregated four studies to examine the differences in mood instability between depressed and non-depressed individuals. Participants completed daily mood diary ratings of negative and positive mood upon awakening and before bedtime for one week. Depressed individuals experienced greater negative mood instability over the course of the week compared to non-depressed individuals. Depressed individuals also reported greater severity in negative mood than the non-depressed group, suggesting depression is characterised by both persistent low mood and more extreme daily variation in its severity.

While depression has also been associated with a blunted emotional response to stimuli and smoother emotional experiences from day to day (inertia) [32,38,39]; variability and instability span major categories of emotion dynamics as they relate to depression and are the focus of the current study. Table 1 outlines the definitions of variability, instability and inertia and describes their conceptual overlap. To best examine the unique associations that emotion dynamic patterns have with mental health it has been recommended that the conceptual overlap between these measures be taken into account and controlled for in analyses [32], as is done in the current study.

Table 1

Definitions and Conceptual Overlap of Variability, Instability, and Inertia.

Name	Definition	Operationalisation	Conceptual Overlap
Variability	The amplitude of an individual's emotion. This is time-unstructured, referring to the "general dispersion" of scores.	Within-person standard deviation (iSD)	Variance
Instability	The amplitude of moment-to-moment changes in emotion. This is time-structured, where higher scores indicate greater variance and less positively correlated between observations.	Mean squared successive differences (MSSD)	Variance, time-dependency
Inertia	How well a previous emotional state predicts the next emotional state. This is time-structured, where greater correlation coefficient indicates increased temporal dependency between observations.	Autocorrelation coefficient (ACF)	Time-dependency

Social Media and Emotion Dynamics

Emotion dynamics may provide important insights into the "building blocks" of depression [28] but it is also challenging and time-intensive to collect adequate longitudinal emotion data. Current approaches rely on experience sampling methods (ESMs), where an individual inputs emotion information throughout a day [1,28,40]. While the potential burden and invasiveness of real-time data collection has been significantly reduced by incorporating new and familiar technologies into ESM design (e.g. smartphones) [41,42], the need to respond to automated prompts creates a context that is different than normal daily activities. Further, these methodologies may not be practical for large-scale monitoring of public mental health.

Social media may be a powerful complementary tool. Considering the frequent use of emotion language in status updates that relate to current experiences [14,15], for a large proportion of the population social media can provide unobtrusive access to time-sensitive and ecologically valid samples of expressed emotion [2,43–45]. Diurnal and seasonal variation in depression severity have been observed at a population [2] and individual level [4] on social media. In these studies, an increase in the linguistic features predictive of depression risk were observed from day to night, and from summer to winter months. Using the social media platform Reddit, De Choudhury et al. [46] considered transitions from mental health subreddits only to also using a suicide support subreddit. Findings suggested that a shift from commonly expressed sentiment (i.e., the average) may represent a change toward better or poorer mental health, particularly where the magnitude of the change is more pronounced. While observations of emotion variability and instability are yet to be applied to social media as a means of automatically screening for individuals at risk of depression, it is likely that in addition to the ability to track macro-level changes in depression on social media, micro-level changes in emotion (emotion variability) relevant to mental health may also be observable.

The Current Study

Evidence is mounting to suggest that emotion patterns, including variability and instability are early indicators for depression risk [19], and there is a need to utilise scalable and unobtrusive means of collecting emotion data to effectively apply these insights to monitoring public mental health. Targeting emotion variability and instability as indicators of maladaptive emotional functioning in depression is a clear area in need of further research on social media. To date, most studies examining emotion language on social media and depression have provided a static view of emotion by compressing the variation of social media language over time into an overall average, stripping the data of what could be meaningful patterns in temporal variation of emotion expression. While the average emotion that individuals express on platforms like Facebook and Twitter can provide accurate and sensitive insights into the presence of depression, the variability in emotion across posts has yet to be examined as a legitimate individual difference (rather than measurement error) that may be indicative of depression severity.

Taking advantage of the time-sensitive and naturally occurring data available from status updates on Facebook and Twitter, the major aim of this study was to demonstrate the feasibility of using status update emotion variability and instability as an indicator of depression severity (measured by the *Patient Health Questionnaire-9, PHQ-9*) [47]. It also aimed to examine if emotion instability was related to depression when controlling for its conceptual overlap with variability.

It was hypothesised that: (1) Self-reported depression severity would be positively related to negative emotion word variability and instability across status updates. (2) Self-reported depression severity would be positively related to the average proportion of negative emotion words used, and negatively related to the average proportion of positive emotion words used in status updates on Facebook and Twitter. (3) Negative emotion word instability would remain positively associated with depression severity when controlling for negative emotion word variability. (4) The emotion word patterns and their association with depression would be consistent across Facebook and Twitter. (5) Depression severity would be positively associated with the average number of status updates per day and negatively associated with the time-interval between consecutive status updates (i.e., shorter periods of time between posts).

Method

Participants

The current study used a subset of users from the *MoodPrism* project. *MoodPrism* is a mood-tracking application (app) that collects data and provides engaging feedback to its users on their mood, mental health, and well-being [42]. *MoodPrism* is available for download on the iOS and Android stores for smartphone. All procedures were approved by the Monash University Human Research Ethics Committee.

Participants were recruited by convenience sampling, community engagement, and targeted online advertising (smartphone owner, interested in mental health, lives in Australia). To be included in this study, participants had to download the *MoodPrism* smartphone app, complete the depression severity index available in the app, and opt-in to contribute their Facebook or Twitter data, which were automatically collected by the *MoodPrism* app. A minimum of 10 status updates over a minimum period of 7 days was required for the inclusion of a participant, to allow robust calculation of emotion word variability and instability over time. Additionally, status updates were only included if they occurred within the 12 months prior to the administration of the *PHQ-9*. For the Twitter data, only original tweets (not retweets) were used. Although retweets may reflect values or interests of a user and include topics similar to self-authored Tweets [48], they also introduce ambiguity about the author's sentiments [49,50]. Further, the Facebook data did not have a similar repost function, such that self-authored Tweets provide a more direct behavioural comparison.

Of the 1,518 users who downloaded the MoodPrism app between April 2016 and May 2017, 223 (14.7%) provided permission to access their social media data. After applying the inclusion criteria outlined above, three participants were found to have contributed both Facebook and Twitter data. These participants had a greater number of language samples on Facebook than on Twitter, and thus were allocated to the Facebook group. A final sample of 29 Facebook users (11 males, 17 females, 1 missing) with a mean age of 32.77 years (*SD* = 8.40, range = 19-45, *n* = 22) and 49 Twitter users (16 males, 32 females, 1 missing) with a mean age of 35.03 years (*SD* = 12.33, range = 16-57, *n* = 39) was obtained. Participants were well educated, with 34.5% (Facebook) and 40.8% (Twitter) of participants having completed tertiary education. Chi-square tests revealed no significant differences gender or education between the included samples and those who had opted-in to contribute social media data but did not meet the inclusion criteria. Independent samples t-tests revealed no significant differences between groups in age. There were also no significant differences between the included Facebook (*n* = 29) and Twitter (*n* = 49) samples in age, gender or education.

Procedure

After downloading and opening *MoodPrism*, participants read an explanatory statement and provided their consent to participate. They then provided an additional opt-in consent to share their Facebook or Twitter data. If consent was provided, the *MoodPrism* app then automatically extracted the participant's previous status updates on Facebook or Twitter and repeated this extraction for all new status updates posted while *MoodPrism* was installed on the participant's smartphone. Status updates were processed locally on the participant's smartphone through the app, pulling out the time, total word count, and number of positive and negative emotion words, and then these summaries were uploaded to a secure server every 24-hours, at which point the status update content was permanently deleted from *MoodPrism*'s memory. Thus, the app provided summaries of how often emotion words were expressed, but the actual status updates were unavailable for analysis.

Participants additionally completed several blocks of questionnaires on *MoodPrism*. These blocks included demographic items collecting gender and age information, and measures assessing mental health, personality, and other psychological characteristics (see [40] for the full list of measures). Blocks could be completed in any order at a time of the participants' convenience and collectively took an average of 37m 14s (*SD* = 11m 33s) to complete.

Measures

All data for the current study was collected via the *MoodPrism* app. Depression symptom severity was measured by *the Patient Health Questionnaire -9* (*PHQ-9*) [47], a nine item self-report measure for depression that indicates the severity of symptoms experienced over the previous two-weeks. Each item on the *PHQ-9* (e.g. "Feeling down, depressed, or hopeless.") is rated from 0 – "Not at all", to 3 – "Nearly every day". These ratings are summed to create a total score ranging from 0-27, where higher scores indicate greater severity of depression symptoms. The *PHQ-9* has been validated for use in the general population (Cronbach $\alpha = .87$) [51] and in primary care settings ($\alpha = .89$) [47]. The internal reliability of the *PHQ-9* was good for both the Facebook (Cronbach alpha=.87) and Twitter (Cronbach alpha=.90) samples.

Language samples from Facebook and Twitter were obtained by *MoodPrism* via the Facebook and Twitter application programming interfaces (API), as detailed in Rickard et al. [40]. The period of posts sampled per participant between their first status update and the administration of the *PHQ-9* ranged from 9 to 365 days (Facebook *M* = 170.69, *SD* = 116.05; Twitter *M* = 145.61, *SD* = 124.97).

MoodPrism's automated scripts identified the number of "words" and positive and negative emotion words in the status updates. Words on social media include both normal words and variants (e.g., misspellings, emoticons, abbreviations) that are common on social media [43]. The scripts incorporated the positive- and negative emotion dictionaries of the *Linguistic Inquiry and Word Count 2007* (*LIWC 2007*) [52], a widely-used corpus of dictionaries commonly used for language analysis. The *LIWC 2007* dictionaries were supplemented by common emoji's and internet slang that indicated positive or negative emotion (see Multimedia Appendix 1). While not definitive, these inclusions were made to better reflect the language used on social media (for further discussion see [43]).

MoodPrism also collected data on the psychological characteristics of participants which included personality, self-esteem, and social desirability. Multimedia Appendix B presents additional analyses, complementary to the findings presented here, exploring Facebook and Twitter user differences across these characteristics that may inform the patterns of emotion expressed over time.

Data Analysis

Within person variability, instability, and the average proportion of positive and negative emotion words in status updates on Facebook and Twitter were calculated for each participant (defined below), and then correlations with PHQ-9 scores were calculated. The distributions of all Facebook and Twitter variables were non-normal, consequently Spearman's rho was selected for computing correlations. Exploratory post-hoc comparison between the Twitter and Facebook samples on their psychological characteristics were also performed using Mann-Whitney U tests due to non-normal distributions. All analyses were performed in IBM SPSS Statistics, Version 24 [53].

Average proportion.

The relative proportion of positive and negative emotion words was calculated for each status update collected to adjust for the total number of words expressed, as described in Kern et al. [43] and defined in Equation 1 below. An average of these proportions was taken for each participant, resulting in the *average proportion of positive emotion words* and *average proportion of negative emotion words* across all status updates (range: 0 to 1):

$$p(category) = \sum_{word \in category} p(word) = \frac{\sum_{word \in category} count(word)}{N\_words}, \tag{1}$$

where *count(word)* refers to the total number of positive emotion words (or negative emotion words; the *LIWC 2007* category) contained in a status update, and *N_words* is the total number of words in that status update.

Variability.

The within person variability (*iSD*) was computed for each participant across their status updates as:

$$iSD = \sqrt{\frac{\sum_i {s_i}^2}{n-1}}, \tag{2}$$

where the sum is taken over posts, i, s_i indicates deviations from the mean in an individual's proportion of positive (or negative) words used in status updates, and n refers to the number of status updates for that individual. This resulted in the *positive emotion word variability* and *negative emotion word variability* across status updates for each participant.

Instability.

The MSSD is defined for an individual as:

$$MSSD = \frac{\sum_{i=1}^{n-1}(x_{i+1} - x_i)^2}{n-1},$$

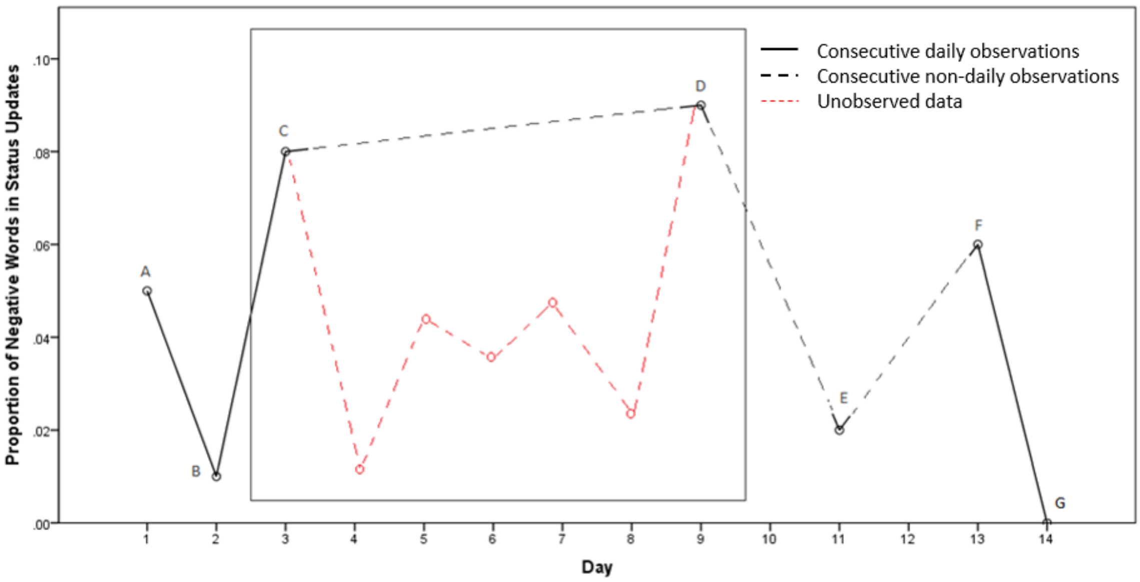
(3)

where x_i indicates the observation at index i, x_{i+1} refers to the next consecutive observation, and n refers to the total number of observations for that individual. A major challenge in applying measures of time-structured variability to social media data is managing the irregularly spaced time-intervals between posts. As observations on Facebook and Twitter occur in a natural setting, they often occur at irregular intervals spanning, for example, between hours and months. Thus, in addition to considering time-order, the time elapsed between successive observations also needs to be considered. Emotion instability, when operationalized as MSSD, assumes even sampling of observations to be computed meaningfully [30,31]. Where this is not possible, adjustments can be applied to the data to provide a weighted estimate of time-structured variability [31]. As in Jahng et al. [31] the following time-adjusted MSSD, which accounts for an uneven sampling of observations through time was applied:

$$\text{time-adjusted}\, MSSD = \frac{median(\Delta t)}{(n-1)} \sum_{i=1}^{n-1} \frac{(x_{i+1} - x_i)^2}{(t_{i+1} - t_i)},$$

(4)

where *median(Δt)* is the median of incremental time differences across the whole recording period. This effectively makes observations closer together in time *more important*, and those further apart *less important* to the reweighted MSSD statistic, relative to a participant's median time increment between posts. Importantly, the time-adjusted MSSD, Eq. (4), reduces to the standard MSSD, Eq. (3), in the case that samples are spaced equally through time. The benefit of this adjustment in relation to social media data is the ability to utilise every observation without imposing strict inclusion criteria on the data (e.g., a status update each day). As illustrated in Figure 1, this means that the overall variability contributed by all points can be included and the potential contribution



from points that may appear temporally correlated, if assumed to have occurred near in time (points C and D), is reduced when observations are in fact distant.

Figure 1. A simulated time-series showing the proportion of negative emotion words used in status updates over 14 days. This irregularity of status updates (i.e., missing observations on days 4-8 above) can be accounted for by reweighting pairs of observations by the time elapsed between them, resulting in a lower weight for the pair of points (points C and D). The observations within the box show similar levels of negative emotion word expression, but occur 6 days apart and may appear to be temporally correlated if their relative temporal distance is not accounted for. The red points show the hypothetical unobserved fluctuations in negative affect that may have occurred during the intermediate 6 days.

Applied to the Facebook and Twitter data for each participant, incremental time differences ($t_{i+1} – t_i$) between each status update were computed. The median of these time differences was then taken for each participant and applied to each incremental time difference and successive difference ($x_{i+1} – x_i$) in the proportion of positive or negative emotion words in a status update as in Equation 4. The average of the squared reweighted successive differences was then computed, resulting in the time-adjusted MSSD, or the *positive emotion word instability* or *negative emotion word instability* across status updates. Here, greater values of time-adjusted MSSD indicate a greater magnitude of change in the proportion of emotion words expressed between all consecutive pairs of status updates relative to their median temporal separation.

Results

In total, 1,856 status updates were collected (Facebook = 538; Twitter = 1,318) with 29,809 words expressed (Facebook = 10,373; Twitter = 19,436). In the Facebook sample participants posted an average 18.55 (SD = 10.01) status updates across the recording period; 55.8% of the collected status updates contained positive emotion words and 29.2% contained negative emotion words. In the Twitter sample participants posted an average 26.90 (SD = 11.71) status updates across the recording period; 63.6% of the collected Tweets contained positive emotion words and 56.2% contained negative emotion words.

Table 2 report the means, standard deviations, median and interquartile range of the *PHQ-9* scores and all Facebook and Twitter variables. It also presents descriptive statistics for the temporal aspects of posting status updates in the sample. Mann-Whitney U tests revealed no significant differences between Facebook and Twitter groups in the length of recording period sampled (U = 590.50, p = .215), though there were differences in the median time difference (U = 344.00, p < .001) and average number of status updates per day (U = 509, p =.038) where Twitter users posted status updates more frequently and, based on their individual median, had smaller intervals in minutes between status updates.

Table 2

Descriptive Statistics of the PHQ-9, Status Update Frequency, and the Emotion Features Expressed in Status Updates on Facebook (n = 29) and Twitter (n = 49).

Variable	Facebook			Twitter		
	Range	Mean *(SD)*	Mdn (*IQR*)	Range	Mean *(SD)*	Mdn (*IQR*)
Depression severity (*PHQ-9*)[a]	1 - 22	11.48 (6.38)	10 (5.5–17)	0 - 26	9.80 (6.81)	9 (4–14)
			Status Update Frequency			
Recording period (days)[b]	22-356	170.69 (116.05)	134 (54 – 290)	9 – 365	145.61 (124.97)	74.00 (33.50 – 272.00)
Status updates per day	.03-1.72	.03 (.36)	.16 (.07 - .51)	.03-4.56	.79 (1.09)	.40 (.09 - .90)
Interval difference (minutes) between status updates[c]	661 – 34827	8446.65 (8724.25)	3818.00 (1877.75–13522.75)	4.0 – 28428.5	3939.79 (6616.84)	1037 (206.25 – 4571.25)
			Positive Emotion Words			
Average proportion	.02 - .57	.10 (.10)	.08 (.05–.11)	.01 - .14	.07 (.03)	.08 (.05 –.09)
Variability (*iSD*)[d]	.04 - .47	.13 (.09)	.10 (.07–.16)	.03 - .17	.07 (.03)	.08 (.05– .09)
Instability (time-adjusted *MSSD*)[e]	0.003 – 11.54	1.14 (2.94)	.11 (.02–.47)	0.0002 – 26.80	1.49 (4.40)	.12 (.02–.83)
			Negative Emotion Words			
Average proportion	.00 - .17	.04 (.04)	.02 (.01–.05)	.01 - .26	.09 (.06)	.09 (.04–.12)
Variability (*iSD*)[d]	.00 - .31	.07 (.08)	.03 (.02–.09)	.02 - .14	.08 (.03)	.08 (.06–.11)
Instability (time-adjusted *MSSD*)[e]	0.00 – 1.23	0.11 (0.24)	.01 (.002–.14)	0.0006 – 37.99	1.31 (5.43)	.15 (.03–.49)

[a] *PHQ-9* = Patient Health Questionnaire– 9

[b] Recording period refers to the range of days between the first status update collected and the administration of the PHQ-9

[c] The median interval differences between status updates

[d] *iSD* = within-person variability

[e] time-adjusted *MSSD* = mean squared successive differences.

Tables 3 and 4 respectively report the two-tailed Spearman correlations (alpha level = .05) between the PHQ-9 and the positive emotion variables and the negative emotion variables from Facebook (above the diagonal) and Twitter (below the diagonal).

Table 3

Spearman's rho Correlation Analyses between Depression Severity (as Rated by the PHQ-9) and the Positive Emotion Features Expressed in Status Updates on Facebook (n = 29) and Twitter (n = 49).[a, b]

Variable	1.	2.	3.	4.
1. PHQ-9[c]	--	.04 [-.33, .40]	.17 [-.21, .51]	-.04 [-.40, .33]
2. Average proportion	.02 [-.26, .30]	--	.79** [.60, .90]	.48* [.14, .72]
3. Variability (*iSD*)[d]	-.09 [-.36, .20]	.49** [.24, .68]	--	.61** [.31, .80]
4. Instability (time-adjusted *MSSD*)[e]	-.20 [-.46, .09]	.31* [.03, .54]	.48** [.23, .67]	--

[a] Twitter correlations are shown *below* the diagonal; Facebook correlations are shown *above* the diagonal

[b] Confidence intervals are reported at 95% and are presented in brackets.

[c] *PHQ-9* = Patient Health Questionnaire– 9

[d] *iSD* = within-person variability

[e] time-adjusted *MSSD* = mean squared successive differences.

* = $p < .05$; ** = $p < .001$.

Table 4

Spearman's rho Correlation Analyses between Depression Severity (as Rated by the PHQ-9) and the Negative Emotion Features Expressed in Status Updates on Facebook (n = 29) and Twitter (n = 49).[a, b]

Variable	1.	2.	3.	4.
1. *PHQ-9*[b]	--	.12 [-.26, .46]	.20 [-.18, .53]	.44* [.09, .69]
2. Average proportion	-.14 [-.41, .15]	--	.95** [.90, .98]	.72* [.48, .86]
3. Variability (*iSD*)[c]	-.36* [-.58, .09]	.57** [.34, .73]	--	.82** [.65, .91]
4. Instability (time-adjusted *MSSD*)[d]	-.20 [-.46, .09]	.28 [-.001, .52]	.49** [.24, .68]	--

[a] Twitter correlations are shown *below* the diagonal; Facebook correlations are shown *above* the diagonal

[b] Confidence intervals are reported at 95% and are presented in brackets.

[c] *PHQ-9* = Patient Health Questionnaire– 9

[d] *iSD* = within-person variability

[e] time-adjusted *MSSD* = mean squared successive differences.

* = $p < .05$; ** = $p < .001$.

Facebook Emotion Variability and Depression

Facebook users reported an average depression rating of 11.48 (*SD* = 6.38) on the *PHQ-9* and expressed 9.5% positive emotion words and 3.5% negative emotion words on average across their status updates. Depression severity was not significantly related to the average proportion of positive or negative emotion words expressed, positive or negative emotion word variability (*iSD*), or positive emotion word instability (time-adjusted MSSD). Negative emotion word instability did, however, show a significant positive association with depression severity ratings, sharing 19% of the variability. This indicates that successive status updates differed more in their proportion of negative emotion words used for individuals with higher self-reported depression symptoms.

When controlling for the average proportion of negative emotion words expressed in status updates, negative emotion word instability remained strongly associated with depression severity (partial Spearman correlation: $r_s(26) = .51$, $p = .006$). Similarly, when controlling for negative emotion word variability, negative emotion word instability remained moderately associated with depression severity ($r_s(26) = .49$, $p = .009$). To illustrate this effect, Figure 2 shows samples of the pattern of negative emotion word instability from two participants; one with low (2a) and one with high (2b) self-reported depression symptoms. As can be seen in Figure 2a, the individual with low depression severity shows small magnitude changes in their use of negative emotion words across status updates. In contrast, the individual in Figure 2b with high depression severity exhibits greater magnitude spikes in negative emotion word expression.

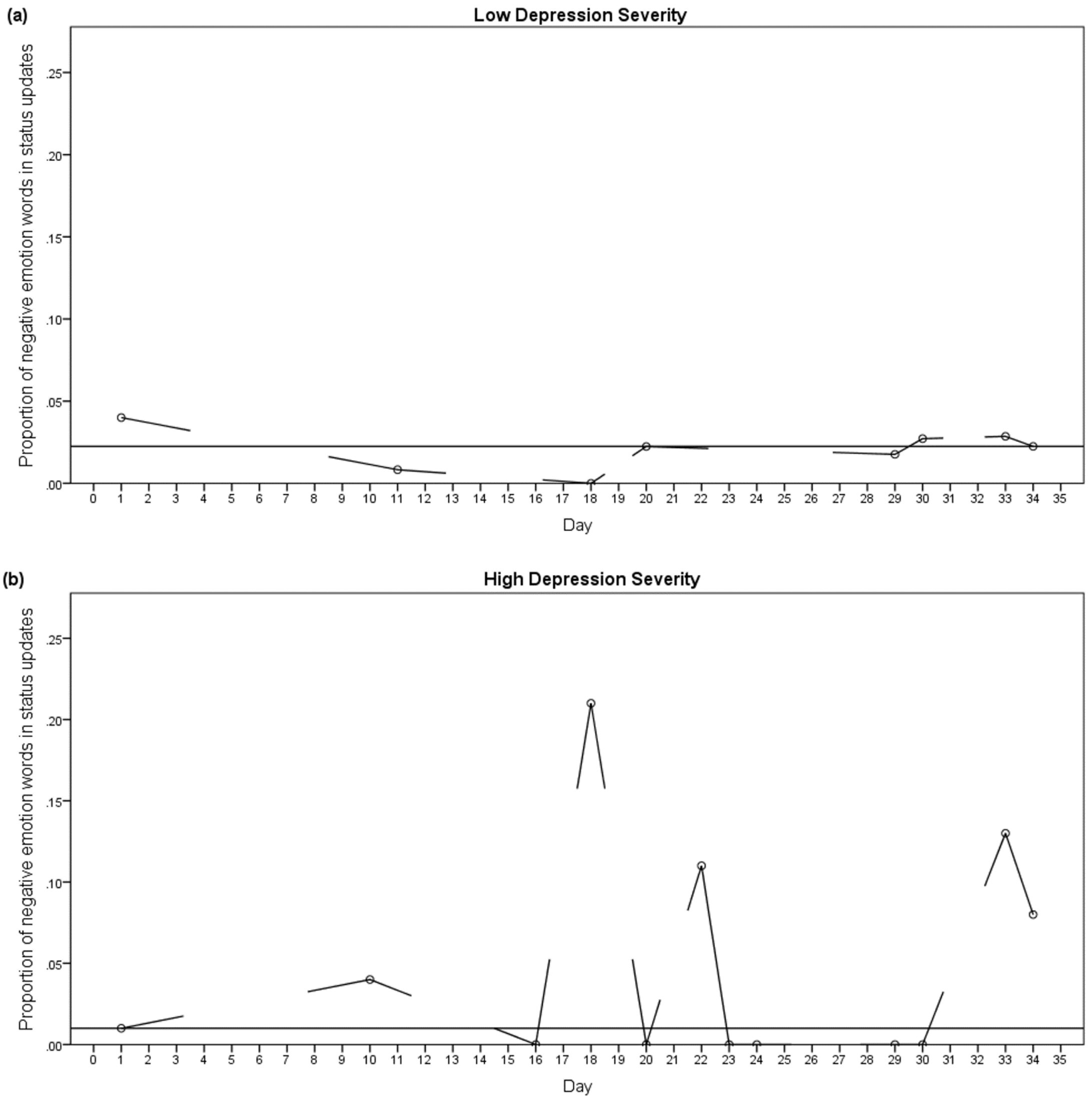


Figure 2. Graphs showing the proportion of negative emotion words used in individual status updates on Facebook across 35 days. (a) Shows an individual with low self-reported depression severity (PHQ-9 score = 9) who demonstrated little post-to-post variation in the proportion of negative emotion words used, with the maximum difference of .03. The horizontal trend line shows the median proportion of negative emotion words used (.022) and interpolation lines link consecutive status updates. (b) Shows an individual with high self-reported depression severity (PHQ-9 score = 22), who demonstrates large post-to-post changes in the proportion of negative emotion words used in status updates with the largest difference being .21. The horizontal trend line shows the median proportion of negative emotion words used (.01) and interpolation lines link consecutive status updates. Here, instability is independent of variability. See Multimedia Appendix 3 for consideration of instability under fixed variability conditions.

Twitter Emotion Variability and Depression

Twitter users reported an average depression rating of 9.80 (*SD* = 6.81) on the *PHQ-9* and expressed 7.4% positive emotion words and 9.2% negative emotion words on average across their status updates. Depression severity was not significantly related to the average proportion of positive or negative emotion words expressed, positive emotion word variability (*iSD*), or positive or negative emotion word instability (time-adjusted MSSD). Negative emotion word variability, however, was significantly negatively associated with depression severity ratings, sharing 13% of the variability. That is, a greater general dispersion of negative emotion across status updates on Twitter was associated with lower depression severity. When controlling for the average proportion of negative emotion words expressed in status updates, negative emotion word variability retained its association with depression severity in a partial Spearman correlation $r_s(46) = -.35$, $p = .014$.

To illustrate this effect, Figure 3 shows samples of the pattern of negative emotion word variability from two participants; one with low (3a) and one with high (3b) self-reported depression symptoms. As can be seen in Figure 3a, the individual with low depression severity shows larger overall variability in their use of negative emotion words across status updates. In contrast, the individual in Figure 3b with high depression severity exhibits more restricted variability in negative emotion word expression. It is important to note that in Figure 3 Tweets often occurred on the same day which accounts for the clustering in the figure.

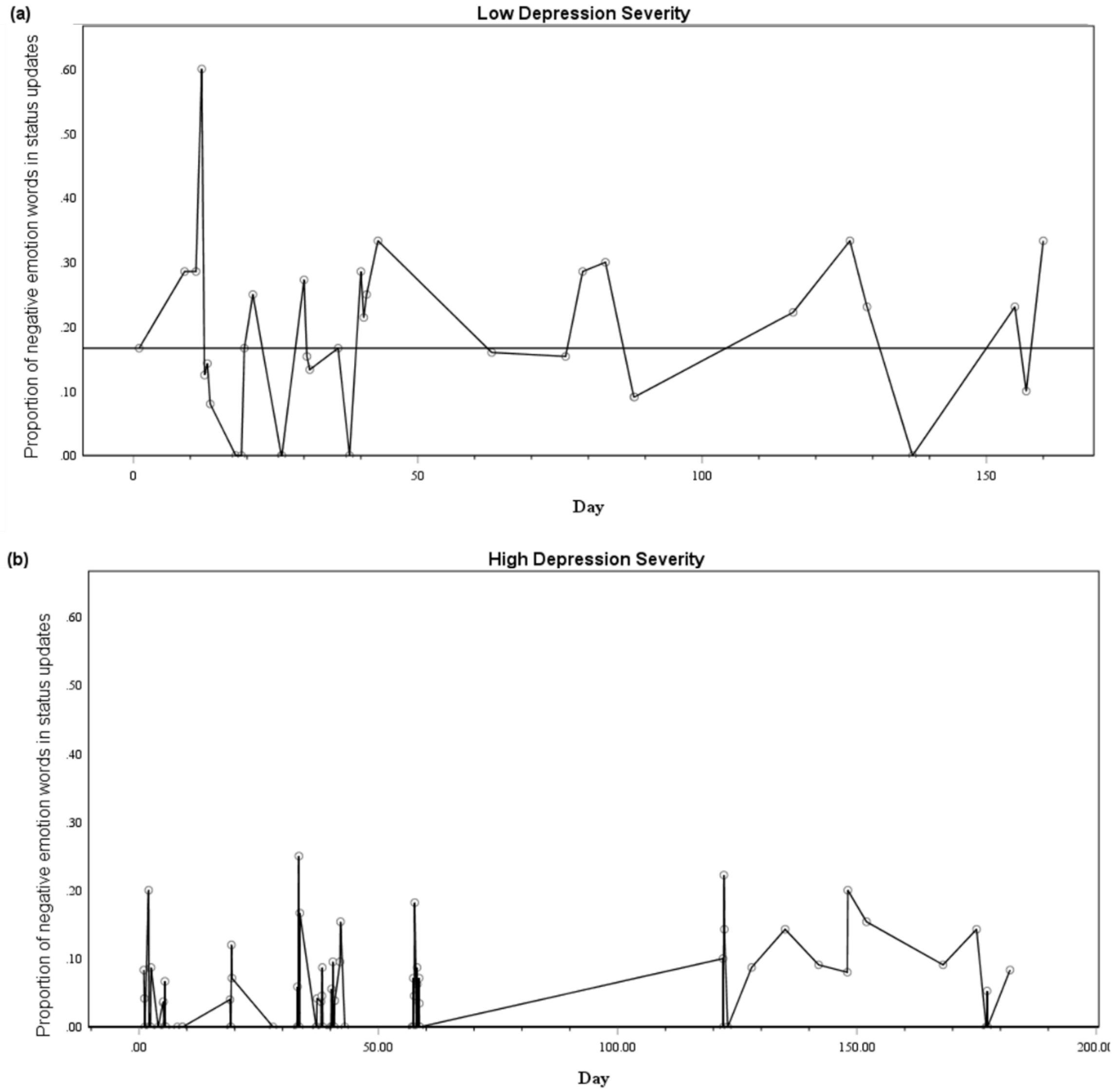


Figure 3. Graphs showing the proportion of negative emotion words used in individual status updates across (a) 160 and (b) 182 days. (a) Shows an individual with low self-reported depression severity (PHQ-9 score = 8) and high variability in the proportion of negative emotion words used across their recording period. The horizontal trend line shows the median proportion of negative emotion words (.17) and interpolation line links status updates. (b) Shows an individual with high self-reported depression severity (PHQ-9 score = 16) and low variability in the proportion of negative emotion words used across their recording period. The median proportion of negative words used was .00 and is therefore not shown. The interpolation line links status updates.

Facebook and Twitter Status Update Frequency and Depression

Descriptive statistics for the average number of status updates per day and the median time interval between status updates are presented in Table 2. Spearman correlations revealed a significant positive association between the average number of status updates per day and depression severity for Facebook users, $r_s(29) = .48$, $p = .008$. There was also a significant negative association between the median time interval between status updates and depression severity for Facebook users, $r_s(29) = -.61$, $p < .001$. Depression severity was not significantly related to the average number of status updates per day or the median interval between status updates for Twitter users.

Differences in Emotion Language Patterns

As indicated in Tables 3 and 4, the pattern of relationships between depression and emotion language use varied between Facebook and Twitter users. To explore this further, comparisons of the social media emotion language variables between the samples were conducted. As all variables were non-normally distributed Mann-Whitney U tests were used to compare the mean rank differences between Facebook and Twitter users in their emotion language patterns. The Twitter sample expressed more negative language ($U = 256.00$, $p < .001$) that was more variable ($U = 400.00$, $p = .001$) and unstable ($U = 379.00$, $p = .001$) than did the Facebook group across the recording period. Twitter users also expressed greater variability in their positive emotion compared to Facebook users ($U = 413.00$, $p = .002$).

Discussion

This study aimed to determine whether emotion variability and instability across status updates on Facebook and Twitter are useful indicators of depression. Differences between the social media platforms were also explored. The findings suggest that instability in the negative emotion content across Facebook status updates may indeed be a useful indicator for depression, and that the time-adjusted MSSD is an effective index of instability that accounts for the uneven temporal sampling of social media posts. As hypothesised, negative emotion word instability retained its association with depression severity when the average proportion of negative emotion word use and negative emotion word variability were controlled. This index may provide additional sensitivity over basic frequency indices that are typically used in social media and depression studies. However, negative emotion word instability did not emerge as a predictor of depression on Twitter. Rather, in contrast to expectations, negative emotion word variability was negatively associated with depression severity. Further, the average proportions of negative and positive emotion word use were not significantly associated with depression severity on either Facebook or Twitter. Other temporal features, the average number of status updates per day and the median time-interval between status updates were also associated with depression severity, but only for Facebook users.

Negative Affect Instability on Facebook

Greater negative emotion word instability on Facebook was associated with individuals experiencing greater depression severity. The time-adjusted MSSD scores were driven by the pattern of frequent, high magnitude changes in negative emotion word use between status updates, not variability alone. This finding is consistent with previous studies measuring negative affect through self-report over time that have demonstrated negative affect instability to be predictive of depression [25,31,33–36].

Many users post on Facebook to broadcast emotion [14], and emotion words are often present in posts [15]. Individuals with depression are more likely to produce more content on social media when experiencing more severe symptoms [16,17] and this often relates to the disclosure of symptoms, negative experiences, or posting to seek social support [3,8,10,11]. Indeed, this was reflected in the current sample where Facebook users with greater depression severity ratings posted more status updates per day, more frequently (i.e. there was a smaller median time-interval between consecutive status updates). Large changes in the proportion of negative emotion words used between consecutive status updates could reflect patterns of Facebook use that mirror the inherent variation in the severity of depression symptoms over time. In this way, the negative emotion word instability in the status updates on Facebook may reveal the ebb and flow of depression symptoms and emotion dysregulation in daily life [36].

Negative emotion word instability on Facebook may also be tied to specific events, capturing momentary responses to internal and external stressors. Individuals exposed to an emotional event generally post status updates in a mood congruent way (e.g., happy or sad) [54]. The proportion of negative emotion words used in a status update may reflect the extremity with which an event is perceived as negative or positive. In this light, status updates could provide insight into emotional reactivity to events. A depression-specific pattern of instability in status update expression on Facebook may exist that reflects the amplification of negative emotion in response to ambiguous or negative events [55] and a mood brightening effect in response to positive stimuli where there is a large reduction in expressed negative affect [36,56].

The unique fluctuating pattern of negative emotion expression in individuals with more severe depression symptoms was further supported by negative emotion word instability, which remained associated with greater depression symptoms when controlling for the average proportion of negative emotion words used in status updates. This suggests that the time-structured patterns of emotion expressed on Facebook may provide better differentiation between individuals with and without depression where they express similar levels of negative emotion words. The current study suggests that the poor hit rate in some keyword approaches to classifying depression in status updates, as described by Mowery et al. [18] may be enhanced by including measures of moment-to-moment variability in emotion word use.

Within Person Variability in Emotional Expression on Twitter

Contrary to expectations, Twitter users who had lower variability in their use of negative emotion words across the recording period were more likely to have greater self-reported depression severity. This sits in contrast with a recent meta-analysis that showed negative emotion variability shares a positive association with depression [1].

It could be that the greater variability in emotion expressed by individuals lower in depression on Twitter reflects adaptive emotional functioning. In addition to personal disclosures and using Twitter to talk about daily events [57], people turn to Twitter to post content about politics, world events, and to share information [58]. Expressing a wide range of negative emotion in response to these diverse personal and community related events may be appropriate to the context or be a part of effective emotion regulation strategies. Indeed, expressive emotional writing has been linked to better psychological and physical outcomes in offline and online settings [59–62].

On the other hand, Twitter users with higher levels of depression expressed a more clustered spread of negative emotion. Emotion appraisals of internal and external events and their subsequent expression in status updates may be more restricted or blunted for Twitter users with higher levels of depression. This is consistent with studies indicating that MDD is associated with reduced emotion reactivity [63].

Variability Differences between Facebook and Twitter

Two divergent emotion patterns relating to depression emerged from the Facebook and Twitter samples. This highlights the importance of collecting data from multiple social media platforms, as differences in the communication mechanisms and population demographics across social media sites greatly impacts on the generalisability of findings [49]. In terms of emotion expression, Twitter users expressed more negative emotion that was more variable across the recording period than Facebook users. This may be due to the 140-character restriction placed on Tweets (recently increased to 280-characters) [64] compared to the 63,206-character limit on Facebook [65] which may impact on the total proportion of emotion words expressed and the magnitude of change observed between posts. On Twitter, when an emotion word is used it is likely to occur in the context of fewer total words and will result in a greater proportion emotion expressed per Tweet. In contrast, when a Facebook user expresses emotion it may occur in the context of more total words, potentially reducing the overall proportion of emotion words expressed.

Other confounding variables may also create differences between negative emotion expression on Facebook and Twitter. For example, Twitter allows users to generate anonymous accounts, whereas Facebook accounts are likely to be linked to a real name. The anonymity may release the user from social norms and increase expression of negative emotion [66,67]. Twitter also is less symmetrical, with weaker relational ties, and less dense network structures, which impacts on the emotion people express to their networks [68,69]. These different social contexts and related norms are a fruitful area for future research.

Averages of Negative and Positive Emotion Word Use Are Not Associated with Depression

Inconsistent with many previous findings [2,3,5,9], the average proportion of positive and negative emotion words used across status updates on both Facebook and Twitter were not significantly associated with depression. Other approaches using the *LIWC 2007* positive and negative dictionaries have found that as negative emotion expression increases, so does the ratings of self-reported depression severity (e.g., [5]). This could be due in part to the small sample used here; language is noisy [43], and with only 29 and 49 participants in the Facebook and Twitter samples respectively, the signal may not be enough to counteract that noise (see Kern et al. [43] for further consideration of language and sample size considerations). Amongst this noise, it is notable with the small number of participants that a robust association between negative affect instability and depression on Facebook was found, suggesting a strong relationship between these two quantities. While this result needs to be replicated in other samples, this suggests that when a smaller number of participants are available, instability may be a more sensitive measure than frequency in detecting depression severity.

The null findings between depression and the average proportion of words in status updates may also reflect the lack of precision that frequency measures provide. As shown by Mowery et al. [18], using a keyword approach to identifying depression in social media posts results in a large proportion of false-positives, reducing the specificity with which depression can be identified through the average emotion expressed over time. Context matters [43], such that the use of a word may not directly link to an experienced emotion (e.g., “I went to visit Happy Valley” does not indicate positive emotion). It is important to acknowledge also that negative emotion expression is not the exclusive domain of individuals with higher levels of depressive symptoms. It is also possible that in this study, the amended negative emotion word dictionary of the *LIWC 2007* alone was not sufficient in identifying the words most indicative of depression. Indeed, the dictionaries were recently updated [70], and future studies should examine whether the updated *LIWC 2015* dictionaries offer a better indication of depression. Personality, gender, and age have all previously been shown to impact on the number of negative emotion words people use online (cf. [71]) and this complexity might also be considered in future research.

Limitations and Future Directions

There are several limitations to the current study. Firstly, while emotion scores were calculated, the actual posts were not available (due to privacy considerations), such that the context of their content could not be considered. It is therefore possible that some posts may have obtained a negative emotion word count where a positive message was conveyed. Future research should seek to apply more sophisticated open vocabulary approaches or postprocessing of status updates [18,43] to provide greater detail and accuracy of the language use context.

Secondly, the sample analysed was small and this may have impacted on the power to detect significant associations between variables. This may have obscured potential associations between the expression of negative emotion words and depression severity. It is also likely that, due to sample size, the findings obtained here may not be generalisable to the Facebook and Twitter populations. Replication is required in larger samples.

Third, only original posts were used, with retweets or shared posts excluded. While retweets may be an indirect indication of a person's emotions, beliefs, values, and behaviours, the intentions underlying reposting are unclear. Further, at the time of data collection, reposting updates was less common in Facebook, so excluding retweets provided a clearer comparison. Future studies might explore the extent to which reposts (retweets and the sharing of posts) reflect a user's values and emotions and indicate depression status.

It is also important to note that it was unknown if the emotion words expressed on Facebook or Twitter accurately reflected same-day subjective changes in mood. Further research should seek to link consecutively measured mood ratings with social media data to strengthen the assumption that interpretation of social media content reflects real-world emotion experience.

Finally, studies should seek to explicitly consider inertia in the emotion expressed in status updates as a predictor of depression and consider how the sensitivity and accuracy of frequency and instability metrics changes across different sample sizes. Such analyses will, however, require adjustments be made to calculations to account the sparseness and irregularity of social media data.

Conclusion

The current study suggests that instability in the negative emotion expressed on Facebook provides insight into the presence of depression symptoms for social media users, and greater variability of negative emotion expression on Twitter may be protective for mental health. These findings provide proof-of-concept that temporally measures of emotion language in social media posts provide a sensitive and specific index of depression. If replicated in other samples, emotion dynamics might be applied to big data approaches for depression screening at a population level, providing insight into the emotion processes underlying depression and improving the specificity of depression identification above using language averages alone. The time-adjusted MSSD appropriately accounts for the uneven temporal sampling of real-world social media data, providing a sensitive measure of emotion instability that may be used as an early indicator of (or identified as a risk factor for) depression. Variability is often seen as a nuisance factor that creates noise and obscures other associations. Treating emotion variability as a legitimate individual difference may be an important step in better describing the micro-processes that lead to psychopathology. The findings also point to possible differences across the online culture created by a particular social media platform, such that different platforms may provide different insights into mental health.

The widespread and frequent use of social media has generated considerable concern around its impact on mental health. Yet social media is also revealing itself to be a valuable avenue for the ongoing monitoring of depression. This study contributes to understanding the best approaches for using the technology to help users suffering from depression.

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Conflicts of Interest

None declared.

Abbreviations

MDD: Major Depressive Disorder

MSSD: Mean squared successive differences

iSD: within-person standard deviation

PHQ-9: Patient Health Questionnaire 9

LIWC 2007: Linguistic Inquiry and Word Count 2007

RSES: Rosenberg Self-Esteem Scale

M-C Form C: Marlowe-Crowne Social Desirability Scale Form C

Multimedia Appendix 1 [Emoji and internet slang supplements to the LIWC 2007 dictionaries]

Multimedia Appendix 2 [Supplementary Analyses: Personality, Self-esteem, and Social Desirability]

Multimedia Appendix 3 [Illustrative participant data showing instability at fixed levels of variability]

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Multimedia Appendix 1

Emoji & internet slang additions to the *LIWC 2007* emotion dictionaries

Positive Emoji’s	Negative Emoji’s		Positive Emotion Internet Slang			Negative Emotion Internet Slang	
=D>	:-l	:-/	Aight	j/j	lyke	Abft	fomo
=D	:l	:/	Aightz	jk	marvy	Acgaf	gank
:D	X(	T_T	Aiight	j/k	njoy	Aiic	grmbl
:-D	X-(	T^T	Aite	jks	ql	Arsed	h8
(:)	O	QQ	Alrt	j2f	qool	Awk	h80r
(:-)	b (	=O::::	alryt	j4f	qt	Bm	h83r
>:D<	>:-(	=’(	Alol	j4g	qte	Boom	h8ed
:))	>:-)	&.(..	Aml	j4l	rofl*	Bord	h8r
:-X	(:-&	(;_;)	Aprece8	jfg	*s*	Bovered	h8red
:X	:@	:’(	Apreci8	jfl	S’ok	Catwot	h8s h8t
:)	:(	:’	Awes	jfk	Snog	Cba	h8t0r
:-)	:-t	:’-(	Awsm	jja	Sok	Cbb	h8t3r
^^	:-ll	:*(	Awsome	jkz	Sof	Cbf	h8te
:,’)	:ll	:*-(	Bahaha	k	Stm	Cbfa	h8tr
:-“)	:t	:_(	Besos	kay	Ub3r	Cbfed	hait
:”)	:-@	:..[	Bilu	kewel	W00t	Cmeo	heyt
;)	:{	;_;	Btwilu	kewl	Woot	Cmw	htr
;-)	:-Z	=\	Btwitiailwu	kk	Xellent	Cof	id10d
\o/	:Z	:l	Byak	kl	Xlnt	Cotf	idjit
;-(	??	:(&	Chillin	koo	xtc	Dc	idot
;(	@_@	:-E	Ctm	kool		Dbm	idyat
:’)	(-_-*)	:-e	Cut3	kss		Dfc	invu
:’-)	(o_o)	DX	Eil	kssd		Dgac	irhy
>-)	b-(	/:(	Fab	kul		Dgaf	isb
:p	%+l	:-[	Fah	kute		Dgara	kmn
:P	:S	:[	Fi9	l0lz		Dgas	kmp
:-P	:-S	:-}	Funee	laff		Eejit	lsr
:-p	(:-	:}	Funy	lal		Eedyat	lzr
:>	:(	#-)	*g*	lol		Ef	nv
:->	:-(	#)	Gtm	lols		Ef-ing	ofcol
l__l	l-o	:-6	Gud	lel		Effed	oh noes
^.^	\-o	:6	Gudd	liek*		Effin	oh noez
^?^	:-o	:-@	Heh	lik		Effing	p/oed
^-^	=((	(:(	Hppy	lk		F#cking	poed
%)	+-((	:-<	Hpy	lke		F’n	ph33r
%-)	</3	><	Haha	llc		f-ing	phayl
<3	(U)	://	I8	llf		fml	phail
<u3	:-c		Iatb	lmao		f.m.l	r8p
	:c		Iight	lmfao		farg	r8pist
	O.o		Iigh	rofl		fck	stupd
	%)		Ijdl	lml		fcked	suk
	%-)		Ili	lov		fckin	sukz
	(@_@)		Ilml	luv		fcking	suxx
	:s		Ilms	luff		feck	wrdo
	:-Q		Ilu*	luvv		fk	wtf
	:Q		Ilshipmp	lurve		fkd	
	:-$		Irly	lv		fker	
	:$		Ite	lve		fkin	
			Jj	lyk		fking	

Multimedia Appendix 2

Supplementary Analyses: Personality, Self-esteem, and Social Desirability

Supplementary analyses were conducted to explore the individual characteristics that may be involved in the different emotion expression patterns between Facebook and Twitter.

Measures

MoodPrism collected data on the psychological characteristics of participants which included personality, self-esteem, and social desirability.

Personality, based on the Five Factor Model (extraversion, neuroticism, conscientiousness, agreeableness, and openness to experience), was measured by the Mini-IPIP scales [1]. The Mini-IPIP has 20-items, with four items addressing each personality factor. Example items include: Extraversion (e.g. “I am the life of the party”); Neuroticism (e.g. “I have frequent mood swings”); Conscientiousness (e.g. “I get chores done straight away”); Agreeableness (e.g. “I sympathize with others’ feelings”); and Openness (or Intellect/Imagination) (e.g. “I have a vivid imagination”). Statements are rated on a 5-point Likert scale ranging from “1- Very Inaccurate” to “5 - Very Accurate”, with a mid-point of “3 – Neither agree nor disagree). The five-factor structure of the Mini-IPIP has been supported across several studies and has adequate internal reliability for all sub-scales (α’s > .60) [1,2].

Self-esteem was measured with the Rosenberg Self-Esteem Scale (RSES) [3]. Participants rate 10 statements about their feelings toward themselves on a 4-point Likert scale from “0 – Strongly Disagree” to “3 – Strongly Agree”. Five items relate to positive feelings (e.g. “I feel that I have a number of good qualities”), and five are negative and are reverse scored (e.g. “I certainly feel useless at times”). Ratings are summed to generate a total score ranging between 0-30 where higher scores indicate greater self-esteem. The RSES demonstrates good reliability across a range of demographic characteristics (α = .91) [4].

Social desirability, the tendency with which an individual presents a desirable impression of themselves, was measured by the short form Marlowe-Crowne Social Desirability Scale Form C (M- C Form C) [5]. Participants respond to 13 dichotomous items describing socially desirable (but rare) or undesirable (but common) behaviours (e.g. “No matter who I’m talking to, I’m always a good listener”). These are rated as being “True” or “False” (items are reverse-scored to the socially-desirable direction) and are summed to create a score ranging from 0-13, where higher scores indicate a greater tendency to present a socially desirable image of oneself to others. The M-C Form C has demonstrated good reliability (Kuder-Richardson r = .76) [5].

Results

Table 1 presents the means and standard deviations of the psychological characteristics for participants with available data in the Facebook and Twitter samples.

Table 1

Means and Standard Deviations of Psychological Characteristics in the Facebook and Twitter Samples.

Variable [a]	**Scale Range**	**Platform**	
		Facebook *M (SD)*	Twitter *M (SD)*
Depression Severity	0 – 27	11.48 (6.38)	9.80 (6.81)
Extraversion	1 – 20	8.95 (3.02)	10.34 (4.50)
Agreeableness	1 – 20	14.35 (3.69)	15.34 (4.09)
Conscientiousness	1 – 20	11.48 (3.57)	13.59 (3.69)
Neuroticism	1 – 20	14.39 (3.27)	13.02 (4.61)
Openness to Experience	1 – 20	12.87 (2.67)	13.10 (3.27)
Self-Esteem	0 - 30	14.05 (2.09)	15.30 (1.91)
Social Desirability	0 - 13	5.13 (2.69)	6.49 (2.50)

[a] Sample sizes differ across variables. For Facebook *n* ranges between 21 -29; for Twitter *n* ranges between 40 – 49.

As all distributions were non-normal, Mann-Whitney U tests were selected to compare mean ranks on psychological characteristics between the Facebook and Twitter users. No significant differences were observed in depression severity, extraversion, agreeableness, neuroticism, or openness to experience. Twitter users did have significantly higher mean ranks in conscientiousness (U = 288.50, p = .034), self-esteem (U = 250.00, p = .017), and social desirability (U = 419.00, p = .046) compared to Facebook users.

Discussion

Compared to the Twitter sample, Facebook users had lower, conscientiousness, self-esteem, and lower scores of social desirability. Lower levels of conscientiousness have associated with less impulse control and can result in greater reactivity in negative emotion [6]. Combined with a reduced tendency to present a positive self-image to others, this may account for the negative emotion instability observed on Facebook but not Twitter; particularly as low conscientiousness also plays as role in less cautious online behaviour [7, 8]. This may elicit status updates on Facebook directly tied to emotional experiences with less reflective construction. Twitter users in contrast may be more inclined to monitor their online emotion expression and present more favourable representations of themselves. Though we lacked the power to control for these characteristics in regression analyses they may be informative targets for future research.

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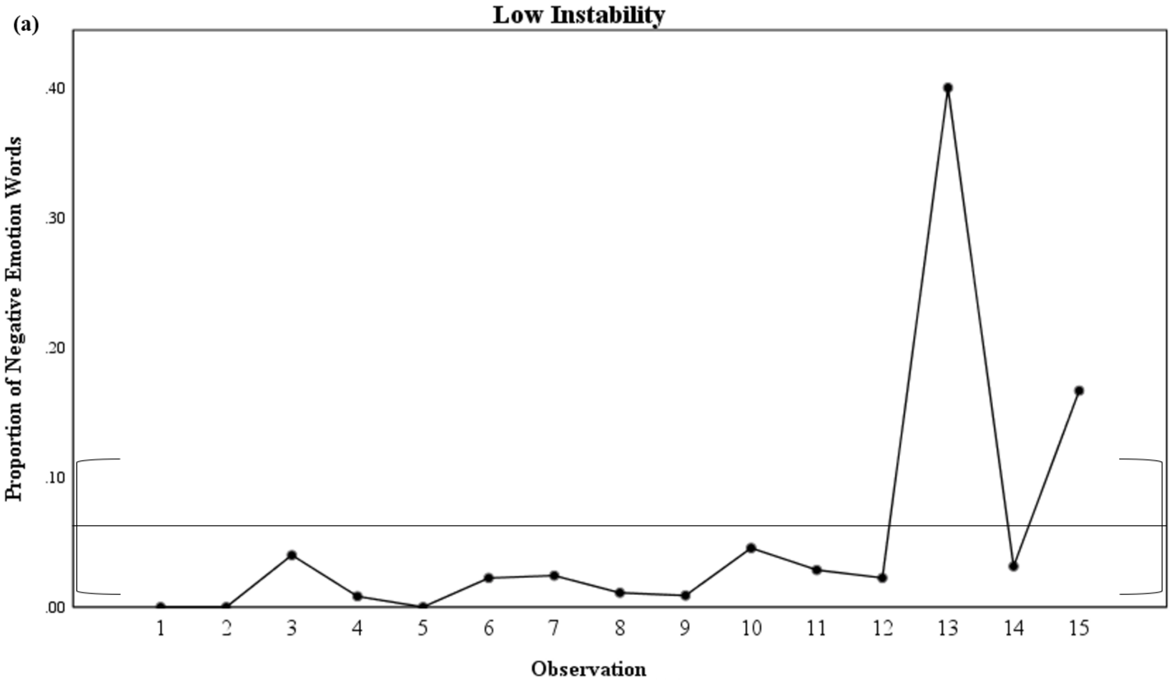
Multimedia Appendix 3

Illustrative participant data showing instability at fixed levels of variability.



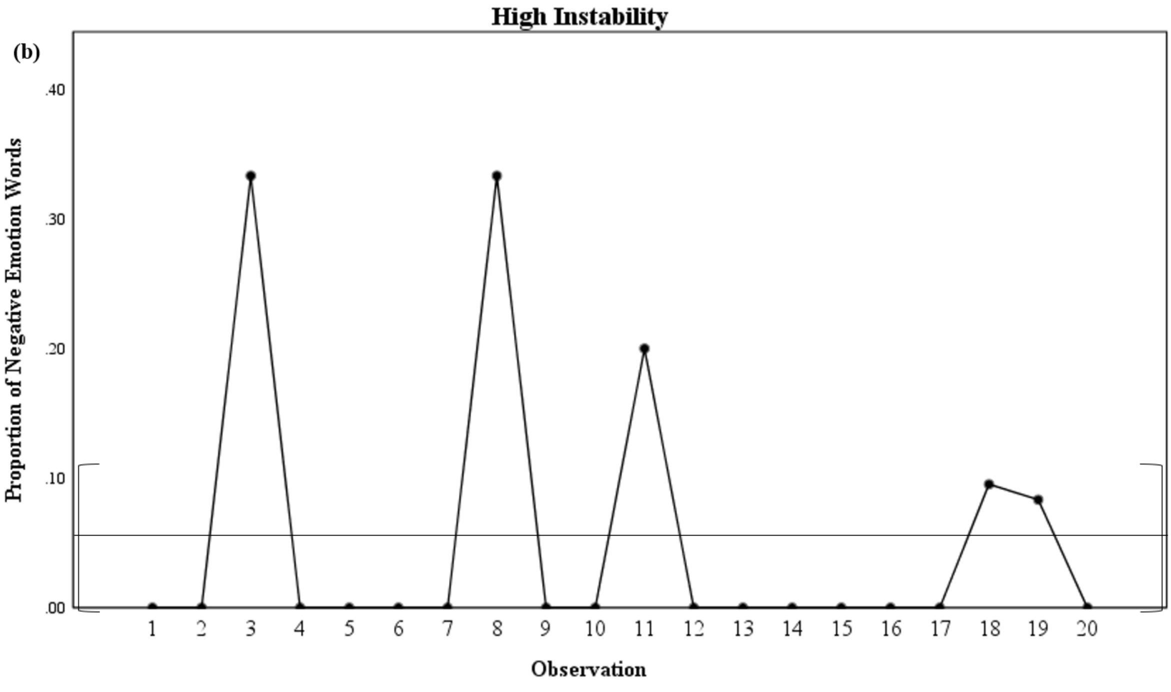


Figure 1. Example participant data showing instability under fixed variability (*iSD)* conditions. Panel (a) shows a participant with a low instability value (.015) and variability of .104. Panel (b) shows a participant with a similar variability value (.108) and a high instability value (.290). Brackets show the *iSD* around the mean (horizontal trend line). Time-scale is not shown here to compress Facebook record into a visible format for both participants.

4.3 Concluding Remarks

In this chapter a paper was presented that applied emotion dynamics indices to the emotion language expressed in status updates on Facebook and Twitter. It found that greater instability in the use of negative words across status updates on Facebook was associated with depression severity. In contrast, lower variability in the use of negative emotion words across the Tweets on Twitter was association with lesser depression severity. For Facebook users only, behavioural features indicating more frequent posting of status updates also predicted depression severity. Supplementary analyses were also presented suggesting individual characteristics, such as personality, may be involved in platform-specific user differences that potential impact on the emotion language patterns expressed over time. While this paper demonstrated the feasibility and potential utility of using emotion dynamics features as a part of identifying depression from social media user's status updates, it is still unclear how well the patterns observed accurately reflect lived experience. This is addressed in the next chapter in a case-series analysis seeking to critically explore the daily use of emotion words on Twitter with concurrent ratings of self-reported mood.

Chapter 5

Do people feel what they Tweet? A case-series exploration of daily mood ratings and the emotions expressed on Twitter

5.1 Preamble to Empirical Paper 2

This chapter presents the second empirical paper of this thesis, titled "Do people feel what they Tweet? A case-series exploration of daily mood ratings and the emotions expressed on Twitter". Measures of self-reported mood and the emotion language used in Tweets were taken concurrently across a 30-day period and the resulting mood profiles are contrasted. This paper provides a critical examination of the reliability and validity issues in using the emotion language on social media as an indicator of experienced mood and the implications this has for depression prediction from social media data. A descriptive case-series approach was taken in this paper due to the sample size obtained. As such, it provides an in-depth description of the mood profiles obtained from *MoodPrism's* daily self-report and from the emotion expressed on Twitter by applying emotion dynamics features as descriptive summaries of the time-series plots. This chapter highlights points of convergence and divergence between the mood profiles and discusses the impact depression may have on the observations obtained.

This paper was submitted to *Computers in Human Behavior*. As such, the paper is formatted in accordance with the journal requirements. References are provided in the style of the *American Psychological Association* (6th edition).

5.2 Do people feel what they Tweet? A case-series exploration of daily mood ratings and the emotions expressed on Twitter

Abstract

Background: Status updates on social media have been used to identify users' mental health status, with emotion words emerging as a primary indicator of assumed depression status. However, it remains unclear how accurately expressed emotions reflect a user's mood.

Objective: This case-series compares the mood profiles of Twitter users with their concurrent self-reported mood to examine how consistently same-day mood co-occurs across data types and collection methods.

Method: Self-reported mood and Tweets were collected from five users over a 30-day period using a mobile app. Tweets were automatically counted for emotion words. Daily levels, individual variability, instability, and acute changes in self-reported mood and expressed emotion were compared.

Results: Across the five participants, Spearman correlations revealed little similarity in terms of mood levels within the same day, but visual inspection suggested variability profiles across 30-days appeared similar. Twitter and self-report mood profiles aligned as depression severity increased.

Conclusion: Although the growing amount of data available through social media makes it possible to detect mental health difficulties at collective levels, greater understanding of how this unfolds over time at the individual level is needed. This study provides a starting point, demonstrating the feasibility of emotion dynamic data analytic methods for language.

Keywords: social media, linguistic analysis, emotion, dynamics, experience sampling methodologies.

1. Introduction

Over the past decade, online social media, such as Facebook, Twitter, Weibo, and Instagram, has become a dominant part of many people's lives. People frequently turn to social media to obtain and broadcast information, express thoughts and feelings, discuss current events, feel connected, and even to discuss mental health issues (e.g., Berry et al., 2017; Deters & Mehl, 2013; Grieve, Indian, Witteveen, Anne Tolan, & Marrington, 2013; Manago, Taylor, & Greenfield, 2012; Park, 2013). The language expressed online has been proposed to be useful for identifying individuals and communities experiencing poor mental health (e.g., Bollen, Gonçalves, Ruan, & Mao, 2011; De Choudhury, Gamon, Counts, & Horvitz, 2013; De Choudhury, Kiciman, Dredze, Coppersmith, & Kumar, 2016; Mowery et al., 2017; Schwartz et al., 2014). Numerous models and algorithms with varying degrees of sophistication have been developed, with adequate ability to predict depression and other mental illnesses (cf. Guntuku, Yaden, Kern, Ungar, & Eichstaedt, 2017).

Emotion is typically included in such models, with studies finding that depressed individuals express more negative emotion words than non-depressed persons (De Choudhury et al., 2013; Schwartz et al., 2014; Settanni & Marengo, 2015). Because language is intricately linked to cognitive and affective processes (Lindquist, Gendron, & Satpute, in press), tracking emotion words over time may be a valuable tool for observing the internal processes that signal change in depression status. However, it is yet to be clearly demonstrated how accurately emotional language used on social media aligns with a user's concurrent mood. Using a case study approach, the current study explores the connections and differences between Twitter language and self-reported mood, providing insights into the reliability and sensitivity with which social media content may be useful at the individual user level for screening or monitoring depression.

1.1 The Language of Depression on Social Media

Evidence is mounting to suggest that social media behaviours can signal the presence of depression (Seabrook, Kern, & Rickard, 2016). Depressed persons post content more frequently on social media, and increases in posting frequency may signal increases in depression severity. On Twitter, people Tweet about mental health (and depression) as a way of accessing social support, developing community, and finding a safe place for expression (Berry et al., 2017). Individuals with greater depression symptoms also self-report that they write negative content in their status updates more frequently than those without depression (Locatelli, Kluwe, & Bryant, 2012). Direct examination of status updates has revealed that young people with a greater number of self-reported depressive symptoms express indicators reflecting symptoms of major depressive disorder (MDD) across their Facebook status updates (Moreno et al., 2011; Moreno et al., 2012).

Language has emerged as one of the core features of social media behaviour that can successfully identify depression (Guntuku et al., 2017). Users with a diagnosis of depression are more likely to use negative emotion words than those without a depression diagnosis (De Choudhury et el., 2013). Depression severity can be observed through social media language content (Schwartz et al., 2014), and there are unique linguistic characteristics that signal suicide risk, such as the use of language related to death (De Choudhury et al., 2016; Larsen et al., 2015). Depression has been shown to influence the linguistic style of an individual in several offline studies (Bernard, Baddeley, Rodriguez, & Burke, 2016; Pennebaker, Mehl, & Niederhoffer, 2003; Rude, Gortner, & Pennebaker, 2004). Aligned with Beck's (1974) cognitive model of depression, negative cognitive biases contributing to depressive thoughts and feelings may colour the negative emotional tone in the language communicated by depressed persons, resulting in the more frequent expression of negative emotion seen online.

1.2 The False-Positives

There is a great deal of variation in the methodological approaches and prediction performance of automated screening methods for depression from social media data (Guntuku et al., 2017). While depression identification from social media has considerable promise, approaches targeting words also return many false-positive identifications of possible depression (Cavazos-Rehg et al., 2016; Mowery et al., 2017).

First, linguistic features, including negative emotion words, are not used solely by those experiencing depression. For example, content analysis of a sample of depression-related Tweets has revealed that while around one-third of the Tweets were directly related to personal experiences of depression, the remainder either made trivial reference to depression or expressed a message of support (Cavazos-Rehg et al., 2016). Recent work has also indicated that the induction of negative mood, regardless of depression status, is the most significant factor linked to later use of negative emotion words in expressive writing tasks (Bernard et al., 2016).

Second, confounding variables such as neuroticism, self-esteem, and age have also been linked to the use of negative emotion words on social media and may be involved in the way people communicate online, potentially obscuring how accurately depression status can be detected (Forest & Wood, 2012; Park et al., 2015; Preotiuc-Pietro et al., 2015).

Third, current approaches to examining linguistic features associated with depression have had limited focus on temporal variation. As an adequate sample of words per user is needed (see Kern et al., 2016), user data is often combined across posts. While this provides greater overall predictive ability, it eliminates the rich temporal structure of responses, information that may help differentiate depressed from non-depressed individuals. If cognitive and affective schemas are visible in language, it is also likely that the dynamic features of emotion might be visible over multiple samples of language. Emotion variability and instability (i.e., time-structured variability) have been consistently linked to depression and even predict depression onset (Houben, Van Den Noortgate, & Kuppens, 2015; Koval, Pe, Meers, & Kuppens, 2013; Wichers, 2014). *Variability* provides information about the general dispersion of emotion observations over time and can be measured by statistics such as the within-person standard deviation (iSD) (Houben et al., 2015). While variability measures are insensitive to the time-ordering of the emotion variation (only their overall spread), measures of *instability* capture patterns in this temporal structure, such as the magnitude of change between consecutive pairs of emotion observations over time, the mean squared successive differences (MSSD) (Houben et al., 2015; Von Neumann, Kent, Bellinson, & Hart, 1941). Instability has been shown to be important to depression prediction in a small sample of Facebook users, where greater post-to-post fluctuations in the expression of negative words (i.e., negative affect instability) was positively associated with depression severity (Seabrook, Kern, Fulcher, & Rickard, 2018).

As individuals frequently post about life events on Twitter, it is possible that patterns of emotion dysregulation better differentiate between depressed and non-depressed individuals than average language use alone. High emotion variability or instability, as seen on social media, is likely to be driven by reactions to positive and negative events. Indeed, specific changes in negative affect may also be observed by computing acute changes in mood between days, and serve as a complementary measure to instability by describing the probability of clinically relevant changes (probability of acute change; PAC) and when they occur (acute change; AC) (Jahng, Wood, & Trull, 2008).

1.3 The Current Study

Social media platforms like Twitter provide a unique opportunity for passive data collection as a means of predicting and monitoring depression. By directly sampling the naturally occurring, real-time expressions of social media users, status updates provide momentary data that offer potential as a practical means of monitoring depressive symptoms (at the individual level), and public mental health status (at the collective level) (Kern et al., 2016; Larsen et al., 2015). The prevalence of negative emotion has been successfully used to distinguish depressed and non-depressed individuals, but less is known about how such symptoms unfold within individual users.

Using a case-series approach, we examine the extent to which self-reported emotions reflect expressed emotion online across five Twitter users. Following other studies that have considered emotion frequency as a predictor of depression (e.g., De Choudhury et al., 2013; Gkotsis et al., 2016; Settanni & Marengo, 2015), we classified emotion using the positive and negative emotion dictionaries from the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007). Ecological momentary assessments (EMAs) of mood have been demonstrated to reveal emotion patterns that predict depression and have high ecological validity (Armey, Schatten, Haradhvala, & Miller, 2015; Ebner-Priemer & Trull, 2009; Houben et al., 2015). Enabling EMAs, *MoodPrism* (Rickard, Arjmand, Bakker, & Seabrook, 2016) is a smartphone application (app) which provides daily self-reports of positive and negative emotion. We had one methodological and two substantive aims.

Methodologically, we used EMAs accessed via smartphones to compare mood profile data across Twitter and self-report (collected by the app) across a 30-day period, addressing a need to provide complementary evaluation of social media data by also sampling non-social media variables (Tufekci, 2014). We computed four simple *time series features* for summarizing each 30-day emotion time series: (i) average mood, (ii) variability, (iii) instability, and (iv) acute changes in mood.

Substantively, we considered how similar (or dissimilar) the time-structured mood profiles obtained from Twitter and *MoodPrism's* self-report were over a 30-day period. We asked:

1. Is there a same-day relationship between the measures of mood obtained through self-report and through Twitter?

2. From visual inspection, are there any time-series features that are similar in magnitude across the self-report and Twitter time-series?

In addition, we considered whether there were any systematic variations in the four time-series features from self-report and Twitter that may be linked to depression severity.

2. Method

2.1 Procedure Overview

Participants for the current study were selected from the larger *MoodPrism* project assessing a mood-tracking app (cf. Rickard, Arjmand, Bakker, & Seabrook, 2016). *MoodPrism* allows users to track their mood once every day for 30 days and presents engaging mood and mental health feedback.

For the broader project, participants were recruited using strategies that included targeted Facebook advertising recruiting individuals who were smartphone users and lived in Australia, and convenience sampling. After downloading *MoodPrism* (available on both the Android and iOS Australian app stores), participants opened the app and read explanatory statements. They provided consent to participate in the research electronically within the app. Participants were then invited to allow access to their Twitter data. It was explained that only word counts and timestamps would be collected and that the content of Tweets would not be stored. They could complete the measures and study without allowing access to their Twitter data.

Participants then completed baseline measures. These were organised into blocks that could be completed at a time of the participant's convenience before unlocking the mood-tracking function of *MoodPrism*. As reported in Arjmand and Rickard (2018) these surveys took on average 37m 14s (*SD* = 11m 33s) to complete. After completing the baseline measures, participants were prompted at a random time within a preferred timeframe every day for 30-days to complete daily mood reports. Participants elected timeframes could range between 3:00 am, and 3:00 am the following day). Completing the daily mood reports took on average 1m 34s (*SD* = 44s) to complete (Arjmand & Rickard, 2018). After 30 days of using *MoodPrism*, participants completed follow-up surveys through the app, which primarily addressed mental health change (including the *PHQ-9*). All procedures were approved by the Monash University Human Research Ethics Committee (Approval # CF14/968 – 2014000398).

2.2 Participants

Five participants were identified from the broader project who: (1) completed the baseline surveys on *MoodPrism*, (2) completed at least 70% of the daily mood reports over 30 days (defined below), (3) provided access to their Twitter account, and (4) Tweeted during their period of *MoodPrism* use. Participants were assigned a pseudonym for data analysis and reporting. They contributed data for a maximum of 30 consecutive days within the data collection period occurring between April and December 2016. Table 1 provides the participants' demographic characteristics. All five participants were female and were aged between 18 and 35 years old. At the time of the study they were employed or undergoing study, and all had achieved at least secondary school qualifications.

Table 1

Demographic Characteristics of Participants/Cases

	Participant				
Variable	**1**	**2**	**3**	**4**	**5**
Age	33	33	18	35	29
Education	Tertiary	Secondary	Secondary	Tertiary	Post-graduate
Occupational status	Part-time	Full-time	Full-time	Full-time	Not employed
Study status	Not studying	Full-time	Part-time	Not studying	Part-time

2.3 Measures

All measures for the current study were delivered and/or collected by *MoodPrism* (Rickard et al., 2016). *MoodPrism* delivered push-notifications to prompt participants to complete daily mood self-report for 30 days and accessed the emotion language expressed in Tweets automatically from the standard Twitter application programming interface (API) during the same period (d1 – d30). Depression severity ratings were also provided to *MoodPrism* at baseline (T1) and at the 30-day follow-up (T2). Age, gender, current occupational status, and highest completed level of education were collected at baseline.

2.3.1 Daily mood reports (d1-d30). *MoodPrism* delivered push-notification prompts asking: “How are you feeling today?” at quasi-random times each day for 30 consecutive days while *MoodPrism* was installed on a participant’s smartphone. The daily mood reports included items assessing mental health, eudaimonic well-being, self-esteem, significant daily positive and negative events, and social- environmental context (Rickard et al., 2016); the current study focused on current mood.

Based on the Circumplex Model of Emotion (Russell, 1980) participants responded to three items rated on a 5-point Likert scale (“1 – Not at all”, “5 – Extremely”) rating their current mood: (1) Positive or pleasant; (2) Negative or unpleasant; (3) Active or alert. These ratings represent the core affect space of an individual at the time of the *MoodPrism* prompt. Mood ratings (positive, negative) were considered as distinct dimensions within each day. The 30-day time series of self-reported positive and negative mood obtained for each participant will be referred to as SR-Positive and SR-Negative, respectively.

2.3.2 Automated Tweet word count (tw1-tw30). To protect the privacy and confidentiality of users, *MoodPrism* pre-processed Tweets, providing information about the contents of the Tweets, but not the Tweets themselves. After consenting to contribute Twitter data, the user’s Twitter handle was automatically accessed by *MoodPrism* via the Twitter API, collecting all Tweets posted during the period *MoodPrism* was installed on the participant’s smartphone. *MoodPrism* parsed the collected Tweets through a word count script that extracted the number of positive and negative words, total words, and time-stamp for each Tweet (process depicted in Figure 1). This script included the LIWC2007 positive and negative emotion dictionaries (Pennebaker et al., 2007) which were supplemented with common emojis and internet slang (see Appendix A for the full list). Retweets were not included in our analysis.

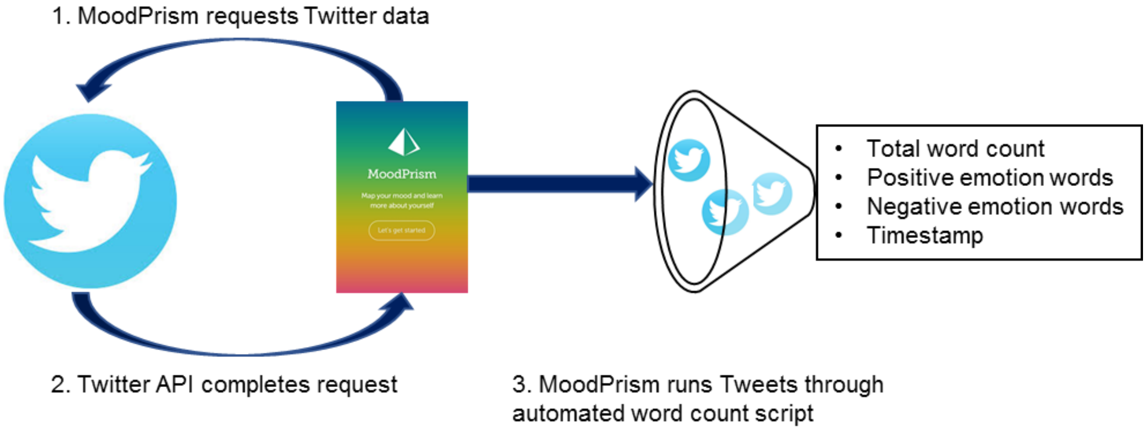


Figure 1. MoodPrism procedure for Twitter word count extraction.

The relative proportion of emotion words used within each Tweet was calculated and is defined in Equation 1 (c.f. Kern et al., 2016).

$$p(category) = \sum_{word \in category} p(word) = \frac{\sum_{word \in category} count(word)}{N\_words}, \tag{1}$$

where *count(word)* refers to the total number of target words (for each of two categories: 'positive' or 'negative' emotion words) within an individual Tweet, and *N_words* refers to the total number of words in a Tweet. This results in a proportion of emotion language ranging from 0-1. A daily average of these proportions was then obtained as summary of the mood expressed on Twitter. The resulting 30-day time series for daily aggregate positive and negative mood Tweets will be referred to as T-Positive and T-Negative, respectively.

2.3.3 Depression severity. Self-reported depression severity was assessed with the nine item *Patient Health Questionnaire -9* (*PHQ-9*; Kroenke, Spitzer, & Williams, 2001) at baseline (T1, immediately after downloading *MoodPrism*) and at follow-up (T2) after 30 days of *MoodPrism* use. Items from the PHQ-9 are rated from "0 – Not at all" to "3- Nearly every day", describing the frequency of depression symptoms such as "Feeling down, depressed or hopeless" over the previous two weeks. Ratings are summed to generate a total score ranging between 0-27. More severe depression symptoms are indicated by higher total scores and cut-off values are provided to aid interpretation (0-4 = minimal; 5-9 = mild; 10-14 = moderate; 15-19 = moderately severe; 20-27 = severe). The PHQ-9 has demonstrated good reliability in the general population (Cronbach α = .87; Kocalevent, Hinz, & Brähler, 2013) and in primary care settings (α = .89; Kroenke et al., 2001).

2.4 Data Analysis

The *MoodPrism* and Twitter mood data sets were collated in chronological order and time-matched for each participant. Spearman cross-correlations were computed to examine the relationship the SR- and T-Positive, and SR- and T-Negative mood profiles on same-day measurements across the 30-day recording period. Feature comparisons (average, variability, instability, and PAC) were conducted by visual inspection.

2.4.1 Within-person time-series features. Four mood profile features were selected for examination, identified from the emotion dynamics literature as targets that may aid depression identification (Houben et al., 2015). Only instability and PAC (defined below) incorporate temporal structure into their measurement. It should be noted that these features are not exhaustive and other indices may also be informative (e.g., spin, autocorrelation), but are beyond the scope of this study.

(1) The **average** positive and negative mood across all observations, defined by:

$$M = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{1}{n}\left(x_1 + x_2 + \Lambda\ x_n\right), \tag{2}$$

where M is the average of emotion values *(x)* taken over observations, *i*, and divided by *n*, the total number of observations for a participant within the 30-day recording period.

(2) **Within-person variability** of positive or negative mood was computed for each participant as:

$$iSD = \sqrt{\frac{\sum_i {s_i}^2}{n-1}}\ , \tag{3}$$

where the sum is taken over observations, i, s_i indicates deviations from the mean of the time series, and n is the number of observations.

(3) **Instability** of positive or negative mood was computed for each participant as:

$$MSSD = \frac{\sum_{i=1}^{n-1}(x_{i+1} - x_i)^2}{n-1}, \tag{4}$$

where x_i indicates the observation at index i, x_{i+1} refers to the next consecutive observation, and n refers to the total number of observations for that individual. Instability was calculated from the z-transformed time-series to allow comparison between self-report and Twitter, and thus represents the relative patterns of fluctuation through time.

Due to missing data the following adjustment was made to the MSSD to weight successive differences based on the time-interval between observations (Jahng et al., 2008).

$$\text{time-adjusted}\,MSSD = \frac{median(\Delta t)}{(n-1)}\sum_{i=1}^{n-1}\frac{(x_{i+1} - x_i)^2}{(t_{i+1} - t_i)}, \tag{5}$$

where $median(\Delta t)$ is the median of incremental time differences across the recording period of the study (Seabrook et al., submitted).

(5) **Proportion of Acute Change** (PAC; Jahng et al., 2008) was computed for each participant as:

$$PAC = \frac{1}{N-1}\sum_{i=1}^{N-1} AC_{i+1}, \tag{6}$$

where successive differences ($x_{i+1} - x_i$) were computed between each consecutive pair of observations, time-adjusted as in Eq. (5), and z-transformed. As there are no theoretically established cut-offs for defining the values of acute change (AC) in this data, a statistical cut-off was selected following the recommendations of Jahng et al. (2008). ACs were defined by a z-score cut point of 1.282 which represents values in the top 10% of the normal distribution. Therefore, $AC_{i+1} = 1$ when $x_{i+1} - x_i \geq 1.282$. The calculation of successive differences disregards the sign, or direction of change, AC falling above the 1.282 cut-off indicate a large magnitude change in either an increasing or decreasing direction. Visual inspection of the data was conducted to elucidate the direction of AC.

2.4.2 Data transformations. To allow qualitative visual comparisons of values between the two data types (self-report and Twitter), data were transformed in two ways. First, before computing the average and iSD, raw scores were rescaled as a proportion of the total range of scores (minimum to maximum values) within self-report and Twitter as defined in Eq. (7).

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{7}$$

where x is the raw value. Minimums and maximums were defined the by range of observed values in the entire sample (n = 5) for the SR- and T- positive and negative series. This resulted in values from both self-report and Twitter ranging from 0-1, where 1 consistently represents the maximum observed value on each scale . The average and iSD was computed from these rescaled values to aid in visual comparison between self-report and Twitter. Second, as noted above, instability was computed from z-transformed time series and represents the pattern of fluctuations relative to the mean and standard deviation of a participant's self-report or Twitter emotion profile. Raw-score values and dual-axis plots of the mood profiles are presented in Appendix B.

3. Results

A total of 386 Tweets were extracted from the five participants. Table 2 presents depression status at baseline (T1) and follow-up (T2), and the Tweet and daily mood report activity across the 30-day study period. Participants 1 and 4 showed no signs of depression at baseline, whereas participants 2, 3, and 5 showed signs of moderate to severe depression. The users typically posted multiple times per day, resulting in a combined total of 5,805 words, 209 (3.6%) of which were positive emotion words and 282 (4.9%) were negative emotion words.

Table 2

Depression Scores (T1, T2), and Tweet and Daily Mood Report Activity across the 30-Day Study Period (d1-d30).

Variable	**Participant**				
	1	**2**	**3**	**4**	**5**
T1 Depression	9 (mild)	26 (severe)	4 (none)	5 (mild)	16 (moderately severe)
T2 Depression	5 (mild)	NA	10 (moderate)	7 (mild)	10 (moderate)
Daily Mood Reports Completed	27	22	29	26	30
Twitter Activity					
Total Tweets	46	53	104	95	88
Total Words	974	972	1228	1403	1228
Tweets per day *M* (SD)	1.53 (3.66)	1.77 (3.50)	3.47 (2.97)	3.17 (2.51)	2.93 (4.55)
Words per day *M* (SD)	32.47 (117.61)	32.40 (83.07)	40.93 (29.63)	46.76 (39.93)	40.93 (62.11)
Words per Tweet *M* (SD)	21.17 (4.16)	18.34 (6.78)	11.80 (5.34)	14.77 (6.07)	13.95 (7.48)

Note: For depression, clinical cut-off labels are present in parentheses. T1 = baseline, T2 = follow up.

3.1 Profile Comparison

Figure 2 provides z-transformed time series plots of positive (left) and negative (right) emotion for self-report and Twitter data for each participant. A reference line is provided at 0.00. Missing observations, which was common in Twitter time series, appear as a blank. Visual inspection suggests that for Participants 1, 3, and 4, SR-Positive and T-Positive are dissimilar over time, whereas for Participants 2 and 5 there is a similar overall shape. SR-Negative and T-Negative series appear similar in shape across all participants.

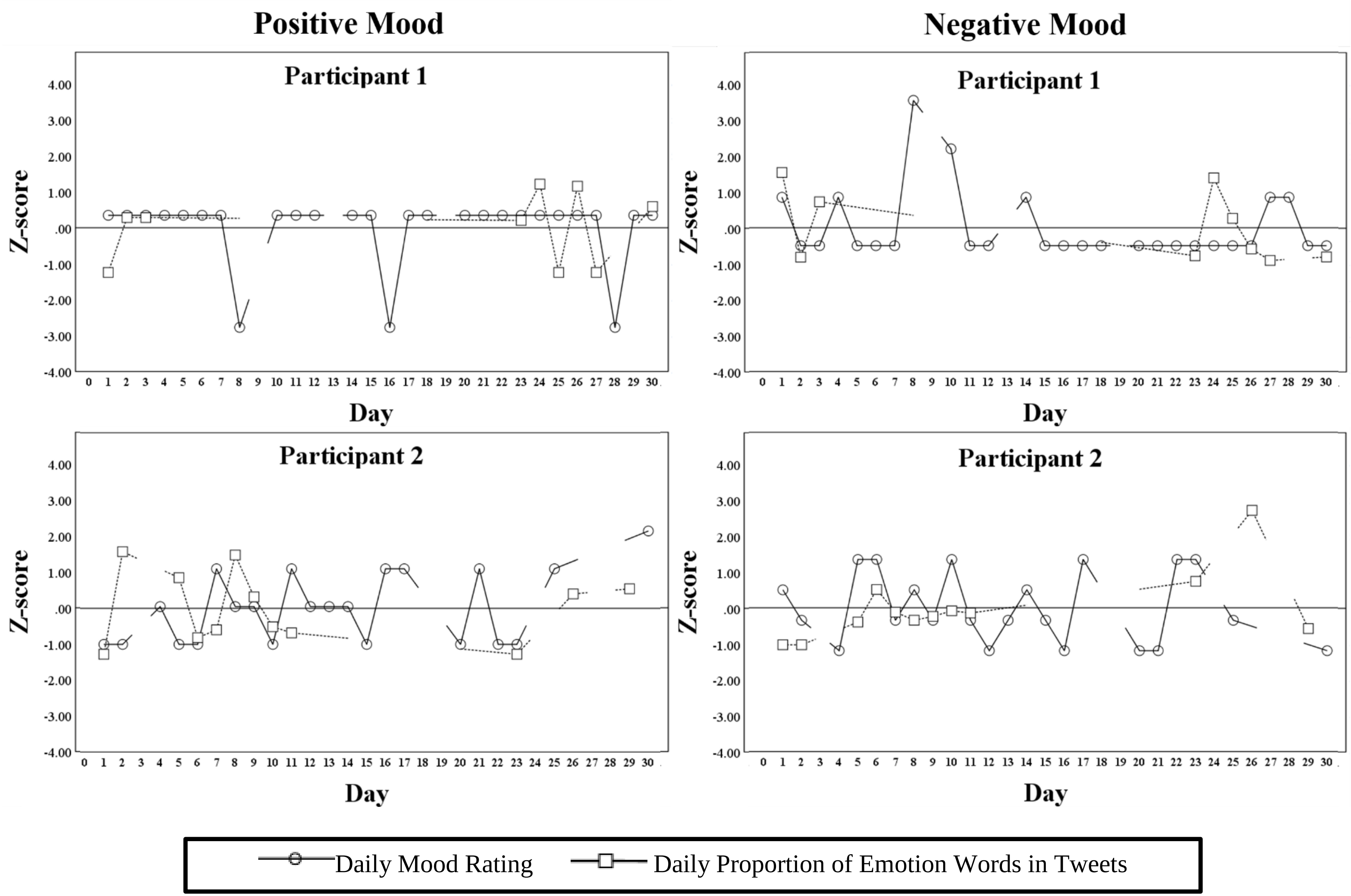


Figure 2. Panel plots of z-transformed positive and negative mood per day from *MoodPrism* self-report and Twitter emotion word use.

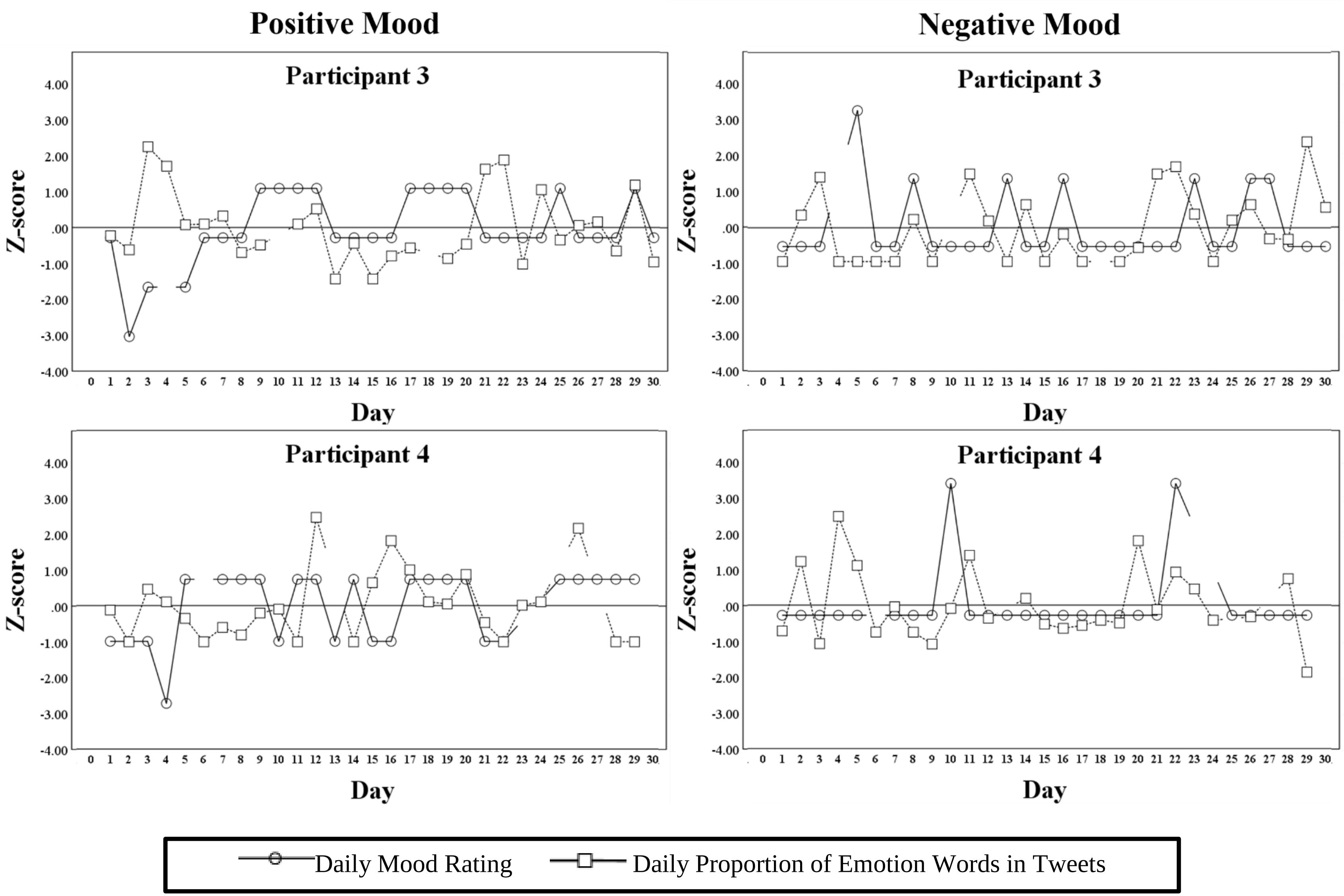


Fig 2 Continued. Panel plots of z-transformed positive and negative mood per day from *MoodPrism* self-report and Twitter emotion word use.

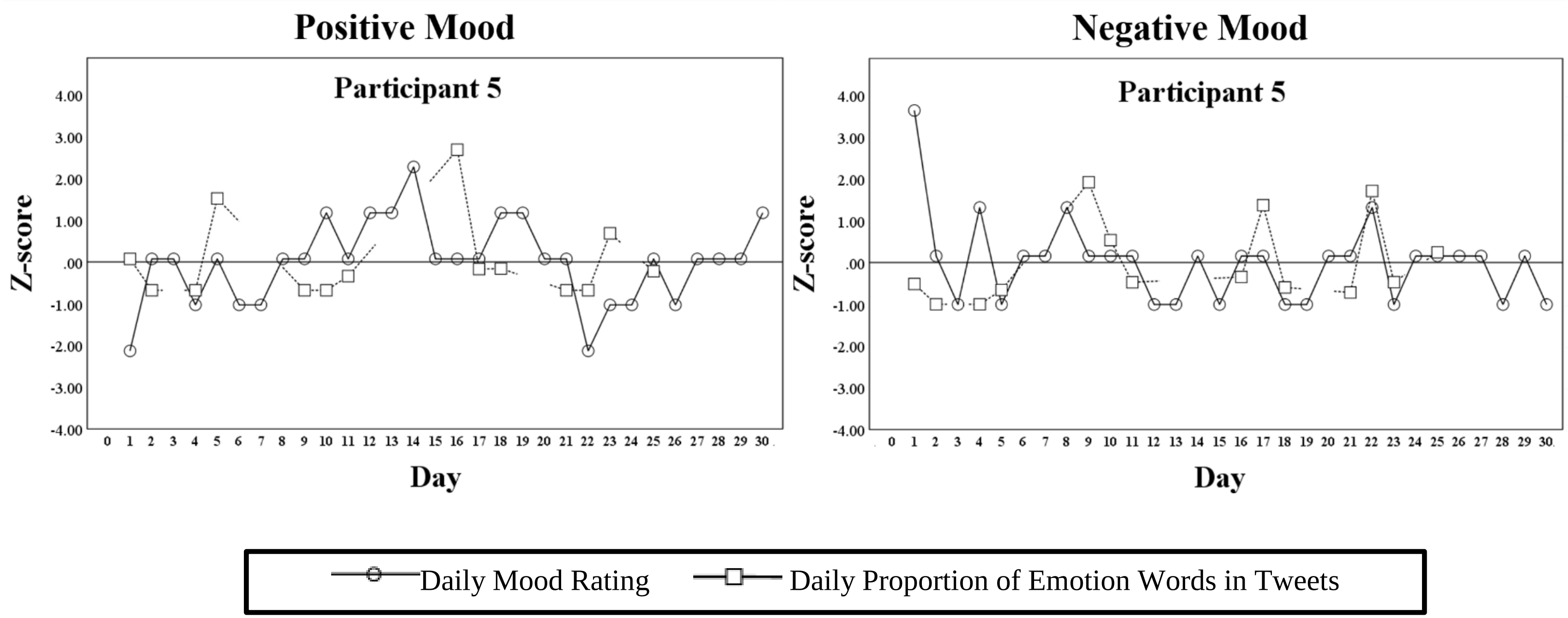


Fig 2 Continued. Panel plots of z-transformed positive and negative mood per day from *MoodPrism* self-report and Twitter emotion word use. A horizontal trend line is provided for reference at 0.00. Daily mood ratings are denoted by circles and the emotion words in Tweets are shown with squares.

Same-day cross-correlations (Spearman's rho) between the SR and T time series for both positive and negative mood, and Lin's Concordance Correlation Coefficient (CCC) are presented in Table 3. The number of observation pairs differ by participant.

Table 3

Spearman Ranked Correlations between SR- and T- Positive (and Negative) Mood Profiles by Participant.

	Participant 1	**Participant 2**	**Participant 3**	**Participant 4**	**Participant 5**
Observations	*n* = 9	*n* = 10	*n* = 27	*n* = 23	*n* = 14
			Positive Mood		
Correlation (*rho*)	--	.11	-.03	-.08	-.03
			Negative Mood		
Correlation (*rho*)	.00	.41	-.05	.19	.09

Note. Correlations could not be computed for Participant 1 positive mood due to constant SR-Positive ratings.

Visual inspection of Table 3 suggests that positive mood expressed on Twitter does not share a consistent relationship with same-day self-reported positive mood over time for these five participants across their 30-day recording period. Participant 2 returned the highest *rho* coefficient, though this was weak; and Participant 4 revealed a very weak negative relationship between their SR-Positive and T-Positive mood profiles. These correlation values are informed by inspection of Figure 2 where Participant 2 appears to have a similar (though not identical) pattern of positive mood across 30-days, whereas, for Participant 4 the mood profiles appear to be at an inverse for most of the 30-days, though does become more similar after d20. For the remaining participants (3 and 5), there is no clear co-varying pattern visible in Figure 2. For example, Participant 3 appears to have an inverse relationship between her SR and T-positive series between d1-25, with it becoming similar from d26-d30.In contrast to positive mood, we observe stronger relationships between negative mood expressed on Twitter and same-day self-reported negative mood for Participants 2, 4, and 5. These relationships are moderate (Participant 2) and weak (Participants 4 and 5). Visual inspection of Figure 2 highlights the close relationship between SR and T negative mood profiles for Participant 2 on days with concurrent observations. Similarly, Participants 4 and 5 appear to have similar SR and T-negative mood profiles over the 30 days, though for Participant 4 between d1-d7 there is a great deal more variation in the T-negative series that does not mirror the SR-negative series.

3.2 Time-Series Feature Comparison

Our methodological aim was to compare four time-series features (average mood, individual variability, instability, and PAC) for the self-report and Twitter mood profiles within individuals. Table 4 presents each feature by participant.

Table 4

Descriptive Mood Profile Features from Self-Report and Twitter Positive and Negative Mood Data.

Feature	**Participant 1**		**Participant 2**		**Participant 3**		**Participant 4**		**Participant 5**	
	SR	Twitter	*SR*	Twitter	*SR*	Twitter	*SR*	Twitter	*SR*	Twitter
Observations	n = 27	n = 9	n = 22	n = 12	n = 29	n = 28	n = 26	n = 26	n = 30	n = 14
Positive Mood										
Average [a]	.47	.11	.24	.20	.55	.33	.64	.15	.48	.06
iSD [a]	.08	.09	.24	.16	.18	.23	.14	.15	.23	.09
Instability [b, c,]	2.06	2.75	1.53	1.69	0.95	1.84	1.47	1.59	1.13	1.47
PAC [b, c]	.19	.00	.28	.09	.04	.11	.04	.12	.10	.15
Negative Mood										
Average [a]	.09	.31	.60	.22	.07	.14	.02	.43	.22	.24
iSD [a]	.19	.34	.30	.21	.13	.14	.07	.23	.22	.24
Instability [b, c,]	1.40	2.13	1.80	0.58	2.05	1.94	1.80	2.14	1.68	1.75
PAC [b, c]	.08	.13	.17	.09	.07	.11	.12	.08	.14	.15

Note: [a] = Features were computed from rescaled raw scores and represent a proportion of the total range of values of positive and negative mood from self-report and Twitter; [b] = Features were computed from z-transformed scores. [c] = observations = n -1 for Instability and PAC as they are calculated from the successive differences between observations. *iSD* = within-person standard deviation; PAC = Probability of Acute Change.

Average positive mood was higher in the SR-Positive time series than in the T-Positive time series for participants 1, 3, 4, and 5, but they were similar for Participant 2. For negative mood, Participants 1, 3, and 4 had higher mean levels in the T-Negative series. Participant 2 had higher levels in the SR series, whereas levels of negative mood on the SR and T series were comparable for Participant 5.

For variance, Participant 5 demonstrated greater variability in the SR-Positive series than in the T series, whereas positive mood variability was comparable across SR-Positive and T-Positive series for the other participants. For negative mood, Participants 1 and 4 had greater variability in the T-Negative series than SR-Negative series, Participant 2 had greater variability in the SR-Negative series, and Participants 3 and 5 demonstrated comparable variability between their SR and T-Negative series.

In terms of instability, Participants 2, 4, and 5 demonstrated comparable instability for positive mood between their SR and T-Positive series, whereas Participants 1 and 3 demonstrated greater instability in the T-Positive series. For negative mood, Participants 3, and 5 demonstrated comparable instability between the SR and T-Negative series. For Participants 1 and 4, there was greater instability in the T-Negative series, and for Participant 2 there was greater instability in the SR-Negative series.

For the proportion of acute change (PAC), Participants 1 and 2 demonstrated a higher PAC value in the SR-Positive series than in the T-Positive series, whereas Participants 3, 4, and 5 had a higher PAC value in the T-Positive series. For negative mood, the PAC was higher in the SR-Negative series than in the T-Negative series for Participants 2 and 4, whereas PAC was higher in the T-Negative series for Participants 1 and 3. PAC was equivalent for Participant 5.

As a complementary approach to examining acute change, Figure 3 illustrates AC by successive difference across the study period. The ACs represented indicate large magnitude increases or decreases in mood between days. Light grey cells indicate AC in either positive or negative T time series, dark grey cells indicate AC in either positive or negative SR time series, and black cells show where there is a AC on both the SR and T time series in the same successive difference.

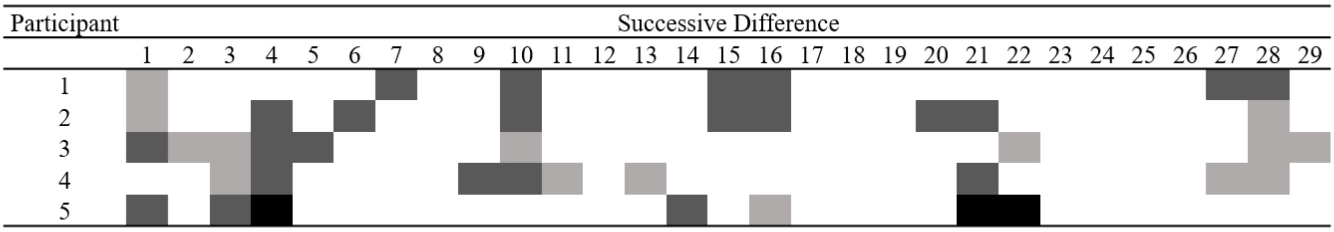


Figure 3. Acute change between mood observations on self-report and Twitter time-series. Light grey cells indicate AC in either positive or negative T time series, dark grey cells indicate AC in either positive or negative SR time series, and black cells show where there is a AC on both the SR and T time series in the same successive difference.

Co-occurrence of AC on both the SR and T time series was only evident for Participant 5 as indicated by the black cells in Figure 3. At successive difference 4 (between days 4 and 5) there was a marked decrease in SR negative mood and an increase in the T positive mood. At successive difference 21, (between days 21 and 22) there was a marked decrease in SR positive mood and an increase in T negative mood. Finally, at successive difference 22 (between days 22 and 23) there was a marked decrease in both SR and T negative mood. Overall, the patterns of AC for Participant 5 suggest similarity between the signals of SR and T in indicating sudden and extreme shifts in positive or negative mood from day to day. The other participants did not demonstrate such shifts.

3.3 The Impact of Depression Severity

Finally, we considered whether the time-series features varied according to depression status. Table 2 indicates baseline and 30-day follow up scores. Participants 1 and 4 demonstrated no or mild signs of depression across both assessments, Participant 3 increased in depression, Participant 5 decreased. As Participant 2 did not complete the T2 administration of the PHQ-9, we examined her responses to the PHQ-2 within the *MoodPrism* daily mood reports. Ratings were summed within each day and averaged across the last 14 days of the study. The resulting average (M = 2.25; range: 0 - 6) suggests Participant 2 would screen positive for the presence of depression (Arroll et al., 2010), with their daily ratings describing depression symptoms that were moderately severe.

Table 5 shows the average, within-person variability, instability, and PAC for positive and negative mood for each participant in terms of their salient differences between the SR and T series. It also presents participants' T1 and T2 depression status.

Table 5

Salient Differences by Feature and by Participant between the Positive and Negative Mood Profile Features of Self-Report and Twitter.

Participant	**Depression Status**		**Positive Mood Profile Comparisons**				**Negative Mood Profile Comparisons**				
	T1	T2	Average	Variability	Instability	PAC	Average	Variability	Instability	PAC	Total by Participant
1	mild	mild	SR		T	SR	T	T	T	T	7
2	severe	mod*				SR	SR	SR		SR	4
3	none	mod	SR		T	T	T			T	5
4	mild	mild	SR			T	T	T	T	SR	6
5	mod-severe	mod	SR	SR		T					3
Total by Feature			4	1	2	5	4	3	2	4	

Note: SR indicates the self-report mood profile had higher values on a feature than the Twitter mood profile. T indicates the Twitter mood profile had higher values on a feature than the self-report mood profile. Blank cells indicate comparable feature values on the SR and T mood profile. mod = moderate depression severity; mod-severe = moderately-severe depression severity.

* = depression status at T2 was calculated from the PHQ-2.

Salient differences between the magnitude of values for mood profile features (SR and T) were identified through visual inspection of the values in Table 4 and were discussed in the Feature Comparisons, above. These are summarised in the context of depression severity within-participants and within features in Table 5 which suggests that there are fewer salient differences between the SR and T series for the participants with higher depression severity at T1 and T2 (Participants 2 and 5). Where salient differences do exist, they are in relation to higher values from the SR series. In contrast, those with lower depression severity at T1 and T2 (Participants 1 and 4) have a greater number of salient differences overall, where the T-series (specifically T-negative) have higher values than the SR-series.

3.3.1 Self-Report

Participants with no-to-mild depression severity at T1 demonstrated higher mean values of positive mood on the SR-Positive series and lower mean values of negative mood on the SR-Negative series (Participants 1, 3, and 4) relative to those with higher severe depression severity (Participants 2 and 5). An exception to this was Participant 5 (moderately-severe depression severity; T1) who improved between assessments (moderate depression severity; T2) who reported equivalent levels of positive mood to those with mild depression severity.

For variability, Participants 1 and 4 with no-to-mild depression severity at both assessments had low variability in the SR-Positive and SR-Negative series. In contrast, variability was higher for Participants 2 and 5 (moderate-to-severe depression severity) on both positive and negative series. Participant 3, who declined between assessments (T1-none; T2- moderate) demonstrated equivalent levels of variability to Participants 2 and 5.

Instability on the SR-Positive series had no clear variations between participants that may be linked depression severity, however, the SR-Negative instability appeared higher for those with moderate-to-severe depression severity (Participants 2 and 5) and for those whose depression severity increased between assessments (Participant 3). Participant 4 also demonstrated equivalent levels of SR-Negative instability to those with more severe depression severity, though visual inspection of Figure 2 suggests that these fluctuations occur in the context of longer periods of stable negative mood which contrasts with Participants 2, 3, and 5 who show frequent and large fluctuations. Similarly, the PAC values do not appear to systematically vary with depression severity. Notably, Participant 2 (severe depression) demonstrated the highest PAC values on both the SR-Positive and SR-Negative series.

3.3.2 Twitter

For T-Positive, those with lower depression severity (Participants 1 and 4), or who improved between assessments (Participant 5), had lower mean levels in positive mood, whereas those with higher depression severity (Participant 2) or had increased depression severity between assessments (Participant 3) demonstrated higher mean positive mood. For T-Negative, mean negative mood was higher for those with no-mild depression severity (Participants 1 and 4) and was lower for those with moderate-to-severe depression severity (Participants 2 and 5) and for those who had increased depression severity between assessments (Participant 3).

In terms of variability, there did not appear to be any systematic variations related to depression severity on either the T-Positive or T-Negative series. Similarly, for instability there did not appear to be any systematic variation based in depression severity in the T-Positive or T-Negative series and this was reflected in the PAC values. Notably, Participant 2 recorded the lowest T-Negative instability and visual inspection of Figure 2 indicates a relatively smooth increase in negative mood over time.

4. Discussion

The growing amount of data available through online social media platforms such as Facebook and Twitter have raised the possibility of using language and other features to detect and monitor mental health difficulties (Guntuku et al., 2017). Yet while there is some predictive success at collective levels, less is known about how social media language intersects with felt daily emotions. Using a case-series approach, this study examined the convergence between mood profiles obtained through the emotion language used on Twitter, and through a self-report mood tracking app for five different users. We examined four different time-series features (average, variability, instability, and PAC), comparing profiles across positive and negative emotion. In addition, we considered how profiles varied based on an individual's depression severity.

Considering the profiles alone, there was little agreement between the same day mood expressed through SR and Twitter. However, the time series features suggested a more complex picture. While there were often salient differences between the SR and T series in terms of average mood, variability and instability appeared more similar. Examination of AC however, suggested that large daily fluctuations in positive or negative mood in this sample rarely co-occurred on both the SR and T series. When considered in the context of depression severity, there was greater similarity between the SR and T series at higher depression severity levels. The average positive and negative mood in the SR and T series appeared to systematically vary by depression severity when comparing participants in this sample. Positive and negative variability and instability also suggested variations based on depression severity in the SR series, though for the T series, no depression-related systematic variations were evident.

4.1 Inconsistencies between Self-Reported Mood and Twitter Language

Overall, concurrent observations of mood from Twitter and self-report were inconsistent. Although the face validity of negative emotion word expression on Twitter may be high, particularly when considered in the context of depression prediction, its concurrent validity as a measure from which to infer mood (i.e., revealing persistent low mood over time) may be low. Several features of posting a Tweet differ from expressive writing in a private or laboratory setting. Posting a Tweet is a brief form of public disclosure and may be intended for a specific audience or crafted to encourage reciprocal communication (Marwick & boyd, 2011). Language choice may be influenced by self-presentation motives (i.e., motivations to present a positive self-image to others in the social network) (Gil-Or, Levi-Belz, & Turel, 2015; Seidman, 2013; Selim, Long, & Vignoles, 2014) and online social norms (that positive disclosures are more favourable) may influence emotional expression (Waterloo, Baumgartner, Peter, & Valkenburg, 2017). These confounding variables may impact greatly on how reliably Twitter emotion language can sample mood from one moment to the next.

4.2 Feature Comparison

Along with comparing profiles, we had a methodological aim to consider various time series features as approaches to considering convergence and inconsistencies across the two types of data. On the whole, SR-Positive mood profiles revealed larger mean values than in T-Positive mood profiles, whereas T-Negative mood profiles tended to have higher mean values than SR-Negative mood profiles. Similarly, the variability features (*iSD*, instability, and PAC) of the positive and negative mood profiles did not clearly converge. These discrepancies may be a result of the specific environments from which the mood data is sampled. The mood data collected in the daily mood reports was signal-contingent and were temporally-bound to the moment a participant responded to a prompt. The mood collected following these prompts was likely to be tapping into current or recent emotional experiences.

A major advantage of using smartphone assisted experience sampling method is that retrospective biases are reduced, and the ecological validity of the data is high (Miller, 2012). In contrast, while Tweets have high ecological validity in the sense they are sampled from a naturally occurring behaviour in real time, it is likely that the mood referred to in Tweets may reflect a broader, less temporally-bound timeframe. Tweets may be past, present or future oriented (Park et al., 2017). This has the potential to introduce retrospective biases into the estimation of mood from Twitter, particularly relevant in the context of findings indicating that retrospective accounts of mood often overestimate negative emotion (Sato & Kawahara, 2011).

These findings highlight prominent differences in emotional responding when sampling experiential emotion and behavioural emotion (i.e. Tweets). Mauss et al. (2005) discuss consistency between measures of emotion as response coherence, where there is a presumed theoretical coordination between the expressive and experienced components of emotion. In practice, however, the relationship between these components is not as clear, particularly where the time-frame for sampling emotion experience and behaviour is broad or varied as it is in this study.

4.3 The Impact of Depression Severity

The five participants varied in terms of their baseline and follow up depression statuses, ranging from mild to moderately severe. The patterns suggested that the signals between mood profiles converged as depression severity increased, a finding consistent with research suggesting coherence between experiential and behavioural emotion increases as emotion intensity increases (Mauss et al., 2005). Those with greater depression severity may have their language use on Twitter more clearly driven by experiences of negative mood resulting in the high sensitivity of identification for these individuals. In contrast, variables other than depression severity may be involved in defining the language used for those with no-to mild symptoms which may contribute to the likelihood of obtaining false positives when using language to predict depression on Twitter.

The pattern of convergence was particularly apparent in Participant 2, who differed from other participants in that they reported severe depression severity (26 on the PHQ-9) at T1 compared to the other participants (ranging 4-16 on the PHQ-9). They also self-reported the most intense negative mood across the period of the study compared to other participants. The moderate association between negative language and negative mood is consistent with recent findings indicating that negative affect drives more negative language use (Bernard et al., 2016) and cognitive theories of depression that suggest negative language use manifests from increased levels of negative thinking, or negative cognitive biases in interpreting information from the environment (Beck, 1974). Depression has also been linked to a greater tendency to post present-focused Tweets (Park et al., 2017). It is likely that at the more severe levels of depression severity, Tweets may act as a more direct measure of experienced mood as there is a present focus (consistent with the methodology of the daily mood reports) and the influence of confounding variables (discussed above) that alter the language used on Twitter may be less impactful in this context.

Notably, different features appeared relevant for SR versus Twitter mood profiles. Features from the SR-Positive and SR-Negative mood profile differed between mild and moderate depression severity in relation to the average, variability and instability. In terms of the average, as might be expected, participants with lower depression severity self-reported higher positive and lower negative mood than those with higher depression severity. Those with moderate depression severity had greater variability in their SR-Positive and SR-Negative mood over 30-days than those with mild depression severity. This is consistent with previous research which suggests that more variable positive and negative emotion is associated with poorer mental health outcomes (Gruber, Kogan, Quoidbach, & Mauss, 2013; Houben et al., 2015).

While there were no clear patterns associated with depression severity and SR-Positive instability, SR-Negative instability was higher for the participants with moderate to severe depression severity. Greater instability of negative mood (moment to moment fluctuations) has been associated with poorer psychological outcomes (Houben et al., 2015). Visual inspection of the SR-Positive and SR-Negative mood profiles suggested that while those with mild depression severity had more pronounced acute changes in positive mood than those with moderate depression severity, they also had longer period of reporting stable positive mood, a characteristic that has been linked to higher levels of well-being and lower levels of psychological distress (Cummins, 2010; Gruber et al., 2013).

Contrary to much of the existing literature, in Twitter across the 30 days, participants with mild depression severity used more negative emotion words than those with moderate depression severity. An example of this pattern can be seen in Participant 4, who at both T1 and T2 reported mild depression severity, but expressed the highest proportion of negative emotion words on Twitter over the 30-day study. This also contrasted with their SR-Negative mood profile, which revealed a significant lower mean negative mood over time than was expressed on Twitter. Negative emotion words are not only used by individuals with high depression severity. Personality is likely to be implicated in the characteristic mood tone people use online. For example, Park and colleagues (2015) found that the use of negative emotion words on Facebook were related to lower levels of agreeableness, lower levels of conscientiousness, and lower levels of emotional stability (neuroticism).

Similarly, the purpose for using Twitter may influence language use. In relation to talking about mental health on Twitter, some users go online to vent how they are feeling and to seek social support (Berry et al., 2017). Talking about emotion on Twitter could be an adaptive combination of self- and interpersonal- emotion regulation strategies for some, where frequently expressing negative experience online may contribute to better mental health. Expressive writing on Twitter may have positive impacts on well-being overtime as it does in offline settings (Baikie & Wilhelm, 2005; Smyth, 1998) and beneficial online interpersonal processes (e.g. social support) also have an opportunity to occur. While our data do not provide insights into the most likely reason those with mild depression severity tended to express more negative language, the findings highlight how important confounding variable explanations may be for interpreting the psychological meaning/context/relevance of emotion language used on social media.

4.4 Strengths, Limitations and Future Directions

Our study provides a detailed exploration of mood data over time from two methods of experience sampling. Importantly, we highlight individual variation in within and between Twitter and self-report measures of mood, and demonstrate potential validity and reliability issues in sampling Twitter data as a measure inferring mood over time.

However, the study is clearly limited by the small sample size. We provide an in depth look at these participants, but all patterns need to be replicated in larger samples. Notably, the study considers four different time series features that might be considered in the future to compare self-report and Twitter profiles over time. The range of depression severity for our participants at T2 was also small (PHQ-9 scores of between 5 and 10).

Secondly, the specificity with which Tweets and self-reported mood was linked was hampered by technical issues. *MoodPrism* was built as a native app for iOS and Android and had varying data collection accuracy and success in recording timestamp data for the daily mood reports. As a result, the capacity to link Tweets (with a discrete/specific timestamp) to daily mood reports was limited to the daily level and the frame within which a Tweet and daily mood report may have co-occurred is unknown. It is likely that there may have been greater similarity between the mood profiles presented if measurements of self-reported mood were linked to Tweets within a more restricted timeframe (e.g. 6hr intervals).

Third, to protect the user privacy, the app automatically pre-processed the Twitter data, such that we only had frequencies of the LIWC categories, and not the tweets themselves. While the LIWC dictionaries have been used across numerous studies to classify sentiment, they are also limited. The use single words, and are prone to signal discrepancies, such as lexical ambiguities and signal negation (Kern et al., 2016).

Finally, it should be emphasised that the interpretation of finding presented here should be read in the context of this sample only and not as findings generalizable to the population. The cases demonstrate just some of the complexity in mood and depression detection on Twitter and place this in the context of one other EMA method (smartphone self-report).

Our findings highlight the individual-level heterogeneity in mood expression and reporting on Twitter and in self-report. However, more research is required to explore third variables explanations for (1) why the mood signals from self-report and Twitter differ; (2) which individual characteristics influence language use in the context of depression and may disguise or augment psychological distress. This has significant implications for the way we use Twitter language as a passive data collection method for predicting depression and may aid in improving the overall sensitivity and specificity of prediction models.

5. Conclusions

Within-person or user-level observations are critical to the ongoing development of tailored and dynamic mental health monitoring. The current study examined the mood profiles of five participants obtained through smartphone self-report and via the emotion language used on Twitter over a 30-day period. Participants mostly did not Tweet in a way that was consistent with their self-reported mood from day-to-day on average, but some patterns in the way people express emotion online, like how variable or unstable their emotion is, may be similar to their self-reported mood experiences over time.

There is a great deal of heterogeneity in the way people express emotion on Twitter and in how they self-report mood over time. The mood features that are informative of depression on social media may not be the same as those informative of depression through self-report. Exploring the individual characteristics that make these two mood signals similar or different is a crucial next step to improving the way information about mood and emotion dysregulation overtime can be used to predict depression, both from Twitter and in self-report.

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Appendix A

Emoji & internet slang additions to the *LIWC 2007* emotion dictionaries

Positive Emoji's	Negative Emoji's		Positive Emotion Internet Slang			Negative Emotion Internet Slang		
=D>	:-l	:s	Aight	Ilms	lmao	Abft	fkd	r8pist
=D	:l	:-Q	Aightz	Ilu*	lmfao	Acgaf	fker	stupd
:D	X(	:Q	Aiight	Ilshipmp	rofl	Aiic	fkin	suk
:-D	X-(	:-$	Aite	Irly	lml	Arsed	fking	sukz
(:)	O	:$	Alrt	Ite	lov	Awk	fomo	suxx
(:-)	b (	:-/	alryt	Jj	luv	Bm	gank	wrdo
>:D<	>:-(	:/	Alol	j/j	luff	Boom	grmbl	wtf
:))	>:-)	T_T	Aml	jk	luvv	Bord	h8	
:-X	(:-&	T^T	Aprece8	j/k	lurve	Bovered	h80r	
:X	:@	QQ	Apreci8	jks	lv	Catwot	h83r	
:)	:(	=O::::	Awes	j2f	lve	Cba	h8ed	
:-)	:-t	=’(	Awsm	j4f	lyk	Cbb	h8r	
^^	:-ll	&.(..	Awsome	j4g	lyke	Cbf	h8red	
:,’)	:ll	(;_;)	Bahaha	j4l	marvy	Cbfa	h8s	
:-“)	:t	:’(	Besos	jfg	njoy	Cbfed	h8t	
:”)	:-@	:’	Bilu	jfl	ql	Cmeo	h8t0r	
;)	:{	:’-(	Btwilu	jfk	qool	Cmw	h8t3r	
;-)	:-Z	:*(	Btwitiailwu	jja	qt	Cof	h8te	
\o/	:Z	:*-(	Byak	jkz	qte	Cotf	h8tr	
;-(	??	:_(	Chillin	k	rofl*	Dc	hait	
;(	@_@	:..[	Ctm	kay	*s*	Dbm	heyt	
:’)	(-_-*)	;_;	Cut3	kewel	S’ok	Dfc	htr	
:’-)	(o_o)	=\	Eil	kewl	Snog	Dgac	id10d	
>-)	b-(	:l	Fab	kk	Sok	Dgaf	idjit	
:p	%+l	:(&	Fah	kl	Sof	Dgara	idot	
:P	:S	:-E	Fi9	koo	Stm	Dgas	idyat	
:-P	:-S	:-e	Funee	kool	Ub3r	Eejit	invu	
:-p	(:-	DX	Funy	kss	W00t	Eedyat	irhy	
:>	:(	/:(	*g*	kssd	Woot	Ef	isb	
:->	:-(	:-[	Gtm	kul	Xellent	Ef-ing	kmn	
l__l	l-o	:[	Gud	kute	Xlnt	Effed	kmp	
^.^	\-o	:-}	Gudd	l0lz	xtc	Effin	lsr	
^?^	:-o	:}	Heh	laff		Effing	lzr	
^-^	=((	#-)	Hppy	lal		F#cking	nv	
%)	+-((	#)	Hpy	lol		F’n	ofcol	
%-)	</3	:-6	Haha	lols		f-ing	oh	
<3	(U)	:6	I8	lel		fml	noes	
<u3	:-c	:-@	Iatb	liek*		f.m.l	p/oed	
	:c	(:(	Iight	lik		farg	poed	
	O.o	:-<	Iigh	lk		fck	ph33r	
	%)	><	Ijdl	lke		fcked	phayl	
	%-)	://	Ili	llc		fckin	phail	
	(@_@)		Ilml	llf		fcking	r8p	
						feck		
						fk		

Appendix B
Raw Data Panel Plots and Features Comparison Table

Table B.1

Raw score values for descriptive mood profile features from Self-Report and Twitter positive and negative mood data.

Feature	**Participant 1**		**Participant 2**		**Participant 3**		**Participant 4**		**Participant 5**	
	SR	Twitter	*SR*	Twitter	*SR*	Twitter	*SR*	Twitter	*SR*	Twitter
Observations	n = 27	n = 9	n = 22	n = 12	n = 29	n = 28	n = 26	n = 26	n = 30	n = 14
Positive Mood										
Average	1.89	.02	0.95	.04	2.21	.07	2.58	.03	1.93	.01
iSD	0.32	.02	0.95	.04	0.73	.05	0.58	.03	0.91	.02
Instability	0.21	.001	1.38	.002	0.50	.004	0.49	.002	0.93	< .001
PAC	.19	.00	.28	.09	.04	.11	.04	.12	.10	.15
Negative Mood										
Average	.37	.07	2.41	.04	0.28	.03	0.08	.09	0.87	.05
iSD	.74	.07	1.18	.04	0.53	.03	0.27	.05	0.86	.06
Instability	.77	.01	2.51	.001	0.57	.002	0.13	.01	1.24	.004
PAC	.08	.13	.17	.09	.07	.11	.12	.08	.14	.15

Note: Self-report mood absolute range from 0 to 4; Twitter emotion word proportions absolute range from 0 to 1.

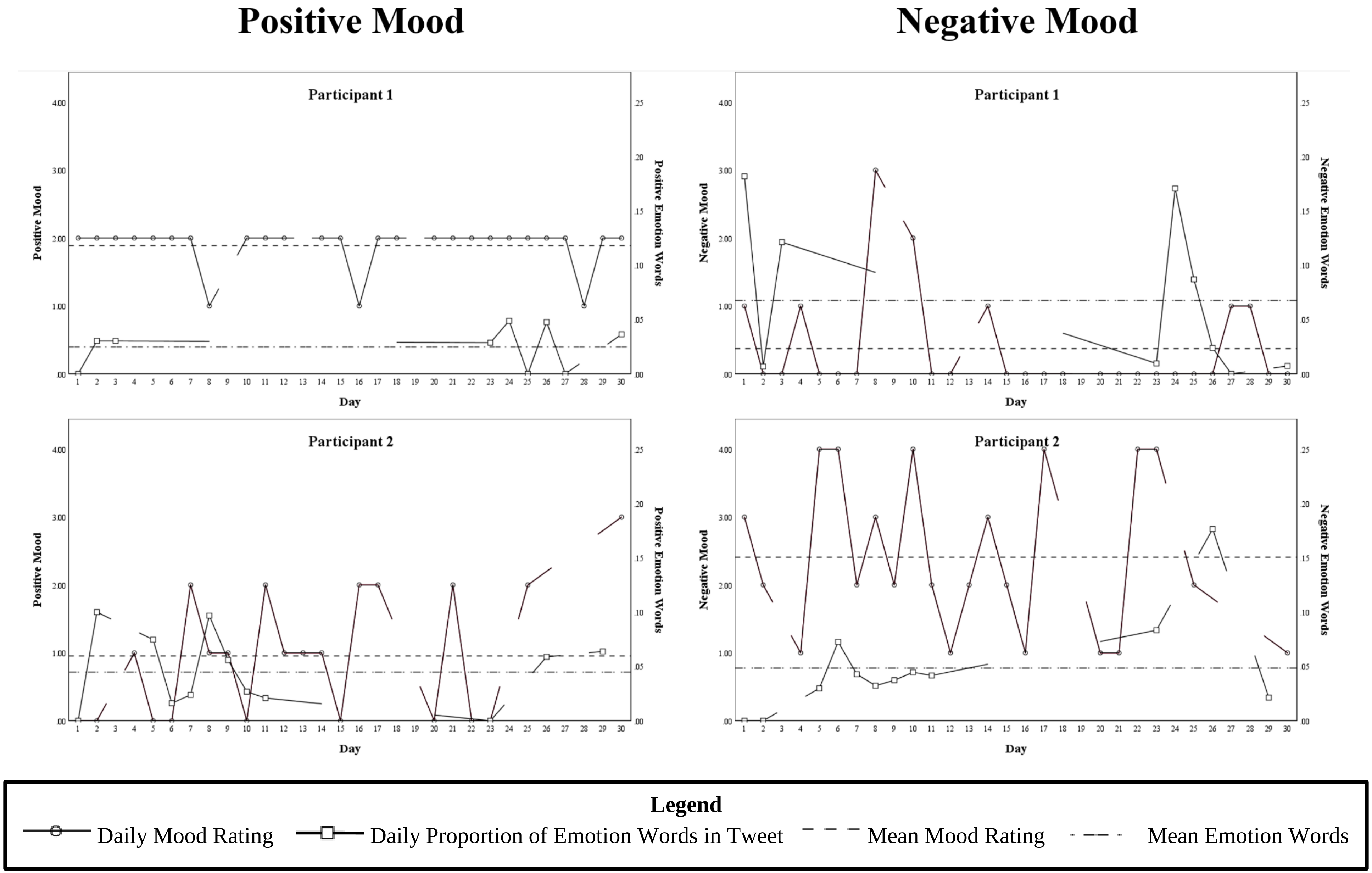
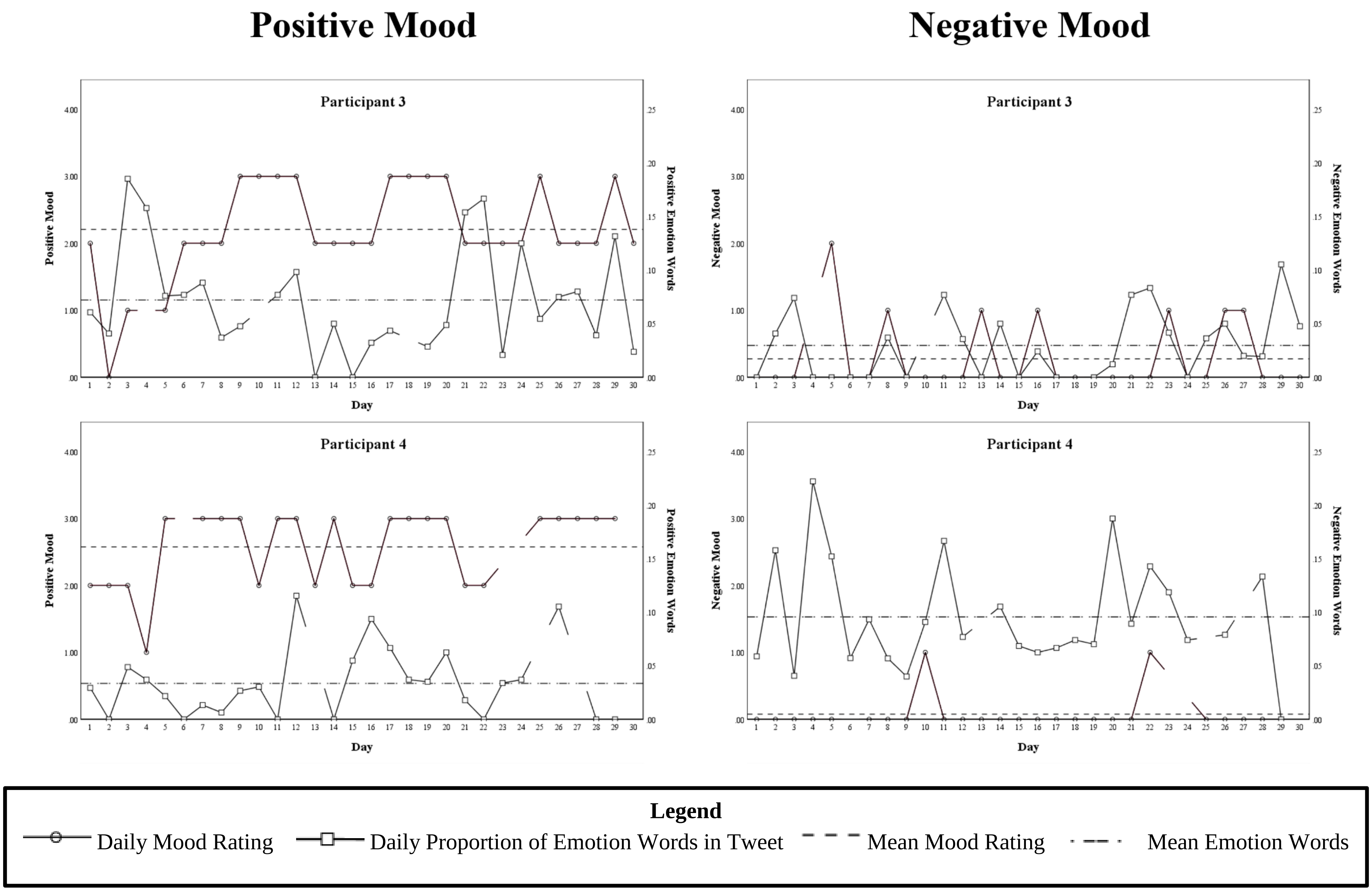
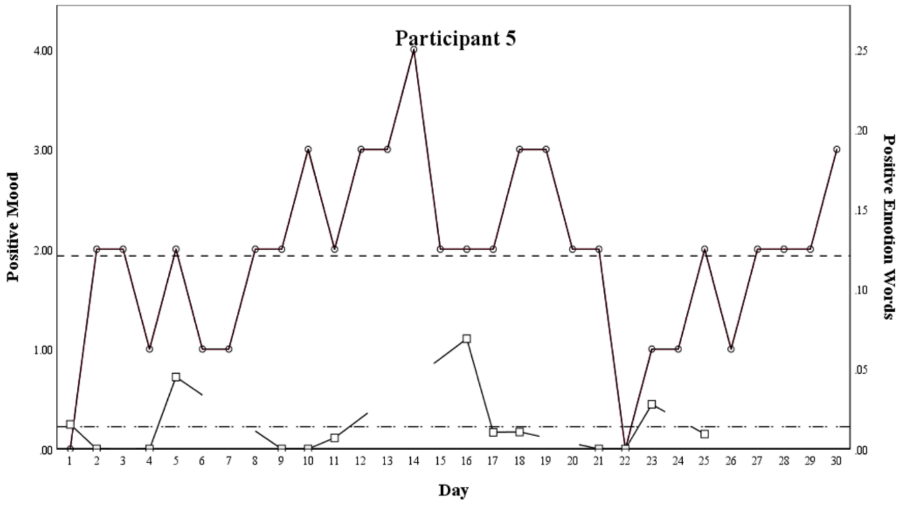


Figure B.1. Raw score dual axis plots of self-reported daily mood and daily emotion words in Tweets across the 30-day study.

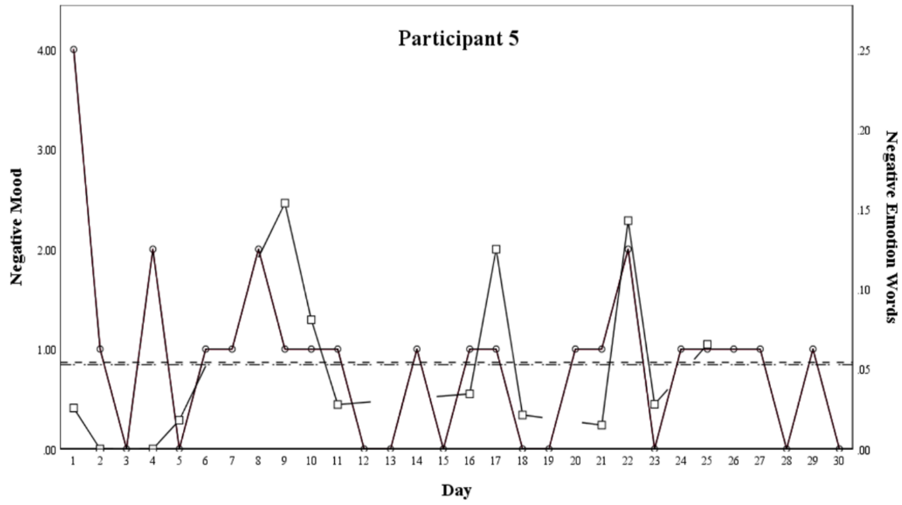


B.1. continued. Raw score dual axis plots of self-reported daily mood and daily emotion words in Tweets across the 30-day study.

Positive Mood



Negative Mood



Legend

Daily Mood Rating — Daily Proportion of Emotion Words in Tweet — Mean Mood Rating — Mean Emotion Words

B.1. continued. Raw score dual axis plots of self-reported daily mood and daily emotion words in Tweets across the 30-day study.

5.3 Concluding Remarks

This chapter presented the self-report and Twitter data from five participants over a 30-day period of using *MoodPrism*. It demonstrated that for these participants, there was considerable inconsistency between their self-reported daily mood and the emotion they expressed on Twitter. Greater depression severity may influence the extent to which self-report and Twitter mood profiles converge, with the cognitive and emotional aspects of depression becoming more salient in Tweets than other confounding factors. In the following chapter, the findings of this thesis are summarised, and an integrated discussion provided.

Chapter 6

General Discussion

6.0 Introduction

This final chapter provides an integrated discussion of the findings presented in the previous chapters. It begins with an overview of the broad research aims, followed by a summary of the key findings and contributions from each of the three studies. The key contributions from each paper are then discussed together and integrated with theory and previous research. Strengths, limitations and implications of the research are presented, including practical recommendations for social media users and providers, clinicians, and researchers. Directions for future research are identified, followed by concluding remarks.

6.1 Summary of the Main Findings

This thesis set out to explore the use of emotion language on social networking sites and its association with depression. To achieve this objective, three studies were conducted. Investigation began with a broad lens encompassing depression, anxiety, and well-being in a systematic review seeking to identify the social media behaviours that were linked to mental health in previous research. Following this review, the scope of the remaining papers was narrowed to focus on depression and the content and tone of social media disclosures to address gaps identified in this literature. Critically, both experimental papers introduced the use of time-sensitive observations of emotion variability identified in social media user's language.

6.1.1 Systematic review of the literature.

The first paper presented in this thesis was a systematic review of the literature. The aim of the systematic review was to integrate the findings related to depression and anxiety across social media platforms. As social networking sites are inherently complex environments, the review also aimed to examine potential mediators and moderators between social networking site use and depression and anxiety. It also explored how well-being has been integrated into the existing research as a part of presenting a balanced view of the impact that social networking site use may have across the dual continuum of mental health. This systematic review also held the purpose of contextualising the development of research questions for the remaining studies presented in this thesis.

Due to the broad focus of the systematic review presented here, the understanding of social networking sites, and their intersection with mental health, has been significantly extended from that of previous reviews that had predominantly focused on adolescents and young people (e.g., Best, Manktelow, & Taylor, 2014; Spies Shapiro & Margolin, 2014) or on a single social networking site platform (e.g**.** Wilson, Gosling, & Graham, 2012)**.** There was also a growing need for a systematic review dedicated to the examination of high prevalence disorders, such as depression and anxiety. This need is highlighted by the simultaneous publication of another systematic literature review examining the association between social networking sites and depression by Baker and Algorta (2016).

The systematic review presented in Chapter 2 returned 70 studies meeting the selection criteria and addressed the following themes: frequency of social networking site use, size and structure of social networking sites, language features and observable social networking site activities, self-disclosure and expression, quality of interactions, social support, social connectivity, social comparison, addictive and problematic behaviours, and physiological associations. Overall the findings from studies within these themes revealed both protective and risk factors for depression and anxiety. The inclusion of both depression and anxiety also highlighted potential differences in the behavioural patterns of social networking site users; predominantly, differences in the way individuals used social networking sites (passively or actively) and in the interactional style with which individuals communicated with peers. Some of the most consistent associations between depression and social networking site use were in relation to the content and tone of status updates; although, there was little evidence to suggest status update content was also linked to detecting anxiety. Other features, such as the size of an online social network and the overall time spent on social networking sites, were less informative of depression and anxiety. Importantly, cognitive aspects, personality, gender, and age were frequently revealed to have moderating or mediating influences on the relationships between social networking site use and depression or anxiety. Therefore, the consideration of individual differences is an important area for future research about social networking site use.

Several gaps in previous research were identified in the systematic review and guided the empirical investigation of Chapters 4 and 5. First, there was a clear sampling bias in the literature where most samples consisted of young people (adolescents to university aged). In the context of an ever-evolving social networking site landscape, both in terms of platform popularity and the types of individuals that that use them (Greenwood, Perrin, & Duggan, 2016), it becomes increasingly important to sample individuals from a wide range of backgrounds to better represent the population of SNS users and the likely changes in usership over time in the online environment. Further, the majority of studies only considered Facebook as the SNS platform for investigation. This limits the generalisability of findings, specifically in relation to understanding the social networking site specific mechanisms relevant to the mental health. Tufekci (2014) discussed this limitation in the context of big data research on social media, with Twitter as a model organism. There are SNS platform-specific interactions and characteristics (e.g., retweets, friending versus following) which attract particular users as well as enable specific patterns of behaviour that may not transfer across different SNS services. Therefore, multi-platform comparisons are needed to reduce *mechanisms bias* and inform how results from different SNS platforms are interpreted (Tufekci, 2014).

Additionally, across the literature there has been an overreliance on the use of self-reported estimates of social media behaviour. As with most self-report methods, sampling retrospective accounts of behaviour may provide inaccurate measures thus threatens the validity of the conclusions that can be made (Trull & Ebner-Priemer, 2009). The potential for retrospective sampling to bias results was demonstrated by Steers, Wickham, and Acitelli (2014) where the association between the frequency of SNS use and depression was assessed by retrospective survey (Study 1) and by daily ESM diaries (Study 2) and findings differed by method (Study 1: positive association; Study 2: no association). While ESM approaches to estimating SNS behaviour increase the precision of recall (Steers et al., 2014; Trull & Ebner-Priemer, 2009), directly sampling SNS data further addresses retrospective biases by taking advantage of observing the digital record of a participants SNS use. From a practical standpoint, building understanding of mental health directly from social networking site data also has the major advantage of providing both (1) an unobtrusive method of data collection from participants and (2) a potential method of intervention or service delivery to social networking site users.

Finally, while not explicitly considered within the systematic review paper there are other unexplored factors that could be important. It became apparent that among the studies directly sampling social networking site data, few studies utilised the time-structured nature of observations to explore behavioural patterns across time at the individual level. While some studies have included cross-sectional follow ups (T1 and T2) (e.g., Davila et al., 2012; Feinstein et al., 2013; Kross et al., 2013; Szwedo, Mikami, & Allen, 2011), fewer have incorporated experience sampling methods or direct observation that included discrete time variables (De Choudhury, Gamon, Counts, & Horvitz, 2013; Jelenchick, Eickhoff, & Moreno, 2013; Kross et al., 2013). Similarly, few studies have sought to critically examine the features extracted from social networking site data that were associated with depression for their content validity. For example, the use of negative emotion words in status updates was frequently associated with depression, though the accuracy with which these expressions sampled negative mood was unknown.

Taken together, these research gaps were addressed by building social media data collection into the *MoodPrism* app. A paper detailing the development and testing of this app was presented in Appendix A of this thesis and a description of the social media data collection development and testing was presented in Chapter 3. This method of data collection indirectly addressed some of the sampling bias in the literature by drawing from the general population, and addressed the mechanisms bias by including a cross-platform comparison capability. Also, *MoodPrism* allowed the explicit introduction of time variables and the collection of non-social networking site variables (e.g., daily mood reports, demographic characteristics) to explore patterns of social media emotion expression over time and in the context of a complimentary smartphone experience sampling method.

6.1.2 Examination of emotion dynamics is social media posts in relation to a static depression severity index.

Building on the findings of the systematic literature review, Chapter 4 aimed to further explore the content and tone of status updates on Facebook and Twitter and their relationship with depression. This was achieved by incorporating emotion variability and instability as potential predictors of depression severity. The time-ordering of emotion word observations was addressed by exploring patterns of instability over the study recording period. It was hypothesised that negative emotion instability would be positively associated with depression severity on both Facebook and Twitter and that variability features would be more sensitive to depression severity than the average proportion of emotion words alone.

The results of this study revealed two different patterns of association on Facebook and Twitter between the emotion language variables sampled and depression severity. For Facebook users, depression severity was significantly and positively associated with negative emotion word instability. This relationship remained even when controlling for the average proportion and variability of negative words used. In contrast, for Twitter users, there was a negative association between negative emotion word variability and depression severity that was retained when controlling for the average proportion of negative words. The average proportion of positive and negative emotion words used was not associated with depression severity on either Facebook or

Twitter, contrary to hypotheses. Further, posting more frequently (greater average number of posts per day, smaller median time interval between posts) was positively associated with depression severity, but only on Facebook.

Exploratory analyses were also performed to explore potential reasons for the different patterns between Facebook and Twitter in the emotion variability features that were associated with depression. Firstly, there were differences in the overall language patterns used between platforms. Compared to Facebook users, Twitter users expressed a greater average proportion of negative emotion words that was more variable and more unstable. Supplementary analyses also revealed several psychological differences between samples, primarily that participants using Twitter had significantly higher levels of conscientiousness, self-esteem, and social desirability than users of Facebook.

6.1.3 Emotion language expressed on social media and concurrent self-reported emotion: The impact of depression severity.

The final study sought to critically explore the use of emotion language as an indicator of depression severity. This was achieved by looking at the link between the mood expressed on Twitter and the same-day self-reported mood to *MoodPrism*. It compared users' mood data from both sources by considering same-day associations as well as looking at broader patterns of mood over time to probe the validity of using social media language as an indicator of daily mood.

Through the exploratory investigation of individual cases, this study revealed that there was little similarity between self-reported mood and the mood expressed on Twitter at a same-day level and at a broader mood profile level (i.e. average, variability, instability, and acute changes). Data suggested that as depression severity increases, there is greater similarity between self-report and Twitter mood profiles. It could be that for individuals with more severe depression severity, Twitter emotion language may be a more valid and reliable indicator of depression risk by accurately tapping into patterns of negative mood. However, this may also highlight emotion language may not be driven by mood experiences or depression symptoms alone for cases with mild depression. Instead, it may be driven by other third variables, thereby reducing emotion language's reliability in sampling mood and contributing to false-positive depression identification in language-driven depression prediction models.

6.2 Contributions of this Thesis

Bringing together the findings from the systematic review and the two empirical papers, this thesis extends the understanding of the links between the emotion expressed on social media and depression by incorporating an investigation of mood profiles over time and considering this in the context of a complementary experience sampling method. The research presented here specifically sought to explore:

(1) What emotion dynamic features in the mood profiles generated across status updates are associated with depression severity?

and;

(2) Do the emotions expressed on social media through language accurately reflect subjective daily mood?

6.2.1 Mood profile features in status updates predict depression severity.

Examining emotion dynamic features through social media language data is a novel approach developed in this work made much more accessible by smartphone technology. While there are caveats to the use of social media language for inferring mood (discussed below), the work reported in this thesis demonstrated that several indices for examining the mood profile features of language across status updates on social media were useful and illustrated how they might predict depression severity. Beyond looking at the average proportion of emotion language use alone, this research introduced variability, instability, and the proportion of acute change as metrics that may provide additional insights for depression by tapping into emotion processes on social media.

By focusing on the time-sensitive nature of the data collected from Facebook and Twitter, the findings in Chapters 4 and 5 revealed that the way emotion is expressed on social media is not necessarily stable over time (as might be described when taking an average) and, for some individuals, there was a great deal of variation in the way they expressed emotion online. Negative emotion word instability was associated with greater depression severity for Facebook users, consistent with the studies examining emotional instability using self-report and experience sampling methods (Houben, Van Den Noortgate, & Kuppens, 2015). Negative emotion variability was associated with lower depression severity for Twitter users. This pattern contrasted with that found for Facebook users and suggested a more restricted range of negative emotion expression for depressed users of Twitter and highlights the importance of considering cross-platform comparisons due to differences in the communication mechanisms and user demographics (Tufekci, 2014).

Exploring the emotion dynamics of language on social media is challenging due to the heterogeneity in the way people post content overtime. Compared to signal-based experiencing sampling methods which seek to collect data from participants following a signal at specific time-points of within certain time-frames, social media data is irregular as it is event-based (i.e., the posting of a status update) and derived from a natural context (Park et al., 2015; Wheeler & Reis, 1991). Measures such as the MSSD and PAC require even time-intervals between observations to be calculated meaningfully. To account for the unique pattern of posting for each individual and to adjust for the uneven spacing between status updates, a median time-adjustment to the MSSD and PAC (introduced by Jahng, Wood, and Trull, 2008) was applied in the current research. In this context, fluctuations in emotion between language samples were considered in the context of an individual's median posting habit. This is an elegant solution to the irregular nature of social media data to implement and is recommended for consideration in samples where the formal assumptions of time-series analysis cannot be met. The research presented in this thesis demonstrated the application of these temporally-sensitive metrics, adding depth to the use of emotion language from social media as an indicator of depression.

6.2.2 The language-mood gap: Implications for depression prediction from social media content.

A major contribution of this thesis was linking subjective daily reports of mood to the daily aggregate mood expressed on social media, specifically on Twitter. This was primarily addressed in Chapter 5 and revealed a ‘language-mood gap’ for most participants between the 30-day mood profiles obtained in self-report and from Tweets.

Psychological constructivist theories argue emotion experiences are partially constructed and understood through language and that language may also play a role in regulating emotion through reappraisal (Brooks et al., 2017; Lindquist, Gendron, & Satpute, in press; Wood, Lupyan, & Niedenthal, 2016). As indicated in the systematic review presented in Chapter 2, the cognitive processes involved in depression (e.g., negative cognitive biases, rumination) manifest on social media, particularly in the content and tone of status updates, providing the opportunity to observe processes of emotion (dys)regulation over time.

This thesis demonstrated that measures of emotion language variability and instability hold important information about depression by potentially sampling emotion processes over time, like heightened reactivity to events or alternatively a restricted range of emotional experiences (discussed in Chapter 4). However, the patterns of emotion expression on Twitter did not clearly reflect the patterns of self-reported mood in Chapter 5. This could indicate that the emotion language expressed on social media is not sensitive to the fluctuations of daily mood, where expressions of emotion on social media are amplified or dulled in relation to lived experiences by other third variables such as personality (i.e. its impact on expressive online behaviours and as factors that may constitute emotional traits [extraversion, neuroticism]; Park et al., 2015). This is important in the context of emotion response coherence, in that behavioural and experiential emotion are impacted upon contextual and personal factors that may distort the similarities between signals (Mauss et al., 2005).

The different patterns in mood profile features between self-report and Twitter may also reflect a key difference in the nature of emotion information that is sampled from the two methods. In the daily mood reports, participants were asked to respond to how they were currently feeling in the moment which is designed to capture emotion-episodes and reduce recall bias (Robinson & Clore, 2002). In contrast to the brief responses provided to *MoodPrism*, expressing emotion on social media is not necessarily temporally bound to the time of the post; it may refer to an event earlier in the day, providing time for social media users to reflect and reconstruct their experiences over time (Park et al., 2017). Writing and editing a status update may perform an emotion regulatory role similar to expressive writing interventions where writing about an experience aids cognitive processing (Baikie & Wilhelm, 2005; Baker & Moore, 2008; Pennebaker, 1997). Rather than sampling emotion in-the-moment, the emotion language on social media may sample emotion 'post-regulation', more closely reflecting the additional cognitive processes tied to written emotion expression. These may include rumination or reframing, and in the context of social media may also reflect conscious choices related to constructing status updates as a part of presenting an online identity or catering to specific audiences (Baikie & Wilhelm, 2005; Derks, Fischer, & Bos, 2008; Lin, Tov, & Qiu, 2014; Lindquist et al., in press; Locatelli, Kluwe, & Bryant, 2012; Qiu, Lin, Leung, & Tov, 2012).

As such, there are several differences between posting a status update on social media and communicating emotion to others face to face or in private online messaging (IM). In contrast to IM which are private messages to a small audience, status updates are a one-to-many, may be broadcast (or intended for) close friends, acquaintances, and/or strangers, and may be posted as a part of presenting an ideal online persona (boyd & Ellison, 2007; Ellison & boyd, 2013; Gil-Or, Levi-Belz,

& Turel, 2015; Lin et al., 2014; Seidman, 2013). Positive self-presentation may be enhanced on social media due to the enduring nature of the content posted and potential audience, impacting on the valence of emotion expressed (Gil-Or et al., 2015; Seidman, 2013). Similarly, emotional traits (extraversion and neuroticism) may also influence the average valence expressed on social media, obscuring the emotion expression related to mental health (Park et al., 2015; Winter et al., 2014). Other personality factors like conscientiousness also impact on social media behaviours by predisposing individuals to impulsive online behaviour (low conscientiousness) or highly controlled online expression (high conscientiousness; Baiocco et al., 2017; Hughes, Rowe, Batey, & Lee, 2012). As demonstrated in the Chapter 4 supplementary materials, these individual characteristics differed between our Facebook and Twitter samples and may partially account for the differences in emotion patterns linked to depression. Similarly, the divergent mood signals between Twitter and the *MoodPrism* self-report may be explained through the influence of other characteristics that impact on the use of emotion language in addition to the presence of depressive symptoms.

This highlights two parallel conversations in the literature. On the one hand, research has consistently demonstrated that personality, social media use motivations, gender and age are implicated in the way people use social media and in the relationships social media use have with mental health (Baker & Algorta, 2016; Frost & Rickwood, 2017; Preotiuc-Pietro et al., 2015; Schwartz et al., 2013; Seidman, 2013; Settanni & Marengo, 2015). In the systematic review presented in Chapter 2, these variables emerged as moderators (or mediators) to the relationship between social media use and depression or anxiety. On the other hand, the practical application of predictive techniques to detect mental illness such as depression have predominantly utilised social-media only variables or features (language, time of use, reciprocity, social network structure) (Calvo, Milne, Hussain, & Christensen, 2017; Guntuku, Yaden, Kern, Ungar, & Eichstaedt, 2017). For instance, in a recent integrative review of the research using social media to detect mental illness, only two of the 12 studies reviewed utilised non-social media predictors like age, gender and personality (Guntuku et al., 2017). These studies showed that personality impacts on who might disclose about mental health and that age improves the detection performance for post-traumatic stress disorder and anxiety from among other comorbid conditions health (Benton, Mitchell, & Hovy, 2017; Preotiuc-Pietro et al., 2015). It is clear the integration of non-social media variables is a necessary next step to improve the predictive accuracy of depression status, particularly in reducing the potential for false-positive.

6.3 Practical Implications

The findings of this thesis suggest that the observation of emotion language on social media can be used to predict depression, though further attention should be paid to the time-dependent nature of observations and the additional insights for depression that we can gain through looking at (maladaptive) patterns in emotion language. Individual variability in emotion expression may be a useful discriminator of depression severity for individuals who express similar levels of negative emotion on Facebook. As a tool for detecting depression, social media is a scalable and unobtrusive means of accessing information relevant to monitoring public mental health. At the same time, there are caveats to the use of social media emotion language alone as a means of inferring mental health and addressing the gap between online expression and self-reported experiences of mood may improve the sensitivity and specificity of language models predicting depression.

6.3.1 For Users of Social Media

In Chapter 2, the use of social media was revealed to potentially have both positive and negative impacts on a social media user’s mental health. Rather than clearly being linked to the time spent online, it is likely that the content and tone of interactions on social media play a greater role in depression and anxiety. Similarly, feelings of social media addiction were linked to poorer mental health. Despite these potential negative impacts, much research revealed positive influences of social media use, particularly in reducing loneliness, increasing social connectedness, and providing a forum to receive social support (Berry et al., 2017; Deters & Mehl, 2013; Lee, Noh, &

Koo, 2013; Radovic, Gmelin, Stein, & Miller, 2017). Social media is a place where people seek mental health support through their personal networks and through the formation of online groups (Berry et al., 2017; Naslund et al., 2017). Social support is likely to be readily accessed by those with high social anxiety, but may less clearly perceived by those with depression (Indian & Grieve, 2014; Park et al., 2016). Self-reflection may be a useful tool for social media user who feel it is having a negative impact on their daily functioning and spending some time away from social media may be a good strategy.

6.3.2 For Researchers

It is clear there is complexity in using language as a means of inferring mood and mental health. This thesis has suggested the presence of a language-mood gap that presents a significant challenge for improving the predictive sensitivity and specificity of automatic language-based screening of depression from social media data. Language is not a perfect data source for inferring internal events and there appears to be a need to conduct research establishing the content validity and reliability of the features extracted from social media records as accurate indicators of the psychological constructs they are argued to reflect. This thesis presented a method for approaching this task – an integrated experience sampling method that collects social media data and concurrent self-reported mood.

There are some notable advantages to developing smartphone apps as a means of collecting data for research. They allow researchers to leverage data from existing databases (e.g., Twitter and Facebook) and can be customised to meet specific research goals (Miller, 2012; Rickard, Arjmand, Bakker, & Seabrook, 2016). The advantages for social media research are more pronounced as data collection via a smartphone app can provide *ground truth* data for a range of psychological and demographic characteristics. There are, however, challenges to using a smartphone app for research. Apps are a consumer choice and require researchers to consider engaging and user-friendly interfaces to ensure participant retention, particularly where an app is required to be on the participants smartphone for an extended period of time to collect data. In the context of *MoodPrism* this was achieved by providing engaging daily feedback to users on their mood experiences. Bakker, Kazantzis, Rickwood, and Rickard (2016) provide further discussion on the integration of gamification, simple user interface, and notification in designing smartphone apps for interventions. Further discussion on of the advantages and challenges to designing and implementing a smartphone app for research are presented in Appendix A.

This thesis also suggested that looking at emotion dynamic features expressed through language, in addition to the relative frequency of emotion word use, may improve the ability to discriminate between depressed and non-depressed individuals. Indeed, the cognitive processes involved in emotion dysregulation may be better revealed through social media language as it is likely to reflect emotion post-regulation. In this way, exploring emotion dynamics on social media may be a useful way to tap into daily experiences that may build toward psychopathology. Across Chapters 4 and 5, this thesis demonstrated the use of several metrics for examining emotion dynamic features and how they may be applied to social media language. Further exploration of these metrics may yield useful reference values or pattern identification for social media language for the detection of depression.

6.3.3 For Social Media Providers and Mental Health Services.

The use of social media undoubtedly has an impact on mental health and, by the same token, has the opportunity to improve access to care for those who need it. Social media providers should be wary of the potential negative impacts of their platforms (reviewed in Chapter 2) and work through design to encourage behaviour that may be beneficial for mental health. For example, Facebook’s research team have recently indicated that they are working on ways to increase prosocial interactions that may have positive impacts for user’s well-being and social connectedness (Morris, 2017).

Increased collaboration between social media providers, researchers, and local mental health services are required to develop comprehensive approaches to depression detection (or triage) and the delivery of interventions or resources to those who may benefit from them. A recent example of such a collaboration is between Twitter and ReachOut an – Australian youth e-mental health support service – who developed online resources to support young people in navigating distressing social media discussions (ReachOut, 2017). Recommendations included reflecting on the impact online discussions were having and encouraging youth to learn to take a break from social media when it was having a persistent negative impact (ReachOut, 2017).

The research in this thesis highlighted several behaviour patterns that are likely to be uniquely associated with depression. Researchers developing predictive models for depression may wish to integrate these tools with local community resources or online interventions (as above) and collaborate with social media providers to deliver this content through push notifications, targeted advertising, or alerts. Indeed, recent findings have indicated that individuals who self-identify with mental illness would be open to the delivery of these approaches via social media (Naslund et al., 2017). Such an approach may be even more impactful for those who are low in help-seeking behaviour or alternatively are little insight into their distress. While key discussions are required around the ethical considerations of using social media data to infer mental health status and how to best obtain social media users informed consent, such collaborations provide the opportunity to apply research and community resources in detecting previously undetected cases of depression, and deliver interventions at an early stage **(**Guntuku et al., 2017).

6.4 Strengths and Limitations

In this section the research strengths and limitations of the research are discussed. This section also reflects on the technical considerations of integrating social networking site data with daily experience sampling of self-reported mood.

A major strength of the method presented in this thesis was the ability to integrate multi-platform comparisons and complimentary experience sampling data collection methods with the use of the *MoodPrism* app. As discussed earlier, comparing social media platforms is critical in ensuring the mechanisms specific to each SNS are accounted for in the interpretation of findings (Tufekci, 2014). As shown in Chapter 4, the patterns of emotion expression across Twitter and Facebook differed significantly, as did their associations with depression, and this may have been due to the type of people using the platform and/or the differing communication mechanisms. A similar multi-platform comparison was not performed in Chapter 5 as there were no participants within the total *MoodPrism* sample who had posted on Facebook concurrently with the completion of the daily mood reports. In our sample, on average Facebook users posted less frequently than Twitter users (see Chapter 4). It suggests the need for an alternate methodology that may better capture Facebook users. This may involve observing Facebook users over a longer time-period (e.g. 12 months) and linking self-report prompt notifications directly to posting activity on Facebook to capture a concurrent mood rating.

The data collection method in this thesis also integrated two methods of ecological momentary assessment of mood, one from signal-dependent self-report (that is, the daily mood reports) and the other from event-contingent sampling (that is, Tweets). These complementary methods collected data in real-time in a minimally intrusive way and allowed the incorporation of temporal features in analysis. This methodology also revealed potential reliability and validity issues in inferring mood from social media content by providing a comparative concurrent external criterion or "ground truth", which had not yet been addressed in other research. While both EMA methods contain their own limitations, Tufecki (2014) suggests that such multi-method approaches generate "richer answers" to research questions on social media.

Despite the benefits provided by the methodology used in this thesis, as highlighted in Chapters 4 and 5, a major limitation of this research was sample size. An original research plan had the intention to incorporate and control for third variables consistently across the analyses (personality, gender, age, social desirability, significant life events), however, the sample size obtained meeting the research inclusion criteria did not make this feasible. There are several potential reasons a larger sample size was not achieved, which are important for researchers embarking on work in this area are advised to be aware:

1) *Trust and Privacy.* While incorporating social media data collection into *MoodPrism* had several strengths, it may have also impacted on participation. Firstly, due to the potentially detailed nature of the information collected from Facebook and Twitter, as well as from *MoodPrism*, it is likely participants may have had concerns around privacy. This was highlighted in focus groups testing the beta version of *MoodPrism* where "trust" in the app was identified as a barrier to contributing social media data (see Appendix A). While changes to the opt-in procedure were made to improve the information around contributing social media data and to provide additional opportunities to opt-in after developing trust in the app, time constraints prohibited the evaluation of if these changes had addressed participant's "trust" concerns and increased their likelihood to opt-in.

The overall sample size in this research may have been increased by making the contribution of social media data compulsory to the study, however, the opt-in procedure was deemed important to increase participant autonomy, provide opportunities to better understand the purpose of each component of the broader *MoodPrism* project (informed consent), and reduce the likelihood of a sampling bias to the broader project by potentially restricting the sample to only those with social media accounts who were also willing to share that data.

2) *Attrition*. While *MoodPrism* was a minimally obtrusive method of data collection, there were approximately 45 minutes of surveys to complete after download and this was followed by the 30-day daily mood report procedure. This may have been burdensome for participants and resulted in a steep attrition rate at the outset of the study impacting on the social media and individual

characteristics data collection for Chapters 4 and 5. This time-cost for participants was unavoidable in the context of the broader *MoodPrism* project, however, future research may overcome this limitation by presenting a limited quantity of brief baseline surveys. Figure 1 shows the compliance rates of social media opt-in and social media opt-out participants across 30 days of *MoodPrism* use from download to the completion of the follow-up surveys. The participants who opted-in to contribute social media data are presented in dark grey. It is important to note here that the social media opt-in participants may have been excluded from analyses due to other criteria in Chapters 4 and 5 and do not necessarily represent final sample sizes.

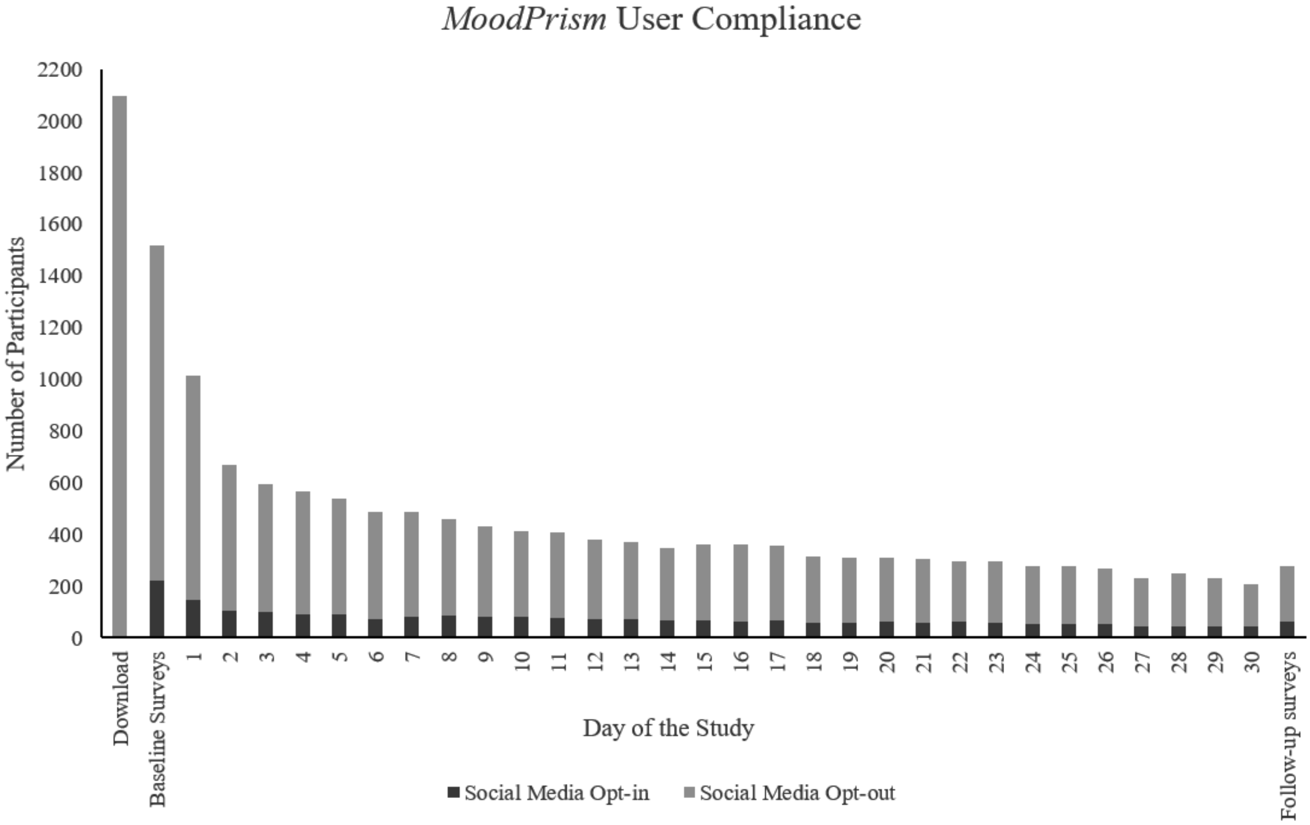


Figure 1. The *MoodPrism* compliance curve across the 30-day study. Social media opt-in users are shown in dark grey and those who opted-out are shown in light grey.

3) *Technical Issues.* During the *MoodPrism* study participants contacted the research team reporting technical issues such as app crashes and not receiving push notifications to complete the daily mood reports (this was an iOS only error). In the backend database timestamp recording errors were also evident for the daily mood reports. While these issues were resolved promptly, data could

not be recovered in cases where a participant had uninstalled *MoodPrism*. Researchers or clinicians seeking to implement mobile ESMs should be wary and responsive to such technical issues. In many cases, this may require an ongoing relationship with an app developer with the technical expertise to resolve bugs in a timely manner. Some of these issues are discussed in more detail in Appendix A.

More broadly, there were several limitations in only looking at the emotion language expressed on social media. First, as the content of social media status updates were not collected we were unable to manually code status updates to ensure the emotion word counts reflected the sentiment in the text. For example, negation and sarcasm often reverse the emotional meaning of a sentence, despite the presence of the opposite emotion word (Hogenboom, Van Iterson, Heerschop, Frasincar, & Kaymak, 2011). This likely would have contributed to false-positive emotion word counts within either the positive or negative emotion categories.

Second, the proportion of emotion words in a status update was used to infer emotion intensity, in that greater values reflected more negative or positive emotion compared to smaller values. As highlighted in Chapter 4, this may be particularly problematic in relation to cross-platform comparisons as the upper-bound on the total number of words expressed may be restricted (as in the case of Twitter), or expansive (as in the case of Facebook), thereby impacting of the proportion of emotion words obtained from each platform. Further, some emotion words may indicate greater intensity than others, for example “bad” may be low intensity and “horrible” may be high intensity. In this research, we used a polarity-based approach (positive or negative) where all emotion words were weighted equally. Valence-based approaches though weighting words to better reflect the intensity of the emotion may have added nuance to the size of emotion fluctuations between status updates (Hutto & Gilbert, 2014).

Third, this research had a narrow scope by only focusing on the emotion language defined by the *LIWC 2007*. Other word categories, such as the use of personal pronouns are also informative to depression as indicators of cognitive processes indicating excessive self-focus (Brockmeyer et al., 2015; Rude, Gortner, & Pennebaker, 2004). Discrete emotions categories, such as sadness and anger, may also increase the granularity in observing emotion processes over time and has previously been shown to differentiate between depressed, anxious, and stressed individuals of different age groups (Settanni & Marengo, 2015). The research presented here only selected those with more than 10 status updates and was therefore not representative of all social media users. Many people use social media in a passive way (i.e. scrolling through the newsfeed) and periods of online social withdrawal may also be informative of depression (Shaw, Timpano, Tran, & Joormann, 2015). This limitation is also true of other language only approaches to examining depression status and highlights the importance of incorporating other observable social media features in prediction models.

Finally, social media is inherently a social environment that encompasses many complex interpersonal interactions that may impact on emotion and more broadly on mental health. Some of these risk and protective factors were outlined in Chapter 2 and it is a limitation of this thesis that these factors were not explored in the experimental chapters. They are, however, important targets for further research, particularly in building a more comprehensive understanding of how personal characteristics, social interaction, and mental health all combine to define the emotion language used on social media and how, in turn, that data may be utilised as a tool for depression detection.

6.5 Future Research Directions

Considering the importance of time-sensitive observations highlighted in this thesis, a clear avenue for future research will be in the formal time series modelling of emotion expression on social media over time. Both variability and instability may be useful predictors of depression and be more sensitive to depression status than taking averages over time. Future research may wish to establish meaningful cut-off values for variability and instability on both Facebook and Twitter that indicate increased depression risk. Time series analysis will be particularly valuable if considered in the context of a complementary experience sampling method (as presented in Chapter 5). While time series modelling of social media data is complex due to its irregular nature, this thesis presented some simple solutions to analysing the time features in social media data (i.e., median timeframe adjustments suggested by Jahng et al., 2008). More sophisticated methods may be applicable in larger datasets (e.g. Gaussian kernels; Rehfeld, Marwan, Heitzig, & Kurths, 2011, autoregressive models; see de Haan-Rietdijk et al., 2017 for a review of methods) that will increase analytic depth and power with which significant and meaningful associations between social media data and external emotion criterions can be detected.

Cross-lagged analyses were not performed here due to data quality (i.e., missing time stamps) and quantity, though including such analyses in future research would provide valuable insights into the potential drivers of emotion language use on social media. While the findings presented in Chapter 5 did not indicate significant associations between same-day self-reported mood and the mood expressed on Twitter, it is possible that lagged relationships may exist. For example, for some the use of emotion language on social media may be in response to significant external events, where subjective mood predicts the use of emotion language at a later point. For others, the emotion expressed on social media may predict subjective mood at a later point, potentially through processes of rumination, or contagion (Coviello et al., 2014; Davila et al., 2012; Kramer, 2012). Improving the time-specificity of observations (exact timestamps, rather than at a daily level) may also better reveal connections between subjective mood and the mood expressed across language samples on social media.

A further important inclusion for future research is the integration of individual characteristics as moderators of language, communication style, and broader social media use. As discussed above, it is likely that predictive language models for depression are working well for those with severe depression severity as fewer third variables obscure the expression on mood or depression symptoms in language. Research has previously inferred age, gender and personality from social media text and controlled for these characteristics when predicting self-identified (that is, disclosed in a social media post) depression or post-traumatic stress disorder (Preotiuc-Pietro et al., 2015). This revealed a substantial overlap between the language associated with demographic characteristics and the language that was predictive of depression or PTSD, highlighting the importance of considering these characteristics as contributors to the emotion patterns visible in the language on social media. Including characteristics known to be associated with emotion expression like personality, gender and age (Deng, Chang, Yang, Huo, & Zhou, 2016; Löckenhoff, Costa, & Lane, 2008; Park et al., 2015) will contribute a more nuanced understanding of language used by individuals without depression symptoms, particularly in describing individuals who express emotion language in a way that is similar to that associated with depression status (i.e., high levels of negative emotion word use). This was highlighted in the case studies in Chapter 5 where participants without depression were expressing negative emotion words in a way that might indicate experiences of persistent low mood (see Participant 4). From a preventative perspective, accounting for individual characteristics may assist in revealing patterns of language use that signal depression onset or risk in a manner tailored to the individual, potentially decreasing false positive or negative identifications of depression from social media content.

6.6 Concluding Remarks

The primary aim of this research was to explore the association between depression levels and emotion expressed on social media, and to apply metrics that may be informative for depression identification and prediction. It sought to strengthen the understanding of the language features predictive of depression by incorporating time-sensitive observations of emotion word variability to better describe patterns of mood change over time. Importantly, this thesis linked social media data with self-report experience sampling via a novel smartphone methodology to critically examine how well the emotion language expressed on social media reflects experienced mood. The studies presented here suggest that examining the dynamics of emotion word expression on social media may provide additional and sensitive insights into the presence of depression for social media users. While these metrics are useful for describing emotion patterns over time, it is also clear that social media records do not clearly mirror lived experiences. This has implications for depression detection from social media language, primarily for finding practical ways to reduce the number of false-positive identifications in prediction models.

The link social media use has with mental health is complex and varied. There are both beneficial and detrimental aspects of using social media for depression, and the quality of social media use can provide greater insight into determining mental health outcomes than quantity of social media use alone. Utilising social media derived data to learn about the mental health of social media users is a key step towards developing automated methods of detecting significant depression risk. Taken together, the findings of this thesis have suggested extensions to the language-based models predicting depression by focusing on the patterns of emotion word change over time. The findings also counsel the need for further research to determine the reliability and validity of using social media language as an indicator of the emotion experiences underlying depression.

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Appendices

Appendix A: Development of a Mobile Phone App to Support Self-Monitoring of Emotional Well-Being: A Mental Health Digital Innovation

Development of a Mobile Phone App to Support Self-Monitoring of Emotional Well-Being: A Mental Health Digital Innovation

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Abstract

Background: Emotional well-being is a primary component of mental health and well-being. Monitoring changes in emotional state daily over extended periods is, however, difficult using traditional methodologies. Providing mental health support is also challenging when approximately only 1 in 2 people with mental health issues seek professional help. Mobile phone technology offers a sustainable means of enhancing self-management of emotional well-being.

Objective: This paper aims to describe the development of a mobile phone tool designed to monitor emotional changes in a natural everyday context and in real time.

Methods: This evidence-informed mobile phone app monitors emotional mental health and well-being, and it provides links to mental health organization websites and resources. The app obtains data via self-report psychological questionnaires, experience sampling methodology (ESM), and automated behavioral data collection.

Results: Feedback from 11 individuals (age range 16-52 years; 4 males, 7 females), who tested the app over 30 days, confirmed via survey and focus group methods that the app was functional and usable.

Conclusions: Recommendations for future researchers and developers of mental health apps to be used for research are also presented. The methodology described in this paper offers a powerful tool for a range of potential mental health research studies and provides a valuable standard against which development of future mental health apps should be considered.

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KEYWORDS
eHealth; emotions; mental health; mobile phone; feedback

Introduction

Background

Emotional well-being is broadly defined [1] as, "a positive sense of well-being and an underlying belief in our own and others' dignity and worth" by the Mental Health Foundation (p. 8). Consistent with dual models of well-being, it encompasses both positive functioning (happiness, a sense of control and self-efficacy, and social connectedness) and an absence of stress and depression [2,3]. Monitoring changes in emotional well-being is fundamental to mental health, with increases in emotional well-being associated with resilience, creative thinking, social connectivity, and physical health [4-9]. In contrast, significant and sustained decreases in emotional well-being are associated with the development of affective disorders such as depression and anxiety, and reduced physical health [4,5,7].

Monitoring for such changes is crucial for early detection of mental health problems. Rapid response to early risk indicators is one of the key predictors of better health outcomes, enabling preventative health approaches to be initiated early [10]. Regular monitoring of emotional health indices is therefore recommended by various national guidelines [11,12]. In practice, however, it remains difficult for clinicians or professional mental health service providers to obtain frequent monitoring in real time [13,14]. A priority challenge facing the health care system is to achieve practicable and sustainable means of supporting self-management of health and well-being. Self-monitoring is a particularly attractive goal for mental health care, given that many individuals with mental health needs do not seek professional health care support [15-17]. In addition, self-monitoring may develop an individual's insight into their need to seek help. In particular, young people consistently indicate that they prefer nonprofessional or self-managed strategies for addressing mental health issues [18,19]. Obtaining temporally sensitive (eg, daily) information on significant changes in emotional state has the potential to profoundly improve the capacity to promote emotional health [12].

Experience sampling methodologies (ESMs), or ecological momentary assessments, involve the systematic collection of self-report data from individuals at multiple time points throughout their everyday lives [20]. ESMs have been used to monitor changes in affective state, and to predict mental health with success to a certain extent [21,22]. In particular, the variability in emotional state over time provides more substantial information for understanding the causes and nature of psychopathology than do cross-sectional "snapshot" assessments. For example, when sampled multiple times a day for 6 days, negative affect was found to vary more in patients diagnosed with major depressive disorder than that in controls across the day [23]. ESM assessments in individuals diagnosed with panic disorder also revealed that the expectation of a panic attack was a significant precursor for the occurrence of a panic attack [24]. Ben-Zeev et al [25] also found that patients diagnosed with a major depressive disorder retrospectively reported higher levels of symptoms relating to anhedonia, suicidality, and sadness than captured in their ESM reports, highlighting the biases of traditional survey methods. To date, however, it has been methodologically difficult and obtrusive to obtain temporally regular and precise measures of emotional state [21]. The resources required to obtain such information repeatedly over lengthy time frames have made such an intensive monitoring prohibitive. In addition, the use of palm pilots and pagers (which were never as familiar to users as mobile phones have become) to prompt users for this information can be intrusive, and makes it less likely that users will continue to use this form of monitoring for extended periods [26].

Mobile phone technology offers an unprecedented opportunity to unobtrusively track everyday behavior and changes in emotional state, all in real time [27,28]. Mobile phone health tools also offer the potential of immediate response to the outcome of this monitoring via delivery of mental health information contingent on changes in real-time emotional state [29]. This technology has not yet been fully leveraged for these purposes, despite mobile phones being one of the few pieces of technology that most people carry on their person every day [30]. This pervasiveness means that mobile phones offer a highly natural and regular means by which information on emotional state could be obtained. Mobile phones now penetrate 77%, 72%, and 68% of the Australian, US, and UK population, respectively [31], and are a cost-effective means of seeking help for mental health issues that may overcome socioeconomic and geographic boundaries [32,33].

Mobile phone health technology holds great potential for facilitating the management of emotional health through its ability to deliver flexible, user-oriented intervention and self-management tools; a feature particularly relevant for young people who often report fear of stigma associated with seeking professional services for sensitive mental health issues [34,35]. In a 2010 study, 76% of an Australian sample reported being interested in using mobile phones to monitor and manage their own mental health [32]. A large number of mobile phone apps are currently available that claim to promote mental health and well-being [36,37] and a subset of these also attempt to track mood or emotional state over time. However, empirical support for the efficacy of these apps is extremely limited [36]. For instance, in a systematic review of 5464 mental health app abstracts, less than 5 apps were found to have experimental evidence [37]. In addition, a few have capitalized on the benefits enabled by the mobile phone technology such as experience sampling and automated data collection in identifying and evaluating potential time-sensitive behavioral indicators of mental health change [36].

Of the mobile phone mental health programs that have utilized ESM to track mood over time, several favorable outcomes have been reported. For example, Reid et al [28,38] found that the majority of their adolescent sample using the mobile phone-based mental health app, *mobiletype*, completed their self-assessments, and that the use of the app increased the practitioners' understanding of their patients' mental health. Harrison et al [29] reported that the use of the mobile phone accessed Web-based cognitive behavioral therapy (CBT) course *MyCompass* for 6 weeks significantly reduced symptoms of depression and anxiety and improved self-efficacy. One of the barriers to sustainability of user engagement in such programs, however, is that they require extensive voluntary input from the user. When evaluated, a common theme is initial compliance, followed by high dropout and poor self-reporting rates (eg, less than 10% of the sample trialing *MyCompass* reported using it every day) [29]. Reasons for discontinued use include problems understanding how to use the program, invasiveness of the questions, the need for repetitive completion of questionnaires, insufficient personalization of the mental health advice, and little motivation to engage with the program [28,29].

An innovative way to meet this challenge is to monitor indices of emotional health using methods that require minimal insight or subjective report from the user. Mobile phones contain a range of embedded sensors and features, including accelerometers and global positioning systems and apps, which can automatically record information about a user's behavior [39]. Two recent studies have obtained a combination of data from mobile phones in an attempt to predict participants' self-reported mood. LiKamWa et al [40] found that up to 93% of mood scores were accurately predicted by social activity, physical activity, and general mobile phone use data collected from mobile phones. Asselbergs et al [41] attempted to predict self-reported mood of 27 participants from metadata of 6 mobile phone indices (phone calls, text messages, screen time, app usage, accelerometer, and phone camera events). Although the accuracy of the models was no greater than models obtained without mobile phone data, the methodology was demonstrated to be technically feasible and to hold promise. The authors recommended that inclusion of more meaningful or relevant features from mobile phone data may be the key to improving prediction.

Interestingly, young people use mobile phones for music listening, fitness, and social networking more than any other demographic [42], and these are among the most effective strategies for optimizing emotional health [43-46]. For example, the frequency of app-switching and the content of social network messages were found to predict depression [43] even prior to its onset [47]. Music listening patterns also appear to predict emotional health [48-50] and given that approximately two thirds of music listening by young people is via mobile devices such as mobile phones [31], it is surprising that relatively few apps have attempted to use music for this purpose [27]. Vocal expression too has been found to be a useful index of emotional state [51,52]. Short voice samples have been found to demonstrate 70% accuracy for simple affect recognition [53]. Monitoring a combination of behavioral indices such as physical activity, online social interactions, and music choices therefore offers a promising means of nonintrusive but sensitive assessment of affective state. Advances in statistical methods available through machine learning also enable powerful analysis of this more complex level of individualized multilevel modeling [52,54].

Another limitation of most mental health apps currently available is that they tend to simplify the emotional well-being spectrum, with positive and negative affect anchors on a unidimensional rating scale. Contemporary conceptualizations of well-being however clearly show that optimal "emotional health and well-being" does not emerge from an absence of affective disorder alone, but also requires a state of positive functioning [2,55,56]. Although positive and negative emotional functioning are correlated, there is substantial evidence that they are orthogonal constructs [57]. Mobile phone technology that differentiates the quadrants created by categorizing according to mental illness or languishing and mental health or flourishing [3,55] is therefore encouraged.

Objective

In this paper, we capitalized on the extraordinary role that mobile phones play in people's lives to develop a tool that has the potential to significantly extend the understanding of emotional health and well-being. The aim of this paper was to describe the design of the mobile phone app, *MoodPrism*, which was developed to monitor emotional well-being in context and in real time, and provide personalized feedback on the full spectrum of emotional well-being. The paper describes in detail the design and data collection functions of the app, which were incorporated to address major challenges for mental health research and practice, and presents feedback from a small sample of trial users (beta-testers), which tested the functionality and usability of the app.

Methods

Design and Development of the App

MoodPrism was designed and developed in collaboration with a commercial digital creation studio, Two Bulls (Melbourne, Australia). The app was prepared for both the iOS and Android mobile phone platforms and was distributed by the Web-based Apple and Google Play stores, respectively. The term "*MoodPrism*" was selected to reflect its primary purpose of collecting emotional state data across the entire spectrum of emotional health and well-being and converting this into an array of color-coded feedback to the user.

The development of *MoodPrism* involved designing 3 different methods of data collection within the software: (1) automated monitoring of selected online behavior, (2) experience sampling of emotional well-being self-reports, and (3) psychological assessment questionnaires. automated monitoring of selected online behavior, experience sampling of emotional well-being self-reports, and psychological assessment questionnaires. This triangulation of data collection is considered crucial for advancing the measurement of emotional state [58]. As part of the sign-up procedure to the app, permissions for sensitive data had to be obtained. Incentives to continue collecting data over an extended period were also generated.

The development of *MoodPrism* was completed in March 2015. The required forms of data collection were achieved by developing a suite of app components, which were then collated into a cohesive app. The outcomes of this development process are described in the following.

Sign Up

As part of the sign-up procedure for the app, options were offered to users to provide the app with access to social networking and music apps as well as general (postcode) location. These data were then collected continuously and without the need for user input over the month's research period. After sign up and consent procedures, *MoodPrism* administered the initial surveys that could be completed in multiple sittings and required 30-60 min in total to complete. The participants were then requested to use the app for at least thirty days, during which they would be prompted daily to answer a set of short questions, and weekly to complete a short audio recording. If they were unable to respond to daily prompts, *MoodPrism* advised they could complete them at a time of their convenience till midnight that day, or alternatively to ignore them. At the end of the 30 days, users were invited to complete a final set of surveys, which in total required 15-30 min to complete.

Users were incentivized to continue using *MoodPrism* through 3 strategies. First, daily mood and mental health feedback was provided to the user, with additional feedback unlocked after sustained use (Multimedia Appendix 2). This promoted engagement by rewarding users and encouraging feelings of achievement, adhering to principles of gamification [59], which is recommended in mental health apps [36]. Second, completion of daily reports as well as the final surveys generated entries into a draw for 1 of the 4 $AU100 (approximately US $75) gift vouchers. Third, users were informed that their data were contributing to research into the value of mobile phone apps for monitoring mental health and well-being.

Automated Monitoring

MoodPrism acted as a portal for data accessed via several mobile phone sensors and apps. Two validated predictors of emotional state change were targeted: music use and web-based social network site activity. As a part of the sign-up process, users were invited to give permission for the app to access Facebook, Twitter, the user's music library, and location (postcode only).

Facebook, Twitter, and music use data were collected once every 24 h, and the information collected is provided in Multimedia Appendix 1. Data were accessed from Facebook and Twitter through their relevant application programming interfaces (APIs). This allows third-party access to selected data collected by both Facebook and Twitter. Facebook and Twitter content was analyzed automatically and locally on the user's phone using several linguistic dictionaries from the Linguistic Inquiry and Word Count (LIWC) [60]. Summaries were obtained for frequencies of emotion words, which were supplemented with a range of emoticons and Internet slang expressions for emotions. Social words and personal pronoun counts were also obtained. A word count for the target categories in the dictionary was extracted and these counts were uploaded to the server. This was repeated every 24 h to collect the posts that occured across the duration of *MoodPrism* use. The post content temporarily stored by *MoodPrism* was then deleted.

Experience Sampling

MoodPrism utilized ESM to deliver a short set of questions to users daily (Figure 1). Prompts were delivered at a quasi-random time between user-defined hours (eg, 9:00 am-9:00 pm) for 30 days.

The questions captured a real-time assessment of the user's emotional well-being, event-related experiences, and their context. Emotional state questions comprised 4 questions on psychological illhealth (depression and anxiety), 4 on emotional state (positive and negative affect, arousal, and control), and 4 on positive functioning (social connection, motivation, meaning, and self-esteem). Positive and negative event-related experiences were assessed by the type of event experienced and a rating of the event's affective strength (from "slightly" to "extremely positive or negative"). The type of event was selected from a range of options drawn from stressor event questionnaires [61-65] and modified as a short list of the most common event domains (eg, school or work, physical health, material possessions, or social experience domain). Context was assessed via 2 questions, 1 for social context (who the user was with at the time of the report) and environmental context (where they were at the time of the report). Specific questions are given in Table 1.

In addition, a weekly prompt was delivered that requested a short voice recording to serve as an implicit measure of emotional state [51,53]. Users were prompted to read a standardized piece of text at the start and the end of the recording, and within that window to describe freely how they were feeling at that time.

Psychological Assessment Questionnaires

A number of questionnaires were available for completion at the onset of the app use, providing baseline measures of emotional well-being as well as data on potential moderators or confounding variables (see Figure 2). These questionnaires were categorized into survey "blocks" and displayed on the *MoodPrism* homescreen until their completion. This served to organize the questionnaires into manageable chunks for users to complete in their own time. A subset of these questionnaires was also delivered at the end of the month-long period to enable assessment of whether the app may have affected the well-being measures. A description of these questionnaires was provided in Table 2.

Figure 1. Screen shots from app showing experience sampling method.

Figure 2. Screenshots showing examples of longer psychological questionnaires.

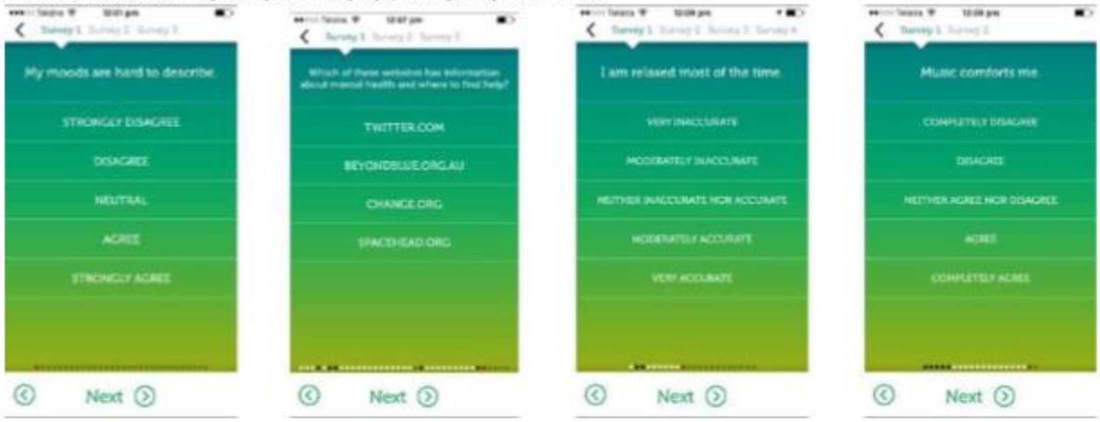


Table 1. Qualitative feedback: questions guiding qualitative feedback forums.

Broad question	Prompts
Was the app easy to use?	**Privacy issues (eg, social networking sites)**
	Was it clear to you why you were providing the information that you did?
	Why did you opt-in or opt-out of connecting your social media accounts? What things would be an incentive to opt-in?
	Can you imagine anyone using the app without incentives?
	Who do you think would benefit from using it?
	Was it clear to you that you were earning entries into a draw to win an iPad? Was it clear how the prize entries were being awarded? Did this consciously motivate you to use the app?
	Were the colors or emoticons used in the mood feedback helpful?
How did you find the daily prompts?	**Did they get in the way at all?**
	Were significant events captured?
	What kind of event did you feel was appropriate to report (major, minor, or both)?
How did you find the feedback?	**Mood feedback**
	Did you notice yourself paying more attention to the way you feel than usual?
	When you started using the app, was it made clear that reporting your mood could improve your mental health and well-being?
	Surveys
	Mental health info or contacts – did you explore any of these? Were they useful?
	Did you ever find the overview upsetting or negative?

Table 2. Sample feedback provided by beta-testers.

Theme	Sample responses
Positive feedback	
Aesthetically pleasant	It looks nice!
Easy to use	Seamless and smooth to use
Daily reports quick to complete	Simple set of responses takes only a few minutes daily – easy to use daily
Feedback useful and specific	Targeted questions give specific feedback about links between mood and daily activities
	Colored display of mood was useful representation [sic]
	Liked unlocking of content - motivated to keep using
	Feedback was not upsetting
Good to be able to get feedback about how feelings change daily	The ease of the app and being able to check in how exactly I'm feeling at a certain time
Negative feedback	
Wording of some questions confusing	Many questions in the introductory questionnaires are confusing double-negative repeats of previous questions, combined with putting negative responses near the top (where you expect positive ones) is confusing.
	I've never been irked when people expressed ideas very different from my own: "Yes or No". Is it possible to put Agree or Disagree instead?
Some content can make you feel negative	Quite morbid things in the list of "most negative thing to happen to you today" -- makes me imagine some pretty terrible rare events like "death of a loved one", etc. -- not a great thing to remind someone with depression to think about on a daily basis. / Many questions are quite negative like this -- you think about how stressed, worried, out of control, etc. you are -- creates a major disincentive to participating -- they're not things you want to dwell on when you're depressed.
Feedback clarity	The summary information for tracking well-being across times seems simplistic. For example, if I was in a good but deactivated mood, it said I was "on my way to thriving" - but of course it's not healthy to be highly activated ALL the time.
	The other thing I thought could be made clearer is what the numbers on the main screen mean - they're all different colors for the different days of the month but not sure what those numbers or colors mean
ESM functionality	There are a couple of categories I felt were missing when logging the things that happened today. On the "who are you with" screen, the option of "partner" would be useful. The "won something" category in the positive events screen was less useful.
	No positive event option for work
Privacy or information issues	Need trust in the app to give permission for social media sharing. So should give permission later on, perhaps after surveys, after built trust in app after some use
	Location information should be clarified to be postcode, not specific GPS point
Installation issues	Hard to download

Feedback

The final design feature of *MoodPrism* was the provision of a range of feedback to the user on their emotional well-being and mental health. This feedback was organized in consultation with the Australian mental health organizations *beyondblue* [66] and headspace [67], research literature on mental health and well-being, and expert advice on currently available mental health apps.

The feedback was available at several stages (see Multimedia Appendix 2):

- On the completion of a survey block, users were provided a summary of their general score on one of the surveys within that block.
- On completion of each daily report, users were provided with a color-coded brief description and custom emoticon representing their emotional state on that day. Weekly and monthly overviews were also available when multiple ESMs were completed.
- On completion of 1 week's worth of ESMs, "positive mental health" data provided individualized feedback (based on their positive health responses), which included links to positive health websites and apps.
- On completion of 2 weeks' worth of ESMs, depression and anxiety data were collated to provide individualized feedback on mental illness risk (based on their PHQ-4 responses). Recommendations and supporting links to mental health websites or contacts were also provided, as well as advice suitable to the user's emotional functioning over the past 2 weeks.

Database Security and Storage

With such extensive and potentially identifiable information being collected by *MoodPrism*, data storage and data security became a major priority. The following considerations were made regarding data storage in adherence with industry and University [68] standards, the *Privacy and Data Protection Act 2014*, and the *Guidelines for Ethical Practice in Psychological Research Online* as outlined by the British Psychological Society [69].

Immediately following the survey collection, data were stored on the user's mobile phone prior to being uploaded encrypted into a secure database every 24 h. All data uploaded from the user's phone was stored on an Amazon Web Services server. This database was protected by a firewall and regularly updated security protocols. The data stored were anonymized at the point of upload. All potentially identifiable information was removed from the data and only the device ID was retained (functioning as a randomly generated participant code). Data were only accessible online by authorized users via Secure Shell (SSH), which authenticates server access with digital certificates and encrypted passwords. All communication between authorized users and the server also occurred through HTTPS. This ensured that all information passed between the server and the researchers was encrypted and cannot be accessed or manipulated by a third party.

With regard to social media data, explicit consent to access Facebook or Twitter accounts ("opt-in") was provided by the user. Their social media credentials were stored locally on the phone but were never uploaded to the server. All Facebook and Twitter posts' content were processed locally in the mobile phone's memory and aggregated word counts were generated. Only the aggregate word count was uploaded to the storage server.

Results

The app was initially tested by both the researchers and the app developers for minor issues and bugs. A small convenience sample of independent, nonclinical users (N=11; age range=16-52 years; 4 males, 7 females) was then recruited to test the app to generate feedback on the functionality and usability of the app to the researchers and app developers. They used *MoodPrism* daily over a 30-day period and kept notes of their user experience. Information about the study was provided to the participants and electronic consent was required before the app could be used.

The test sample was invited to provide more intensive qualitative feedback by either Web-based questionnaire (n=5) or via attendance at a focus group session (n=6). Focus group participants also provided quantitative feedback by completing the Mobile Application Rating Scale (MARS) [70]. The MARS is a multidimensional measure for trialing and rating the quality of mobile phone apps, and has demonstrated interrater reliability and internal consistency. All beta-testers were also invited to discuss or provide emailed notes on their user experience. Broad questions were posed, and prompts were provided where necessary (see Table 1). (No attempt was made to analyze the emotional well-being data from the beta-testers, as the sample was small, and this aim was beyond the scope of the current paper, the primary aim of which was to provide information on the development of the app.)

Themes extracted from the comments provided via the focus group or Web-based feedback are presented in Table 2.

The testing of the app with this sample was approved by the Monash University Human Research Ethics Committee (Approval # CF14/968 – 2014000398). App development was completed in 2015 and tested over June-July 2015. The app was then revised in response to feedback received and the final version of the app prepared. The app was then released on the Google Play (Android) and Apple (iOS) stores. Future publications will report empirical data from this app, with the scope of the current publication limited to the development process only.

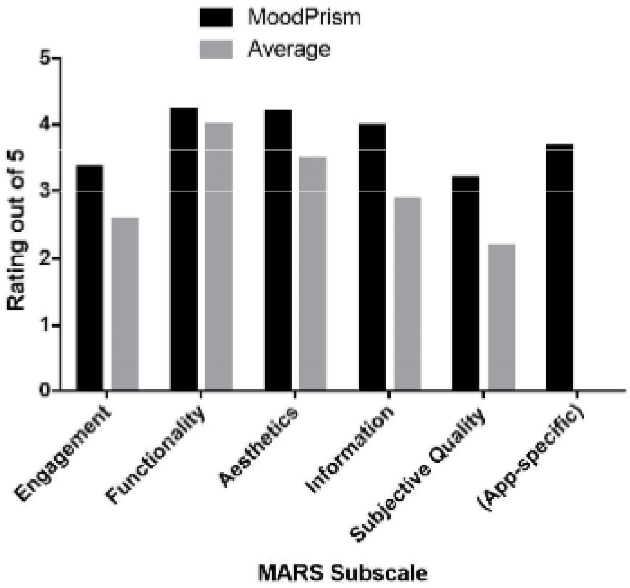
Feedback about the functionality and usability of the app was obtained from 11 beta-testers, who completed a standard survey of app usability, the MARS. The results are presented in Figure 3.

MARS ratings for the *MoodPrism* app exceeded the average rating for 50 apps reviewed by Stoyanov et al [70] for each MARS subscale. Highest satisfaction ratings were obtained for items relating to the app's graphics quality (eg, buttons, icons), gestural design (eg, swipes, scrolls), ease of use (eg, clear menus), credibility of the information sources, the layout aesthetics, and increased awareness of mood. Lowest ratings were obtained for entertainment value (eg, fun to use), customization options, likelihood to change behavior, motivations to address mood and interest, and likelihood to recommend to others.

The results from the focus group sessions and emailed responses from all 11 beta-testers are also summarized in Table 2.

The majority of issues identified by the beta-testers were addressed in the final version of the app. For instance, the order of positively or negatively worded options was made consistent across all questionnaires, additional information on how location and social networking data will be used was provided, with reassurance that information collected was deidentified was added, and an explanatory key was provided for interpreting colors and emoticons. The only issues that were not able to be addressed related to the integrity of psychometrically validated questionnaires (and therefore wording could not be altered), inclusion of negative content (which was important to the primary purpose of the app), or installation difficulties (as they related to the trial version only, and would not be present in the Apple and Android Web-based stores).

Figure 3. Quantitative feedback: beta-tester ratings on the Mobile Application Rating Scale (MARS) subscales (N=11).



Discussion

Principal Findings

In this paper, we demonstrated how mobile phone technology could be harnessed to overcome several challenges in current mental health research and practices. Key needs we aimed to meet by developing this tool included the following: real-time monitoring of emotional functioning, assessing the full spectrum of emotional well-being, confidential access to mental health support and information when required, and to reduce obtrusiveness of regular monitoring.

MoodPrism was developed on both iOS and Android mobile phone platforms as an app to monitor emotional well-being in real time. It achieved this using ESM and collection of behavioral data via mobile phone apps (addressing challenge 1). It included assessment of daily positive psychological functioning (or "flourishing" [55]) in addition to more traditional assessment of negative psychological functioning (depression and anxiety) (addressing challenge 2). *MoodPrism* offered users a range of resources and links to enhance mental health literacy and access to professional mental health support, which vary depending on their current emotional functioning (addressing challenge 3). *MoodPrism* also incorporated voice monitoring, social networking site, and music playlist data collection as the first steps toward less obtrusive monitoring of emotional well-being for extended periods (addressing challenge 4)—although extensive algorithmic modeling will be necessary to achieve this goal. In sum, *MoodPrism* successfully responded to 4 key challenges in the emotional mental health domain. A number of important learnings were also achieved during this project, which may be helpful to outline for future researchers considering developing a mental health app [36].

Considerations When Developing a Research-Based Mental Health App

Development of mental health apps is a relatively young field, and the guidelines to support researchers and app developers are not yet widespread. During the development of *MoodPrism*, a number of key issues were identified that could be helpful to researchers developing apps for mental health research and practice. These issues are briefly outlined in the following and then recommendations for consideration in future research are summarized in Figure 1.

First, it is important to recognize the different priorities of app developers and researchers (and mental health practitioners). For example, the *MoodPrism* researchers' main goals were database integrity, psychometrically sound questionnaires, and ethical administration of sensitive content. The app developers' main goals were an enjoyable user experience, good design, simple user interface, brief page content, and anonymous data storage. Identifying these goals and coming to an agreement on how they should be prioritized could help design an app that optimizes functionality (and therefore will be used by the participants) with integrity (so that the data are suitable for analysis). With *MoodPrism*, the researchers' priority to maintain psychometric properties of questionnaires was in conflict with the app developers' priority for good user interface and design. Administration of long questionnaires was overcome by creating brief checkpoints or "blocks" of surveys to complete, each with a portion of feedback provided as a reward to incentivize completion of long surveys. Similarly, the developers' database priorities were guided by industry standards for data collection and storage. At times, this conflicted with the researchers' need to obtain sufficient details; for example, anonymity of social media posts initially prevented the integrity of coding processes from being verified. Coding solutions were eventually achieved, but considerable delays could have been avoided if the database requirements were thoroughly discussed at the project's outset. When these conflicting priorities were identified, a solution was often achieved that produced the unexpected benefit of optimizing outcomes for both stakeholders. For example, the chunking of questionnaires not only improved the user experience, but also was likely to improve the validity of data as participants were less likely to fatigue, or resort to nonserious responding.

Second, sufficient time should be quarantined at the outset for planning, and at the completion for beta testing and revision. App developers' schedules can overlook the details involved in translating research requirements into the app space, and as a result underestimate the time involved. Database APIs for commercial apps also tend to have simpler output requirements than is often essential for advanced statistical analyses. A failure to identify the more complex necessities of the app's function at the outset can result in over simplistic transition of features into the app, and subsequent delays in revision to meet research needs. Time spent presenting the entire app's contents clearly up front to app developers will help avoid significant delays during development. Time should also be sufficient at the outset for complete storyboarding and wireframing of the app to ensure both parties agree on the app's format and presentation. Aesthetics that work well in commercial apps do not always translate well for research content, which may out of a necessity include lengthier content or inflexible formatting or labeling of items (eg, traditional Likert-type scales in psychological questionnaires). Samples of similar app presentations that are known to work effectively with this type of content should if possible be reviewed and the best features identified. Allowing sufficient time for planning should also ensure that clear milestone dates are set, post which no further changes or additional content can be made by researchers or practitioners until trialing. Ongoing modifications can magnify delays for app developers and confuse versions being delivered. Sufficient time when the app is being finalized is also critical. Users should be allowed a sufficient trial period to allow testing of the app in various contexts, and the schedule should also ensure that they are able to report back both individually, and where possible as a part of group discussion. Focus groups are invaluable for identifying common themes across users, as well as allowing more singular experiences to emerge.

Third, communication among app developers and researchers or practitioners should be managed centrally. A flexible Web-based platform (such as "Basecamp") provides project management tools such as discussion threads, allocation of tasks, a central file repository, and reminders. Progress of tasks should be monitored regularly and updates provided when item check off is delayed. Clear assignment of tasks avoids tasks being overlooked, and ensures accountability.

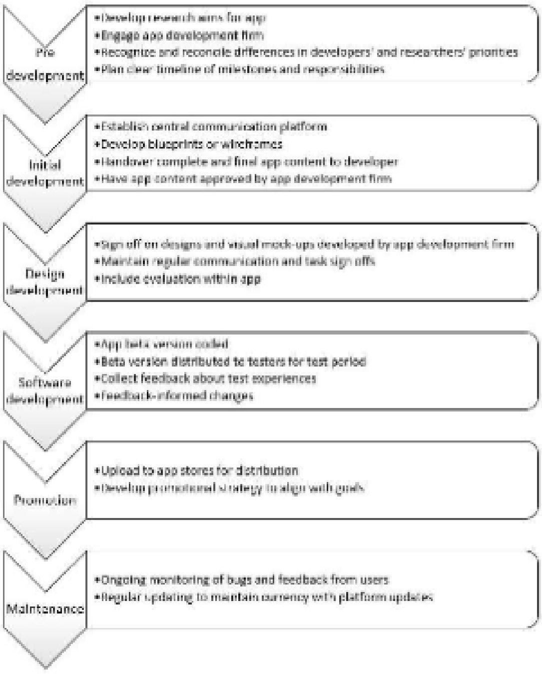
Fourth, methods to evaluate the app should be included within the app itself. Commercial apps can contain simple "thumbs up" or star ratings, but this is unlikely to be sufficiently informative for research or practitioner needs. Importantly, it is helpful to obtain assessments of the various aspects of the app, including commercial considerations such as aesthetics and functionality as well as those of central interest to researchers, such as ethics or trust and integrity. Published app assessment measures such as the MARS for health apps should be considered if possible. This will allow standardization and comparability across apps in the mental health space, and to build integrity and an evidence base for improvement of mental health apps over time.

Our experiences researching and developing mental health apps have yielded a number of important practical insights of value to researchers in this field. The issues highlighted during the development of *MoodPrism*, taken together with our recommendations documented elsewhere [36], are summarized in Figure 4.

Potential Applications of *MoodPrism* in Psychological Research

The development of a research mobile phone tool such as *MoodPrism* has enormous potential within the mental health field. Several applications of *MoodPrism* currently in progress are summarized in the following to illustrate the power of flexible, real-time monitoring using this platform.

Figure 4. Recommended steps for researchers engaging in the app development process.



Automated Prediction of Mental Health Risk

One of the most exciting promises for data-rich apps like *MoodPrism* is the development of algorithms which allow automated prediction of emotional health. This modeling could determine the minimum number of constructs required to reliably predict significant changes in emotional well-being, which could be used to inform a more streamlined and userfriendly app. Importantly, it is unlikely that any 1 or 2 variables will provide reliable prediction of such changes; a strength of *MoodPrism* is that it provides a breadth of variables that can be used to answer diverse and important research questions. Various algorithms may be identified, for instance, which discriminate between periods of stability and decline, and *MoodPrism* could then unobtrusively monitor for this change, and provide targeted mental health support to the user. This extends previous research that demonstrates feasibility of such modeling [40,41,71] by utilizing predictors already established in previous research to be associated with mental health (such as online social networking) rather than only those mobile phone sensors that are convenient to record (such as app use and activity).

Improving Emotional Self-Awareness, Mental Health Literacy, and Mental Health and Well-Being Outcomes

Bakker et al [36] detail how mental health apps can be categorized as reflection-, education-, or problem-focused. *MoodPrism* is largely a reflection-focused app aimed at improving a user's emotional self-awareness by encouraging the user to report their thoughts, feelings, or behaviors and then reflect upon them. There is also an education component in *MoodPrism* that provides access to mental health information and resources. Use of this type of mental health app may therefore result in improvements in mental health and well-being. Kauer et al [72] found evidence that using a mobile phone app that promotes self-reflection through mood tracking can increase ESA and decrease depressive symptoms. Furthermore, rigorous study is needed to explore the mental health benefits of *MoodPrism* and other similar reflection-focused or education-focused apps, as very few randomized controlled trials have been conducted to investigate the efficacy of mental health apps [37]. Importantly, mobile phone technology complements traditional emotion monitoring techniques such as CBT-based recording worksheets [73,74], by increasing recording of subtle changes in behavior in real time. The innovative pairing of changes in emotional well-being with rapid delivery of mental health information has the potential to improve a user's access to relevant resources such as Web-based health portals (eg, eheadspace, eHub), or local GPs when it is needed [75-77].

Leveraging Behavioral Data on Social Media to Gain Insight Into Mental Health and Social Context

Users of social networking sites leave rich digital traces of their social behavior, which includes the structure of their friendship networks and the written interactions between connections [78-80]. The quality of interactions on social network service (SNS) has been shown to hold important relationships with mental health. Positive interactions are associated with better mental health outcomes, and negative interactions may exacerbate mental illness [81-83]. However, how certain individual characteristics might lead a user to gain benefit or detriment from their SNS use is yet to be clearly described [84]. This requires access to both SNS data and the administration of psychometrically sound surveys to profile the users of SNSs. By profiling SNS users and better tapping into the interindividual variation in SNS use, the accuracy of SNS language models for mental health prediction could be improved [85] and some of the conflicting findings around the use of SNS and its mental health impact could be disentangled [85]. Furthermore, apps like *MoodPrism* enable SNS data to be associated in real time with ESM assessments of mood and psychological surveys. Time-sensitive linking of self-reported mood change and emotional expression in SNS posts may also provide evidence to support the use of SNS data and language analysis as a tool for mood and mental health tracking overtime.

Predicting Resilience Patterns to Everyday Significant Events

Event-based resilience research explores individual capacities to maintain healthy psychological functioning in response to naturally occurring stressor events [86,87]. Previous research methodologies use cross-sectionally designed studies and typically rely on retrospective reports [88-90]. These provide only partial snapshots of an individual's capacity for resilient responding and can be subject to recall biases. The collection of *MoodPrism's* daily reports of psychological well-being, as well as the presence or absence of stressor events, is therefore pertinent to advancing event-based resilient research methodologies. Such methodological approaches allow for multiple snapshots in mood responding that, when compiled, create more representative, real-time observation of dynamic fluctuations that occur in an individual's mood responses to stressor events. Such data will permit a more accurate exploration and identification of the heterogeneous mood trajectories that individuals display following stressor experiences [85,87,91-93]. Favorable patterns of responding, reflecting the maintenance of psychological functioning, can be identified and profiled to explore important factors that discriminate resilient individuals from other groups that reflect less-resilient patterns of responding.

Conclusions

Development of mental health apps such as *MoodPrism* maximize health impact by harnessing the opportunities offered by mobile phone technology. Approximately, three quarters of the US and Australian populations own a mobile phone, and around 3 in 4 of those never leave home without their mobile device [31,94]. People check their mobile phones up to 150 times a day [30], demonstrating that mobile devices offer unprecedented access to everyday behavior. Incorporating evidence-based monitoring of emotional health into routine mobile phone apps can provide a powerful and flexible methodology for increasing personal control over one's own emotional health. Capitalizing on inbuilt tools within mobile phones—such as music players, voice recorders, and social network media—to contribute data further enhances the potential of such apps to sensitively monitor emotional health over extended periods of time, while remaining unobtrusive. People (particularly young people) often find mobile phone technologies more engaging, anonymous, and less stigmatizing than other means of accessing help, and therefore are much more likely to use this methodology [16]. The new technologies described in this paper not only complement traditional approaches or educational tools supporting mental health but also have the potential to enhance their reach by overcoming many of the barriers currently challenging the reliable surveillance of emotional well-being.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Details on 3 forms of data (automatic, experience sampling, and psychological surveys) collected from *MoodPrism*.

[PDF File (Adobe PDF File), 55KB - mental_v3i4e49_app1.pdf]

Multimedia Appendix 2

Feedback generated by the subjects while using *MoodPrism*.

[PDF File (Adobe PDF File), 594KB - mental_v3i4e49_app2.pdf]

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Abbreviations

APIs: application programming interfaces
CBT: cognitive behavioral therapy
ESM: experience sampling methodology
LIWC: Linguistic Inquiry and Word Count
SSH: Secure shell
SNS: social network service

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Multimedia Appendix 1

Table 1. Details on 3 forms of data (Automatic, Experience sampling, and Psychological surveys) collected from MoodPrism.

Automated data collection		Experience sampling items		Psychological questionnaires		
Source	**Data (downloaded once every 24 h, subject to user permissions)**	**Target and questions**	**Source**	**Questionnaire**	**Purpose**	**Source**
Facebook	For each post in history (up to last 50): - Date and time of post - Length of message (characters) - Number of words in message - Number of positive, negative, self-pronoun, other-pronoun words - Number of likes - Number of comments - Number of tags - City and postcode (if available) of where posted	**Emotional well-being** How were you feeling just before you were prompted by this app? (rated on a 5-point scale from "not at all" to "extremely") **1.** Nervous, anxious, or on edge **2.** Not able to stop or control worrying **3.** Little interest or pleasure doing things **4.** Feeling down, depressed, or hopeless **5.** Active or alert **6.** Negative or unpleasant **7.** Positive or pleasant **8.** In control of what I'm doing **9.** Socially connected and supported **10.** Motivated, engaged, and interested **11.** Life is meaningful and with purpose **12.** Feeling good about myself	Drawn from PHQ-4 [59]; 3 dimensional models of affect [60,61]; The WHO' emotional well-being scales (WHO-5) [62]; positive health literature [55]; single item self-esteem measures [63]	**At baseline only**		
				Demographics	Sample description or Potential moderator or confounding variable	Custom developed
				Life event scale	Potential moderator or confounding variable	[69]
				Multidimensional scale of perceived social support	Potential moderator or confounding variable	[70]
				Social desirability scale	Assessment of reliable responding	[71]
				IPIP	Potential moderator or confounding variable	[72]
				Rosenberg's self-esteem	Potential moderator or confounding variable	[73]
				Barcelona music rewards scale	Potential moderator or confounding variable	[74]
				Technology use survey	Potential moderator or confounding variable	Custom developed except for 1 item drawn from [75]
				At baseline and 1 month follow up		

Twitter Music library	For each tweet in timeline (up to last 50): - Date and time of tweet - Tweet client site or software or app used - Length of message (characters) - Number of words in message - Number of positive, negative, self-pronoun, other-pronoun words - Number of retweets - Number of favourites For each song in the user's music library - Song Title - Genre - Artist - Album - Last Played - Play count - Rating - Release date - Duration	**Event-related experiences** What's the most positive thing that's happened to you in the past 24 h? • Nothing positive happened • Positive social experience (with friends, family, strangers, etc) • Obtained material item (bought or won something, received a gift, etc) • Positive experience at work or school • Positive experience outside of work or school • Positive health or fitness experience • A happy occasion (e.g., birthday, wedding, holiday) • Other (with option to type in detail) What's the most negative thing that's	Items modified from various stressor event questionnaires [64-68]	Emotional self-awareness scale	Evaluation of emotional awareness change	[76]
				Warwick Edinburg well-being scale	Evaluation of well-being change	[77]
				PHQ-9[c]	Evaluation of well-being change	[78]
				GAD-7[d]	Evaluation of well-being change	[79]
				Mental health literacy questionnaire	Evaluation of mental health literacy change	Vignettes adapted from [80] Additional questions drawn from *beyond blue* website.
				Brief resilience scales	Evaluation of mental health literacy change	[81]
				Coping self-efficacy scale	Evaluation of mental health literacy change	[82]
				At 1 month follow up only		

		happened to you in the past 24 hours? • Nothing negative happened • Negative social experience (with family, friends, strangers, etc) • Loss of valued material item (misplaced, theft, etc) • Negative experience at school or work • Negative experience outside of work or school • Personal health problems (illness, injury, etc) • Health problems of someone close to you (illness, injury, death, etc) • Other (with option to type in detail) Followed by options for all (except "nothing"): How positive or negative was it? • Slightly • Moderately				
				Feedback questionnaire	Assessment of app quality	Custom developed (although broadly consistent with factors of MARS[b]).

		• Very • Extremely **Context** Where are you? (drop-down selections) • At home • At someone else's place • At work, uni, or school • At a leisure venue (eg, cinema, shops, park, sporting venue) • Travelling or commuting • Other (with option to type in detail) Who's with you? (Drop-down selections) • I'm alone • Mainly friends • Mainly family or my partner • Mainly work colleagues • Mainly strangers Other				

[a]WHO: World Health Organization.

[b]MARS: Mobile Application Rating Scale.

[c]PHQ-9: Patient Health Questionnaire-9

[d]GAD-7: General Anxiety Disorder scale-7

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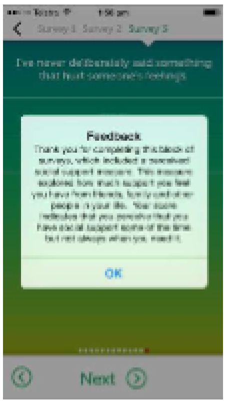
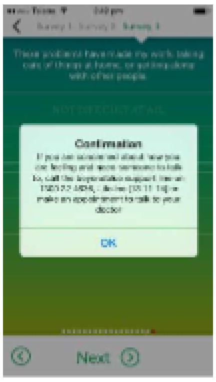
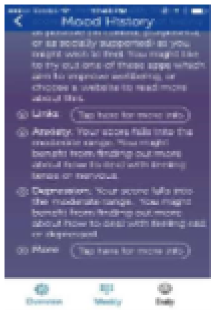
Multimedia Appendix 2

Feedback generated by the subjects while using *MoodPrism*

Feedback type	Trigger	Scoring	Sample
Psychological surveys			
Normative feedback	When block of surveys completed	Scoring based on published guidelines, and feedback based on published normative data). For example: (<45) in the lower range of positive health scores (less than 75% of people) (45-50) on the lower end of the average range of positive health scores (less than 50% of people) (51-56) on the higher end of the average range of positive health scores (more than 50% of people) (>56) in the higher range of positive health scores (more than 75% of people)	

Feedback type	Trigger	Scoring	Sample
Risk assessment			
Prompt to seek mental health support	Red flag high score	PHQ or GAD score above 15 (as per published recommendations)	

Feedback type	Trigger	Scoring	Sample
Experience sampling self-reports			
Visual (icon, colour) and descriptions of emotional state, as well as context information. Reported either in detailed (1 day), brief form (weekly), or overview (complete log) format.	On user request from day 1.	Based on 2-dimensional (arousal and valence) circumplex model of emotion (see below); color coding based on subjective convention.  	Overview: 
Description of positive health function	On user request unlocked from day 8.	Scoring based on the sum of ESM items reflecting feelings of: positive, control, social connection or support, motivation or engagement, and meaning or purpose • 5-10: Low score • 11-19: Medium score • 20-25: High score Further information link options (rotating over time) include Smiling Mind, Healthy Habits, and Buddhify apps, and well-being websites such as "Authentic Happiness" and "Soul pancake"	Weekly view:  Daily detail: 

Feedback type	Trigger	Scoring	Sample
Description of depression or anxiety levels	On user request unlocked from day 15.	Scoring based on PHQ or GAD frequency of behaviors over a 2-week period (none, less than half the days, around half the days, every or most of the days) Summed to produce • 0-2: low • 3-4: moderate • 5-6: high Further information link options (rotating over time) include	
Progress toward entries into prize draw	Frequency counts and countdowns	**Day 1-7**: Counts down to unlocking further mood feedback (positive functioning feedback) **Day 8-14**: Counts down to unlocking further mood feedback (depression or anxiety feedback) **Every day:** Counts up number of days completed to yield number of entries into prize-draw.	

Appendix B

Human Ethics Certificate of Approval

MONASH University

Monash University Human Research Ethics Committee (MUHREC)
Research Office

Human Ethics Certificate of Approval

This is to certify that the project below was considered by the Monash University Human Research Ethics Committee. The Committee was satisfied that the proposal meets the requirements of the *National Statement on Ethical Conduct in Human Research* and has granted approval.

Project Number:	**CF14/968 - 2014000398**
Project Title:	**Monitoring emotional wellbeing via a mobile phone app**
Chief Investigator:	**Assoc Prof Nikki Rickard**
Approved:	**From: 10 June 2014 to 10 June 2019**

Terms of approval - ***Failure to comply with the terms below is in breach of your approval and the Australian Code for the Responsible Conduct of Research.***

1. The Chief investigator is responsible for ensuring that permission letters are obtained, if relevant, before any data collection can occur at the specified organisation.
2. Approval is only valid whilst you hold a position at Monash University.
3. It is the responsibility of the Chief Investigator to ensure that all investigators are aware of the terms of approval and to ensure the project is conducted as approved by MUHREC.
4. You should notify MUHREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.
5. The Explanatory Statement must be on Monash University letterhead and the Monash University complaints clause must include your project number.
6. **Amendments to the approved project (including changes in personnel):** Require the submission of a Request for Amendment form to MUHREC and must not begin without written approval from MUHREC. Substantial variations may require a new application.
7. **Future correspondence:** Please quote the project number and project title above in any further correspondence.
8. **Annual reports:** Continued approval of this project is dependent on the submission of an Annual Report. This is determined by the date of your letter of approval.
9. **Final report:** A Final Report should be provided at the conclusion of the project. MUHREC should be notified if the project is discontinued before the expected date of completion.
10. **Monitoring:** Projects may be subject to an audit or any other form of monitoring by MUHREC at any time.
11. **Retention and storage of data:** The Chief Investigator is responsible for the storage and retention of original data pertaining to a project for a minimum period of five years.

[redacted]

Professor Nip Thomson
Chair, MUHREC

cc: Assoc Prof Dianne Vella-Brodrick; Mr Hussain-Abdulah Arjmand; Ms Elizabeth Seabrook; Mr David Bakker

[redacted]

Appendix C

Victorian Government Department of Education and Training Research Permission

Department of Education & Training
Strategy & Review Group

[redacted]

2015_002812

Mr Hussain-Abdulah Arjmand
[redacted]

Dear Mr Abdulah-Arjmand

Thank you for your application of 13 July 2015 in which you request permission to conduct research in Victorian government schools titled *Monitoring emotional wellbeing through smartphone technology.*

I am pleased to advise that on the basis of the information you have provided your research proposal is approved in principle subject to the conditions detailed below.

1. The research is conducted in accordance with the final documentation you provided to the Department of Education and Training.
2. Separate approval for the research needs to be sought from school principals. This is to be supported by the Department of Education and Training approved documentation and, if applicable, the letter of approval from a relevant and formally constituted Human Research Ethics Committee.
3. The project is commenced within 12 months of this approval letter and any extensions or variations to your study, including those requested by an ethics committee must be submitted to the Department of Education and Training for its consideration before you proceed.
4. As a matter of courtesy, you advise the relevant Regional Director of the schools or governing body of the early childhood settings that you intend to approach. An outline of your research and a copy of this letter should be provided to the Regional Director or governing body.
5. You acknowledge the support of the Department of Education Training in any publications arising from the research.
6. The Research Agreement conditions, which include the reporting requirements at the conclusion of your study, are upheld. A reminder will be sent for reports not submitted by the study's indicative completion date.

Your details will be dealt with in accordance with the *Public Records Act 1973* and the *Privacy and Data Protection Act 2014*. Should you have any queries or wish to gain access to your personal information held by this department please contact our Privacy Officer at the above address.

VICTORIA State Government

I wish you well with your research. Should you have further questions on this matter, please contact Youla Michaels, Project Support Officer, Insights and Evidence Branch, by telephone on [redacted] or by email at [redacted]

Yours sincerely

[redacted]

Eleanor Williams
Acting Director
Insights and Evidence Branch

31/08/2015

VICTORIA
State Government

Appendix D

Participant Information Sheet and Consent Process

USER INFORMATION SHEET

Project: **Monitoring emotional wellbeing via a mobile phone app**

Nikki Rickard
Department of Psychological Sciences
email: [redacted]

You are invited to take part in this study. Please read this Explanatory Statement in full before deciding whether or not to participate in this research. If you would like further information regarding any aspect of this project, you are encouraged to contact the researcher via the email address listed above.

What does the research involve?

The aim of this study is to explore whether people's mobile phone behaviours can help us understand or predict their emotional well-being.

If you agree to be in this study, you will be asked to:

(1) Download the "MoodPrism" app on your smartphone, and leave the app on during the 1 month research period

(2) Give permission to the researchers to automatically access your mobile phone behaviours (anonymous). The type of data that you will be asked to give researchers access to will include your music use details (e.g., artists and songs, time you listen), social networking information (e.g., which apps you use and for how long, your friend network size, and some anonymous content) and your activity levels and locations. All this information will only be stored ANONYMOUSLY (without any way of linking it to you).

(3) The app will ask you to complete a set of surveys at the start and end of the 1 month. These surveys will take about an hour in total to complete, but can be broken up and completed at a few different times if you wish. The end surveys will only take about 20 minutes.

(4) The app will also ask you to answer quick questions (less than 5 minutes each) including a voice recording when prompted at different times on most days during that 1 month

(5) The app will also deliver some mental health messages to you. This will include information about your moods (which you can access at any time), whether you are flourishing, and after 2 weeks, information about depression and anxiety levels from mental health organizations such as Beyond Blue and Headspace.

Why were you chosen for this research?
We are interested in how people's emotional health (both good and poor) might be reflected in their use of mobile phones. We are therefore seeking all sorts of people (e.g., males and females, living in the country or city, who might be feeling emotionally healthy or might not be feeling that healthy).

This invitation is being sent openly through websites and other means, and is a call for anonymous participation in this research.

Please note that you will **not** be able to participate in this research if you:

- Are currently taking any psychotropic medication (e.g., antidepressants, or anti-anxiety drugs)
- do not own your own smartphone

Consenting to participate in the project and withdrawing from the research
After reading this, the app will ask you whether you want to be in the research. By clicking on the "Yes" button, you are consenting to being involved in the research and give permission for the researchers to access your mobile phone behaviours during the research (for 1 month).

If you decide during the research that you no longer want to participate, you can withdraw from it at any time. The data already collected will already have been sent to us, and as it is not linked to your name in any way, we will not be able to find and withdraw that data.

Possible benefits and risks to participants
Being involved in this research has a number of benefits for you:

(1) You can enter a draw for one of four $AU100 gift cards. Everyone who agrees to be part of this research and completes just 7 days will go into the prize draw. For every week you complete after that, you will be awarded another entry in this draw, and if you complete the final surveys you will receive double entries to the prize draw. The prizes will be drawn in January 2017, and winners will be notified via a push notification on their device. At that time they will be invited to contact the researchers to receive their prize.
(2) You will receive messages from experts about emotional health. These might include suggestions for improving your emotional wellbeing, or perhaps some suggestions for what you might do if you're feeling down a lot or stressed a lot.
(3) You will be helping us understand how mobile phones might be used to improve emotional wellbeing of young people like yourself.

Being involved in the research will however involve some regular time from you over this month, and this could be inconvenient at times. Some of the questions we ask are also personal, and about your emotions or mental health – these could cause some upset or concern.

We recommend that if you do feel any distress or concern when you are involved in this research, that you contact your doctor or school/university or work's welfare officer to discuss this, or seek help from help services such as:

Headspace Headspace provides mental and health wellbeing support, information and services to young people and their families across Australia. www.headspace.org.au	*Kid's Help Line* Free 24 hour telephone counselling service for young people aged 5-18. Phone: 1800 551 800	*Lifeline Australia* Lifeline Australia is a 24/7 phone counselling service. Phone: 13 11 14 Website: http://www.lifeline.org.au/

Confidentiality
All information we collect from the app about you will be stored anonymously (without your name) on our secure and private servers. We will be publishing results of our study but these will there will be no way anyone could identify you and your individual information when we do this.
The only time we will ask for a name and contact details is if you wish to go into the draw to win one of the $AU100 gift cards for being involved in the research. However, your details will be kept totally separate from the other information about you collected by the app, and the two could never be linked.

Storage and use of data
During data collection, data will be stored confidentially on a secure storage site behind a firewall. Only the research team will be able to access the server, via SSH (encrypted tunnel). All communications with the server will be via HTTPS.

Your information may also be used for future research projects by the researchers, but again only anonymously and as group data.

Results
If you are interested in finding out the results of this study, you can contact us at the end of 2017, when all data will have been analysed. Please contact [redacted] and you will be advised where you can access our findings.

Complaints
Should you have any concerns or complaints about the conduct of the project, you are welcome to contact the
Executive Officer, Monash University Human Research Ethics (MUHREC):

Executive Officer
Monash University Human Research Ethics Committee (MUHREC)
[redacted]
Research Office
Monash University VIC 3800

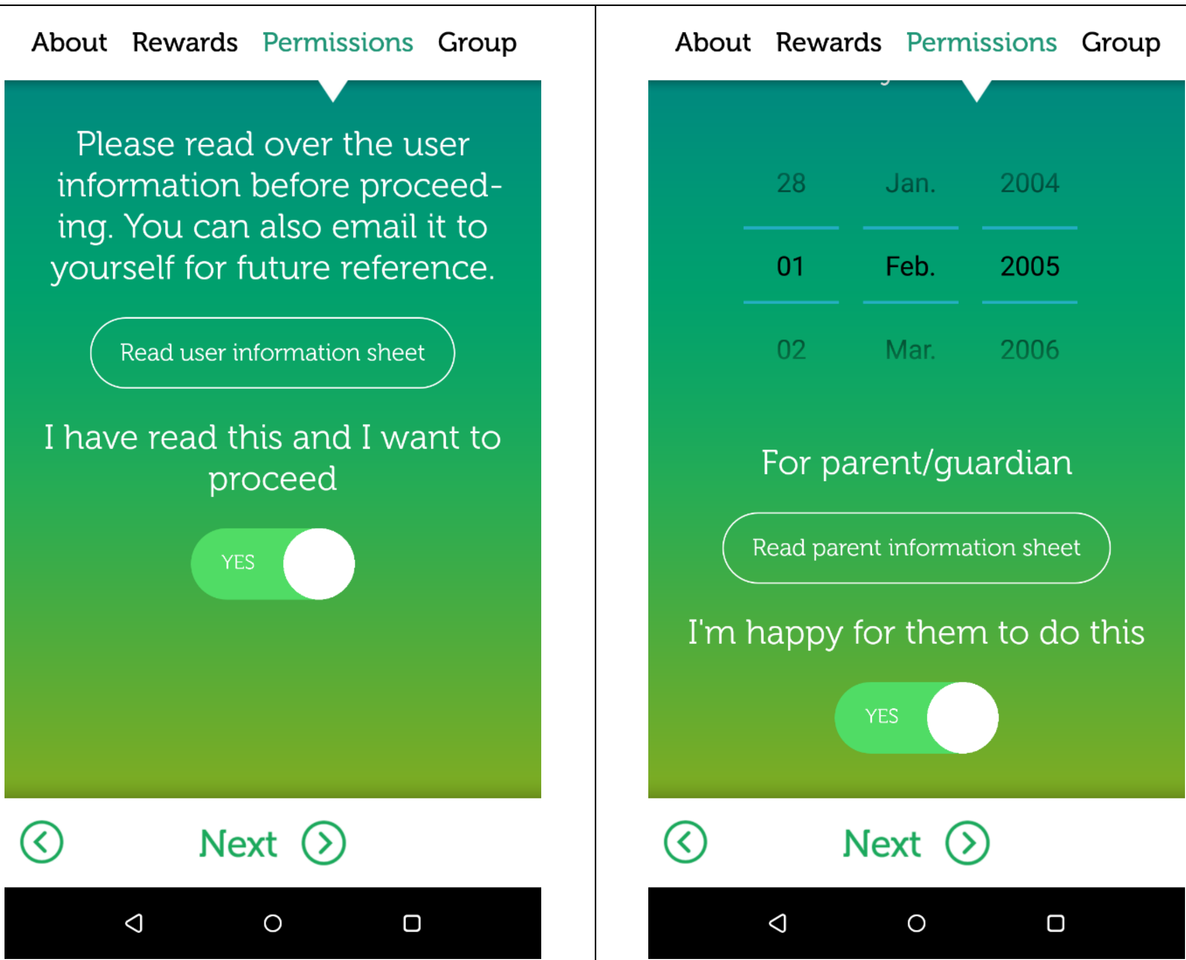
Tel: [redacted] Email: [redacted] Fax: [redacted]
[redacted]

Thank you,

[redacted]

Associate Professor Nikki Rickard

Informed Consent Screens in *MoodPrism*



(a) Informed consent process for all participants

(b) Parental consent screen for minors

Appendix E

Supplementary Positive and Negative Emojis and Internet Slang for the *LIWC 2007*

Positive Emoji’s	Negative Emoji’s		Positive Emotion Internet Slang			Negative Emotion Internet Slang	
=D>	:-l	:-/	Aight	j/j	lyke	Abft	fomo
=D	:l	:/	Aightz	jk	marvy	Acgaf	gank
:D	X(	T_T	Aiight	j/k	njoy	Aiic	grmbl
:-D	X-(	T^T	Aite	jks	ql	Arsed	h8
(:)	O	QQ	Alrt	j2f	qool	Awk	h80r
(:-)	b (	=O::::	alryt	j4f	qt	Bm	h83r
>:D<	>:-(	=’(	Alol	j4g	qte	Boom	h8ed
:))	>:-)	&.(..	Aml	j4l	rofl*	Bord	h8r
:-X	(:-&	(;_;)	Aprece8	jfg	*s*	Bovered	h8red
:X	:@	:’(	Apreci8	jfl	S’ok	Catwot	h8s h8t
:)	:(	:’	Awes	jfk	Snog	Cba	h8t0r
:-)	:-t	:’-(	Awsm	jja	Sok	Cbb	h8t3r
^^	:-ll	:*(	Awsome	jkz	Sof	Cbf	h8te
:,’)	:ll	:*-(	Bahaha	k	Stm	Cbfa	h8tr
:-“)	:t	:_(	Besos	kay	Ub3r	Cbfed	hait
:”)	:-@	:..[	Bilu	kewel	W00t	Cmeo	heyt
;)	:{	;_;	Btwilu	kewl	Woot	Cmw	htr
;-)	:-Z	=\	Btwitiailwu	kk	Xellent	Cof	id10d
\o/	:Z	:l	Byak	kl	Xlnt	Cotf	idjit
;-(	??	:(&	Chillin	koo	xtc	Dc	idot
;(	@_@	:-E	Ctm	kool		Dbm	idyat
:’)	(-_-*)	:-e	Cut3	kss		Dfc	invu
:’-)	(o_o)	DX	Eil	kssd		Dgac	irhy
>-)	b-(	/:(	Fab	kul		Dgaf	isb
:p	%+l	:-[	Fah	kute		Dgara	kmn
:P	:S	:[	Fi9	l0lz		Dgas	kmp
:-P	:-S	:-}	Funee	laff		Eejit	lsr
:-p	(:-	:}	Funy	lal		Eedyat	lzr
:>	:(	#-)	*g*	lol		Ef	nv
:->	:-(	#)	Gtm	lols		Ef-ing	ofcol
l__l	l-o	:-6	Gud	lel		Effed	oh noes
^.^	\-o	:6	Gudd	liek*		Effin	oh noez
^?^	:-o	:-@	Heh	lik		Effing	p/oed
^-^	=((	(:(	Hppy	lk		F#cking	poed
%)	+-((	:-<	Hpy	lke		F’n	ph33r
%-)	</3	><	Haha	llc		f-ing	phayl
<3	(U)	://	I8	llf		fml	phail
<u3	:-c		Iatb	lmao		f.m.l	r8p
	:c		Iight	lmfao		farg	r8pist
	O.o		Iigh	rofl		fck	stupd
	%)		Ijdl	lml		fcked	suk
	%-)		Ili	lov		fckin	sukz
	(@_@)		Ilml	luv		fcking	suxx
	:s		Ilms	luff		feck	wrdo
	:-Q		Ilu*	luvv		fk	wtf
	:Q		Ilshipmp	lurve		fkd	
	:-$		Irly	lv		fker	
	:$		Ite	lve		fkin	
			Jj	lyk		fking	