Mental Health Smartphone Apps:

Development of Two New Apps and

Exploration of Mental Health Benefits

David Bakker

BPsych (Hons)

A thesis submitted in partial fulfilment of the requirements of the degree of:

Doctor of Psychology (Clinical Psychology)

at

Monash University in 2018

Monash Institute of Cognitive and Clinical Neurosciences

& School of Psychological Sciences

Faculty of Medicine, Nursing, and Health Sciences

Monash University

Victoria, Australia

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Table of Contents

List of Tables

List of Figures

Abbreviations

ACT: acceptance and commitment therapy

ARG: alternate reality game

BA: behavioural activation

CBT: cognitive behavioural therapy

CCBT: computerised cognitive behavioural therapy

CE: collaborative empiricism

CSE: coping self-efficacy

DBT: dialectical behaviour therapy

EMA: ecological momentary assessment

ESA: emotional self-awareness

ESM: experience sampling method

GAD-7: 7-item Generalized Anxiety Disorder Scale

iCBT: internet cognitive behavioural therapy

MARS: Mobile App Rating Scale

MHapp: mental health app

MHL: mental health literacy

PDA: personal digital assistant

PHQ-9: 9-item Patient Health Questionnaire

RCT: randomised controlled trial

SDT: self-determination theory

TCBT: transdiagnostic cognitive behavioural therapy

UP: unified protocol

Abstract

Smartphones have become ubiquitous personal devices, and many applications (apps) for mental health (MHapps) are now available to the public. MHapps hold great promise as preventative and low-intensity interventions for depression and anxiety, and as ways to improve positive mental wellbeing. However, the majority of MHapps currently available lack empirical support for their efficacy, and there is little research into the underlying mechanisms used by MHapps to generate therapeutic change. This thesis aimed to progress the field by reviewing the available evidence, formulating sixteen recommendations for MHapp development, developing two apps based on these recommendations, and evaluating their effects on mental health. The effects of different MHapps could be attributable a range of mechanisms, including increases in emotional self-awareness (ESA), mental health literacy (MHL), or coping self-efficacy (CSE), so these underlying treatment processes were also investigated.

The first app developed, MoodPrism, contained mood-tracking features, hypothesised to improve mental health by increasing ESA. After a collaborative building and testing process, the app was released on the public iOS and Android stores. Regression analyses examined data from 234 participants who downloaded and used the app for 30 days. App engagement ratings predicted increases in mental wellbeing and decreases in depression and anxiety. These effects were mediated by increases in ESA, but only for participants who were depressed or anxious at the time of the baseline assessment. MHL and CSE did not play mediating roles.

The second app developed, MoodMission, recommended cognitive behavioural therapy (CBT) strategies as remedies for low moods or anxiety. The development of this app was crowdfunded, and throughout the iterative building and testing process MoodMission was rated significantly higher than other health apps on measures of usability and functionality. As

with MoodPrism, regression analyses were used to investigate the relationships between app engagement and mental health outcomes over 30 days of use. Among the 617 participants, there was a significant relationship between app engagement and mental wellbeing. Although there were no direct effects on depression and anxiety, there were significant indirect effects via the mediator of CSE for participants who were moderately depressed or anxious at the time of the baseline assessment.

In addition to these engagement studies, a randomised controlled trial (RCT) was conducted to compare MoodPrism, MoodMission, and an existing MHapp called MoodKit, against a waitlist control condition. Following intent-to-treat principles, each group contained 48 participants. Mixed ANOVAs revealed that all app groups experienced increases in mental wellbeing, compared to the control. The MoodPrism group also experienced a decrease in anxiety, and the MoodMission group experienced a decrease in depression. All effects were mediated by CSE.

Exploration of the findings reported in this thesis reveal ways that future MHapps can be improved, with reference to CBT theory, self-determination theory, emotion regulation models, and the behavioural health continuum of care. MHapps can be effective at increasing mental wellbeing, and depending on their features, can also decrease anxiety and depression. Two MHapps were successfully developed and evaluated, and unlike many other MHapps involved in research, these will remain accessible freely accessible offering an evidence-based and sustainable public mental health strategy.

Publications, Conference Proceedings, and Awards During Candidature

This thesis contains the following manuscripts published in, accepted by or submitted to journals:

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2016). Mental health smartphone apps: Review and evidence-based recommendations for future developments. *JMIR Mental Health*, *3*, e7. https://doi.org/10.2196/mental.4984

Bakker, D., & Rickard, N. (2017). Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism. *Journal of Affective Disorders*, *227*, 432-442. https://doi.org/10.1016/j.jad.2017.11.016

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2018). Development and pilot evaluation of smartphone delivered Cognitive Behavior Therapy strategies for mood and anxiety related problems: MoodMission. *Cognitive and Behavioral Practice*. Manuscript submitted for publication.

Bakker, D., & Rickard, N. (2018). Engagement with a cognitive behavioral therapy mobile phone app predicts changes in mental health and well-being: MoodMission. *Journal of Consulting and Clinical Psychology.* Manuscript submitted for publication.

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2018). A randomized controlled trial of three smartphone apps for enhancing public mental health. *Journal of Consulting and Clinical Psychology.* Manuscript submitted for publication.

The following publication was published during candidature and is included in Appendix B, as the thesis author is a secondary author but the publication is relevant to this thesis:

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. https://doi.org/10.2196/mental.6202

Parts of this thesis were presented at the following conferences and events:

Bakker, D. (2017, October). Development and evaluation of a new CBT strategies mobile app for low moods and anxiety: MoodMission. *Oral presentation at the International Society for Research on Internet Interventions (ISRII) 9th Scientific Meeting, Berlin, Germany.*

Bakker, D. (2017, October). MoodMission: Development and validation of a new evidence-based smartphone app for low moods and anxiety. *Oral presentation at the 6th European Conference on Mental Health, Berlin, Germany.*

Bakker, D. (2017, July). Apps for mental health and wellbeing. *Workshop at the ELMHS Social Media and Health Development Symposium, Melbourne, Australia.*

Bakker, D. (2017, June). Developing apps for mental health. *How-to session at the ASSBI 40th Annual Brain Impairment Conference, Melbourne, Australia.*

Bakker, D. (2017, May). MoodMission: Developing and evaluating an app for monitoring and coping with low moods and anxiety. *Oral presentation at the Ambulatory Assessment and Intervention (AAI) Symposium, Melbourne, Australia.*

Bakker, D. (2017, March). MoodMission: Empowering you to change the way you feel. *Oral presentation at the Digital Health Show, Melbourne, Australia.*

Bakker, D. (2016, November). MoodMission: Empowering you to change the way you feel. *Oral presentation at the Convergence Science Network Innovations in Psychology Symposium, Melbourne, Australia.*

Bakker, D. (2016, November). MoodMission: A new evidence-based app for prevention and treatment of depression and anxiety. *Poster at the Australian Clinical Psychology Association Annual Conference, Melbourne, Australia.*

Bakker, D. (2016, September). MoodPrism and MoodMission. *Oral presentation at the Global Ideas Lab, Melbourne, Australia.*

Bakker, D. (2016, September). MoodMission: A new evidence-based app for low moods and anxiety. *Oral presentation in the Digital mental health care Symposium at the Australian Psychological Society (APS) Congress, Melbourne, Australia.*

Bakker, D. (2016, September). MoodMission: Development of a new evidence-based smartphone app for low moods and anxiety. *Poster at the Australian Psychological Society (APS) Congress, Melbourne, Australia.*

Bakker, D. (2016, August). Breaking the wall of mental health support. *Oral presentation at the Australian Academy of Science Falling Walls Lab, Melbourne, Australia.*

Bakker, D. (2016, April). MoodMission: Learn new ways to deal with low moods and anxiety. *Oral presentation at the Digital Health Show, Sydney, Australia.*

Bakker, D. (2016, April). MoodMission: An app for finding ways to cope with low moods and anxiety. *Oral presentation at the REALISE Canberra Pitch and Connect Event, Canberra, Australia.*

Prizes awarded at conferences and events:

Malcolm Macmillan award for three-minute thesis submission (2017, November). *Australian Clinical Psychology Association Annual Conference, Adelaide, Australia.*

Innovators Challenge award for oral presentation (2017, October). *International Society for Research on Internet Interventions 9th Scientific Meeting, Berlin, Germany.*

Best poster prize (2016, November). *Australian Clinical Psychology Association Annual Conference, Melbourne, Australia.*

People's Choice award and Top 5 Pitch for entry into Monash University Accelerator Program (2016, September). *Monash University Generator Elevator Awards, Melbourne, Australia.*

Best overall pitch (2016, April). *REALISE Canberra Pitch and Connect Event, Canberra, Australia.*

General declaration

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 three submitted publications. The core theme of the thesis is the development and evaluation of mental health smartphone apps. The ideas, development and writing up of all the papers in the thesis were the principal responsibility of myself, the student, working within the Monash Institute of Cognitive and Clinical Neurosciences and School of Psychological Sciences under the supervision of Adjunct Associate Professor Nikki Rickard.

The inclusion of co-authors reflects the fact that the work came from active collaboration between researchers and acknowledges input into team-based research. No co-authors are Monash University students.

In the case of chapters one, four, five, six, and seven, 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*
1	Mental health smartphone apps: Review and evidence-based recommendations for future developments.	Published	70%. Primary development of design, data collection, analysis and interpretation, manuscript synthesis and preparation.	1) Nikolaos Kazantzis, input into manuscript 10% 2) Debra Rickwood, input into manuscript 10% 3) Nikki Rickard, supervision of study design, input into manuscript 10%
4	Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism.	Published	70%. Primary development of design, data collection, analysis and interpretation, manuscript synthesis and preparation.	*1)* Nikki Rickard, supervision of study design, input into manuscript 30%
5	Development and pilot evaluation of smartphone delivered Cognitive Behavior Therapy strategies for mood and anxiety related problems: MoodMission.	Returned for revision	70%. Primary development of design, data collection, analysis and interpretation, manuscript synthesis and preparation.	*1)* Nikolaos Kazantzis, input into manuscript 10% *2)* Debra Rickwood, input into manuscript 10% *3)* Nikki Rickard, supervision of study design, input into manuscript 10%
6	Engagement with a cognitive behavioral therapy mobile phone app predicts changes in mental health and well-being: MoodMission.	Submitted	70%. Primary development of design, data collection, analysis and interpretation, manuscript synthesis and preparation.	*1)* Nikki Rickard, supervision of study design, input into manuscript 30%

7	A randomized controlled trial of three smartphone apps for enhancing public mental health	Returned for revision	70%. Primary development of design, data collection, analysis and interpretation, manuscript synthesis and preparation.	1) Nikolaos Kazantzis, input into manuscript 10% 2) Debra Rickwood, input into manuscript 10% 3) Nikki Rickard, supervision of study design, input into manuscript 10%

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

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

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.

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

Acknowledgements

I would like to thank my amazing supervisors, Adjunct Associate Professor Nikki Rickard, Associate Professor Nikolaos Kazantzis, and Professor Debra Rickwood. We sure have shared many journeys through Word's *tracked changes* together. You have all been an absolute pleasure to work with and learn from, and you will continue to inspire me long into the future. Nikki, I am particularly grateful for your unwavering support, even after leaving your position with Monash. This was tremendously kind of you.

To the teams at Two Bulls and Spark Digital, thank you for being so terrific to work with in developing MoodPrism and MoodMission respectively. Your skill, dedication, and professionalism ensured that both apps were a success. Thank you also to my lab mates Liz Seabrook and Abdullah Arjmand for all your work on MoodPrism.

Thank you to all the people who downloaded MoodPrism or MoodMission. I hope the app has been useful and I will continue to listen to you as the experts who can make the apps better. And to everyone who pledged to MoodMission's two crowdfunding campaigns, a massive thank you and I hope you enjoyed your pledgers' rewards. I hope the poems I wrote for you weren't too trite, and I hope you are proud of your contribution.

Thanks to the following artists for making the best music to write to: Three Trapped Tigers, Mick Gordon, Flying Lotus, Four Tet, Caribou, and Radiohead.

To my parents, thank you for getting me into this whole psychology malarkey in the first place. You've always enthusiastically supported me in whatever I've done (except for when I rode motorbikes on the farm, and yeah, fair enough), and I purely and simply could not have done this without you.

And finally, my fantastic fiancé Em. You have put up with *a lot* and you have contributed to this document in so many ways. Your love keeps me going no matter what. And despite the PS4 you gave me for my birthday, I managed to finish this thing.

Preface

Over the last decade, smartphones and mobile devices have become commonplace in many people's lives and central to the way they work, play, and communicate. One of the appeals of these devices is their large range of available "apps", which are small, web-delivered software applications that usually have some discrete, specific purpose. There are now apps for many purposes, such as ordering food, tracking fitness regimes, organising calendars, interacting with vast social networks, and more recently, for mental health support. This follows the development of online computerised programs for the treatment of depression, anxiety, and other mental health issues. While elements from computerised therapies can be applied to mobile contexts, they are not optimal and new paradigms that are better suited to mobile technologies should be considered. For example, most current internet Cognitive Behavioural Therapy (iCBT) programs are based on self-guided workbooks and contain large blocks of text, some images, and a few opportunities for the user to enter text. The main paradigm for interacting with a desktop or laptop computer has been well established, and involves the user becoming immobile, dedicating their attention to the screen, and inputting information through use of a keyboard and mouse. Mobile devices now offer new opportunities, and novel paradigms for interacting with apps are still being developed and explored (Chou, Bry, & Comer, 2017).

One reason underlying the lack of exploration into new paradigms is the duty of care that mental health professionals uphold to provide support and interventions with known effectiveness. It is important for an intervention to have direct scientific or theoretically-based evidence supporting it before it can be ethically offered. This means it is much easier to build interventions for new technical platforms that are direct translations of previously validated interventions that rely on established paradigms. In contrast, developers who approach the design of mental health apps from outside the field of mental health tend to be less aware of the established paradigms and therefore less reliant on them. This means that some of the most innovative mental health apps have been developed by entrepreneurial start-ups rather than mental health practitioners or researchers. While these innovations are admirable attempts to establish engaging mobile intervention paradigms, the apps often lack experimental validation of effectiveness, which means their actual utility is unknown.

Currently a limited amount of research has been published supporting the efficacy of a few select app-based mental health interventions. While the findings thus far are promising, there are three major shortcomings of the literature. Firstly, most of the researched apps are no longer available to the public because they were developed as part of research projects with no planned continuation. Secondly, most of the apps rely on intervention paradigms that have been established in other modalities, such as CBT pen and paper workbooks or iCBT education modules. Thirdly, the evaluations have focussed on the outcomes of using the intervention tool, rather than the underlying mechanisms or mediators that may reveal how to improve intervention design. The purpose of this thesis was therefore to develop two new mental health apps that would: a) be publicly and freely available, during and after the completion of their linked research projects; b) use innovative interaction paradigms, combining features of established interventions with mobile-optimised interactions; and c) collect data to support their efficacy as recommendable tools, and enable investigation of the interventions' underlying mediators of success.

The research aims of this thesis were to:

1) develop a reflection-focussed, mood-tracking MHapp;
    a. explore the relationships between engagement with this reflection-focussed app and mental health and wellbeing outcomes;
    b. examine whether emotional self-awareness (ESA) mediates this effect;
2) develop a problem-focussed, CBT strategy MHapp;

a. explore the relationships between engagement with this problem-focussed app and mental health and wellbeing outcomes;
b. examine whether coping self-efficacy (CSE) mediates this effect; and

3) evaluate the efficacy of three different MHapps in a RCT.

These aims were aligned with the overall goal of this thesis, which was to collect and organise evidence that could guide the improvement of current and future MHapps.

This thesis comprises eight chapters that detail the development and evaluation of two new mental health apps, MoodPrism and MoodMission, and explore their mental health benefits with an aim to improve future app-based interventions. *Chapter 1* presents a published literature review that supports sixteen recommendations for the design and development of MHapps. This review was pursued because there was no existing published guide to developing MHapps, so it spanned a broad range of literature from diverse fields and informed the development of MoodPrism and MoodMission. *Chapter 2* outlines the approach for the rest of the thesis and details some of the common methodologies employed across the remaining chapters. *Chapter 3* provides detail about the collaborative development process of a mood-tracking app called MoodPrism, and *Chapter 4* comprises a published empirical manuscript that reports data collected from MoodPrism, revealing improvements in participant mental health and wellbeing via the hypothesised mediator of emotional self-awareness (ESA). *Chapter 5* presents the development methodology and pilot evaluation of MoodMission, an app for the delivery of cognitive behavioural therapy (CBT) strategies for low moods and anxiety. *Chapter 6* then details the effectiveness of MoodMission by reporting outcome and mediator data using similar analyses to Chapter 4. *Chapter 7* presents a randomised controlled trial (RCT) that compares the efficacy of MoodPrism, MoodMission, and an existing app called MoodKit, against a waitlist control condition. Finally, *Chapter 8* provides an integrative summary of the previous chapters, relating the findings to three different psychological intervention theories to better guide future MHapp development and research. The final chapter also discusses broader issues related to the field of MHapps, acknowledging the complex environment that MHapp interventions are developed and researched in.

As this thesis contains manuscripts that are published or submitted for publication, there will be some repetition of concepts. The chapters happen to be ordered chronologically according to time of submission, so later chapters may cite more recent references. Manuscripts are presented in the form in which they were published or submitted for publication. Throughout the thesis the word “intervention” will be used to refer to any program or structure with which an individual interacts to achieve outcomes, regardless of whether it is considered a treatment for clinical disorder. This includes preventative interventions.

CHAPTER 1: MENTAL HEALTH SMARTPHONE APPS: REVIEW AND EVIDENCE-BASED RECOMMENDATIONS FOR FUTURE DEVELOPMENTS

Explanatory Note

The following chapter presents a narrative literature review that was published in JMIR Mental Health in January 2016. This serves as an introduction to the field of MHapps and summarises the most relevant, recent research to inform a series of practical recommendations for future MHapp developments. A preliminary review of available MHapps is also included to indicate the strengths and shortcomings of the apps currently available to the public. The conclusions of this review form the rationale for the development and evaluation of MoodPrism and MoodMission, which is detailed in the remaining chapters of this thesis.

JMIR MENTAL HEALTH Bakker et al

Review

Mental Health Smartphone Apps: Review and Evidence-Based Recommendations for Future Developments

David Bakker[1], B Psych (Hons); Nikolaos Kazantzis[1,2], PhD; Debra Rickwood[3], BA (Hons), PhD; Nikki Rickard[4], BBSc(Hons), PhD(Psych)

[1]School of Psychology and Monash Institute of Cognitive and Clinical Neurosciences, Faculty of Medicine, Nursing and Health Sciences, Monash University, Clayton, Australia

[2]Cognitive Behaviour Therapy Research Unit, School of Psychological Sciences, Faculty of Medicine, Nursing and Health Sciences, Monash University, Clayton, Australia

[3]Psychology Department, Faculty of Health, University of Canberra, Canberra, Australia

[4]Centre for Positive Psychology, Melbourne Graduate School of Education, University of Melbourne, Parkville, Australia

Corresponding Author:
David Bakker, B Psych (Hons)
School of Psychology and Monash Institute of Cognitive and Clinical Neurosciences
Faculty of Medicine, Nursing and Health Sciences
Monash University
18 Innovation Walk
Wellington Road
Clayton, 3800
Australia
Phone: 61 3 9905 4301
Fax: 61 3 9905 4302
Email: david.bakker@monash.edu

Abstract

Background: The number of mental health apps (MHapps) developed and now available to smartphone users has increased in recent years. MHapps and other technology-based solutions have the potential to play an important part in the future of mental health care; however, there is no single guide for the development of evidence-based MHapps. Many currently available MHapps lack features that would greatly improve their functionality, or include features that are not optimized. Furthermore, MHapp developers rarely conduct or publish trial-based experimental validation of their apps. Indeed, a previous systematic review revealed a complete lack of trial-based evidence for many of the hundreds of MHapps available.

Objective: To guide future MHapp development, a set of clear, practical, evidence-based recommendations is presented for MHapp developers to create better, more rigorous apps.

Methods: A literature review was conducted, scrutinizing research across diverse fields, including mental health interventions, preventative health, mobile health, and mobile app design.

Results: Sixteen recommendations were formulated. Evidence for each recommendation is discussed, and guidance on how these recommendations might be integrated into the overall design of an MHapp is offered. Each recommendation is rated on the basis of the strength of associated evidence. It is important to design an MHapp using a behavioral plan and interactive framework that encourages the user to engage with the app; thus, it may not be possible to incorporate all 16 recommendations into a single MHapp.

Conclusions: Randomized controlled trials are required to validate future MHapps and the principles upon which they are designed, and to further investigate the recommendations presented in this review. Effective MHapps are required to help prevent mental health problems and to ease the burden on health systems.

(JMIR Mental Health 2016;3(1):e7) doi:10.2196/mental.4984

KEYWORDS

mobile phones; mental health; smartphones; apps; mobile apps; depression; anxiety; cognitive behavior therapy; cognitive behavioral therapy; clinical psychology

Introduction

A smartphone is an advanced mobile phone that functions as a handheld computer capable of running software apps. Within the last decade, smartphones have been integrated into the personal, social, and occupational routines of a substantial proportion of the global population. Over half of the population in the United States owns a smartphone and 83% of these users do not leave their homes without it [1]. Average users check their phones as often as 150 times a day [2], which reflects how smartphone apps can generate, reward, and maintain strong habits involving their use [3,4]. Apps are also capable of implementing behavior change interventions [5], which may improve users' physical health [6], such as through promotion of physical exercise [7].

Over recent years, numerous mental health apps (MHapps) have been developed and made available to smartphone users. These apps aim to improve mental health and well-being, ranging from guiding mental illness recovery to encouraging beneficial habits that improve emotional health [8]. The demand for MHapps is strong, as evidenced by a recent public survey that found that 76% of 525 respondents would be interested in using their mobile phone for self-management and self-monitoring of mental health if the service were free [9].

MHapps and other technology-based solutions have the potential to play an important part in the future of mental health care [10], making mental health support more accessible and reducing barriers to help seeking [11]. Innovative solutions to self-management of mental health issues are particularly valuable, given that only a small fraction of people suffering from mood or anxiety problems seek professional help [12]. Even when people are aware of their problems and are open to seeking help, support is not always easily accessible, geographically, financially, or socially [13].

Smartphones are not constrained by geography and are usually used privately by one individual. This means that smartphone apps can be extremely flexible and attractive to users, empowered by the confidentiality of their engagement. Seeking help by downloading and using an MHapp is well suited to the needs of young adults and other users with a high need for autonomy [14]. Users also prefer self-help support materials if they are delivered via a familiar medium [15], such as a personal smartphone. Smartphones apps are almost always accessible to users, so they can be used in any context and in almost any environment [16]. Using these apps, users can remind themselves throughout the day of ongoing goals and motivations, and be rewarded when they achieve goals [17].

However, many MHapps have not capitalized on the strengths and capabilities of smartphones. Design principles that have led to the huge success of many physical health and social networking apps have not been utilized in the MHapp field. Furthermore, evidence-based guidelines that have been developed for other self-help mental health interventions have not been applied to many MHapps. For example, many available MHapps target specific disorders and label their users with a diagnosis. Much research has suggested that this labeling process can be harmful and stigmatizing [18].

There also appears to be a lack of appreciation for experimental validation among MHapp developers. Donker et al [8] revealed that there is a complete lack of experimental evidence for many of the hundreds of MHapps available. Their systematic review identified only 5 apps that had supporting evidence from randomized controlled trials (RCTs). A search of the Apple and Google app stores as of January 2014 reveals that none of these RCT-supported apps is currently available to consumers.

For a mental health intervention to be effective, there must be a process of rigorous experimental testing to guide development [19]. Appropriate theories of engagement and implementation should also be consulted when introducing an evidence-based intervention to the public [20]. However, such research is currently lacking. A series of recommended principles based on evidence and substantiated theories would be valuable in guiding the development of future MHapps and future RCTs. A review of the literature highlights the numerous ways by which the design, validation, and overall efficacy of MHapps could be improved.

Methods

This review aims to provide a set of clear, sound, and practical recommendations that MHapp developers can follow to create better, more rigorous apps. As such, this review covers work from a number of different research fields, including mental health interventions, preventative health, mobile health, and mobile app design. A review of currently available MHapps was also necessary to gain a clearer idea of where improvements can be made.

Databases such as PsycInfo, Scopus, and ProQuest were consulted for peer-reviewed sources. Search terms included (but were not restricted to) "mhealth," "anxiety," "depression," "help seeking," "self-help," "self-guided," "smartphones," and "gamification." Articles published between March 1975 and March 2015 were considered for inclusion. Meta-analyses and systematic reviews were sought for each relevant area of investigation. Several synoptic texts were also consulted to guide foundational understanding of theoretical concepts relating to mobile apps and product design [3,5]. Sources were excluded from the review if they did not relate directly to mental health or computerized health interventions. Because this was not a systematic review, and as such was not based on a single search of the literature, the specific number of articles found and excluded was not tracked. Furthermore, multiple searches were used to explore the concepts and formulate the recommendations presented. The lead author (DB) conducted these searches and formulated the basic recommendations. The secondary authors provided individual feedback on the review, suggested sources, and guided further searches that the lead author undertook.

Most research into mobile health has focused on validating single entrepreneurial apps, rather than pursuing rigorous RCTs to validate principles that can guide development of future apps [21]. Because of the infancy of the field, the recommendations presented in the results of this review have not been rigorously validated by RCTs in an MHapp setting. Instead, each recommendation should be treated as a guide for both development of MHapps and future research. Each recommendation could well be the target of a future RCT.

Currently Available Apps

The recommendations explored in this review should be considered in the context of the existing range of MHapps available. The suggested recommendations are as follows: (1) cognitive behavioural therapy based; (2) address both anxiety and low mood; (3) designed for use by nonclinical populations; (4) automated tailoring; (5) reporting of thoughts, feelings, or behaviors; (6) recommend activities; (7) mental health information; (8) real-time engagement; (9) activities explicitly linked to specific reported mood problems; (10) encourage nontechnology-based activities; (11) gamification and intrinsic motivation to engage; (12) log of past app use; (13) reminders to engage; (14) simple and intuitive interface and interactions; (15) links to crisis support services; (16) experimental trials to establish efficacy. This is a recommended direction for future research. To demonstrate the necessity of such a future review or some form of accreditation system to ensure the quality of health care apps [22], the lead author conducted a brief overview of the range of currently available MHapps via a series of preliminary searches of the iTunes App Store. The search terms used included "anxiety," "depression," "low mood," "mental health," "therapy," "relaxation," and "self-help." Inspection and use of the apps found in these searches revealed some major gaps in their capabilities when compared with the recommendations of this review. Table 1 compares a selection of these apps across the recommended features discussed in this review.

Results

The recommendations formulated by this review of the literature are summarized in the following section. Recommendations 1-7 have been chiefly extrapolated from the mental health literature, and Recommendations 8-14 have origins in research on user engagement and designing apps for behavior change. Recommendations 15 and 16 are recommendations specifically related to MHapps.

It may not be possible to build every single listed recommendation into a single app. Rather, this list has been compiled based on the available evidence to guide decisions when embarking on an MHapp development project. Many currently available MHapps lack features that would greatly improve their functionality, or include features that are not optimized. Thus, the purpose of this review is to collate a list of easily followed recommendations to be used by developers when creating future MHapps.

Some of these recommendations will be relevant to informing both the interface design and the marketing of MHapps. It is important to note that the marketing of an app is tied to the way that users will interact with it [23], in the same way that pretherapy expectations can influence engagement motivation and hopefulness [24]. For example, if a user downloads an app because its description on the app store lists "relaxation," the user will plan to use the app for relaxation purposes. When app design is mentioned in the recommendations, this is inclusive of an app's marketing.

Recommendations

Cognitive Behavioral Therapy Based

Cognitive behavioral therapy (CBT) is a type of collaborative, individualized, psychological treatment that is recognized as the most supported approach to generate behavioral, cognitive, and emotional adaption to a wide range of common psychological problems [25]. The efficacy of CBT has been supported by a comprehensive review of 106 meta-analyses across different clinical groups [26]. Other meta-analyses have found strong support for CBT as an effective treatment for a huge range of psychological disorders, including depression [27,28], generalized anxiety disorder [29], social anxiety [30], health anxiety [31], panic disorder [32], posttraumatic stress disorder [33], obsessive-compulsive disorder [34], phobias, and anxiety disorders overall [35]. Meta-analytic evidence for CBT also extends to anger expression problems [36], insomnia [37], pathological gambling [38], hoarding disorder [39], irritable bowel syndrome [40], psychosis prevention [41], and occupational stress [42].

Although CBT's most researched application is as a therapeutic technique delivered collaboratively by a trained clinician, its principles have also been used as the foundation of many self-help support measures. Using technology is a cost-effective way to enhance the efficiency of CBT treatment [43,44], and research has already demonstrated that CBT-based self-administered computerized interventions are successful for improving depression and anxiety symptomatology in adults. A meta-analysis of 49 RCTs revealed a significant medium effect size (g=0.77, 95% CI 0.59-0.95) for computerized CBT (CCBT) for depression and anxiety [45]. Another meta-analysis of 22 RCTs found an even greater effect size (g=0.88, 95% CI 0.76-0.99) [46]. Similar findings for CCBT's efficacy have emerged from meta-analyses that have focused on anxiety [47], depression [48], and its use with young people [49]. CCBT interventions can be administered by a mobile device and still retain their therapeutic validity [50]. RCTs have established the efficacy of CBT-based interventions delivered via smartphone apps that reduce depression [50], chronic pain [51], and social anxiety disorder [52]. CBT-based features can also be appealing to users. In an analysis of features used on a smartphone app for smoking cessation, 8 of the top 10 used features were CBT based [53], such as progress tracking and journaling (see the "Reporting of Thoughts, Feelings, or Behaviors" section).

JMIR MENTAL HEALTH Bakker et al

Table 1. Currently available iOS apps compared across recommended features.

App	Recommended feature[a]														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
AnxietyCoach	4	8	8	4 [b]	4	4	4	4	4	4	8	4	8	4	8
Behavioral Experiments	4	4	8	8	4	8	8	4	8	8	8	4	8	8	8
Breathe	8	8	4	8	8	8	8	4	8	8	8	8	4 [c]	4	4
DBT Diary Card and Skills Coach	8	8	8	8	4	4	4	4	8	4	4	4	4 [c]	8	8
Depression Prevention	8	8	8	8	8	4	8	8	8	4	8	8	8	4	8
Happify	8	4	4	4 [b]	8	4	4	8	8	8	4	4	4	8	8
HealthyHabits	8	4	4	8	8	4	8	8	8	4	4	4	4	8	8
HealthyMinds	4	4	4	8	4	4	4	4	4	4	8	4	4 [c]	4	4
HIAF	8	8	4	8	4	8	4	8	8	8	8	4	4	8	4
iCouch CBT	4	4	8	8	4	8	8	8	8	8	8	4	8	8	8
iCounselor[f]	4	8	8	8	4	4	8	4	4 [d]	4	8	8	8	4	8
iMoodJournal	8	8	4	8	4	8	8	8	8	8	8	4	4	4	8
In Hand	8	4	4	8	4	4	8	4	8	8	8	8	8	4	4
MindShift	4	8	8	8	4	4	4	4	4	4	8	8	8	8	8
MoodKit	4	4	8	8	4	4	8	4	4	4	8	4	4 [c]	8	8
Moodlytics	8	8	4	8	4	8	8	8	8	8	8	4	4 [c]	8	8
Moody Me	8	8	4	8	4	8	4 [e]	8	8	8	8	4	4 [c]	4	8
Pacifica	4	8	4	8	4	4	8	4	4	4	8	4	8	4	8
Pocket CBT	4	4	8	8	4	8	8	8	8	8	8	4	8	8	8
SAM	4	8	8	8	4	4	4	4	4	4	8	4	8	4	8
Smiling Mind	4	4	4	4	4	8	8	8	8	8	4	4	8	4	4
Stress & Anxiety Companion	4	8	4	8	4	4	4	4	8	8	8	4	8	4	8
SuperBetter	8	4	4	4 [b]	8	4	8	8	4	4	4	4	4	8	8
ThinkHappy	8	4	4	8	8	8	4	8	8	8	8	8	8	8	8
What's Up?	4	4	4	8	8	4	4	4	8	4	8	8	8	4	8
WorkOut	4	4	4	8	4	4	8	8	4	4	8		4 [c]	4	8
WorryTime	4	8	4	8	8	8	8	4	8	8	8	8	4	4	4

[a]See the "Currently Available Apps" section for the 16 recommendations.

[b]Not using automated processes.

[c]Default is for reminders to be off.

[d]Only because there are separate apps for separate problems, so each app recommends activities for that target problem.

[e]Accessible via forums

[f]Includes separate iCounselor: Depression; iCounselor: Anger; and iCounselor: Anxiety apps.

Although primarily applied in clinical contexts, CBT is also fundamentally a prevention technique acting to prevent psychological problems from precipitating or maintaining clinical disorders [54-56]. This means that CBT-based MHapps have the potential to be effective for managing both clinical and subclinical psychological problems [57], provided that such apps avoid using CBT-based techniques that are used for very specific clinical psychological problems, are marketed correctly, and employ well-designed interfaces.

To ensure that an MHapp is indeed CBT based, it is important to keep the core principles of CBT in mind. Mennin et al [58] summarize the unifying factors that underlie all CBT approaches into three change principles: context engagement, attention change, and cognitive change. Context engagement involves training clients in a way that promotes more adaptive associative learning, which involves having them learn cues for threats and rewards that are more reasonable and lead to better functioning than existing cues. This includes CBT techniques that aim to recondition maladaptive associations, such as exposure and behavioral activation. The app SuperBetter [59] prescribes "power-ups" that may incorporate these techniques. Attention change is the ability to focus attention adaptively on relevant, nondistressing stimuli. This includes therapeutic processes such as attention training, acceptance or tolerance training, and mindfulness. These techniques are employed in Smiling Mind [60], and can be seen in the meditations displayed in Figure 1. Finally, cognitive change is the ability to change one's perspective on an event, which then affects the emotional significance and meaning of that event [61]. This includes metacognitive awareness and cognitive distancing, which are promoted through therapeutic processes such as decentering or defusion and cognitive reframing or reappraisal. An example of this can be found in using the Thoughts tool in MoodKit [62], as seen in Figure 2. If these three change principles are being employed to some degree by an intervention, then it can claim to be based on CBT's core principles.

To employ these change principles effectively, a therapist and client must develop a relationship that involves collaborative empiricism (CE) [63]. CE refers to shared work between client and practitioner to embed a hypothesis testing approach into interventions [64]. CE empowers clients to explore their behaviors and beliefs outside of therapy sessions using between-session (homework) interventions [65]. A meta-analysis of studies that compared therapy with and without homework found an effect size of d=0.48 in favor of using between-session activities [66]. In the context of CBT-based MHapps, CE may refer to how the app interacts with the user to complete therapeutic tasks, and whether it does it in a collaborative, experimentation-based way. This would ideally involve encouraging users to develop their own hypotheses about what may happen as a result of using the app or participating in certain activities (see the "Recommend Activities" section). An app that embraces CE is Behavioral Experiments-CBT [67], which affords users the ability to predict the outcomes of any behavioral experiments they participate in. Behavioral experiments are CBT-based challenges that individuals perform to challenge their own beliefs about the negative outcomes of various situations [68]. This process of comparing predictions with actual outcomes can challenge unhelpful beliefs [69].

Self-determination theory (SDT) can aid in understanding CE's benefits in CBT [64]. SDT emphasizes the effects of autonomy and mastery on intrinsic motivation [70]. Intrinsic motivation is the "prototypic manifestation of the human tendency toward learning and creativity" [71]. Autonomy feeds this motivation by affording individuals opportunities for self-direction and choice [72], and fostering self-efficacy [73]. Self-efficacy and a feeling of competency lead to a feeling of mastery, which is an intrinsic reward and motivator in itself [74]. CE and between-session activities promote autonomy and provide opportunities for development of competence in behavioral, emotional, or cognitive self-management. SDT can inform MHapps on how to best engage users in CBT-based interventions (ie, by intrinsically motivating them). Users will be more motivated to engage with apps and products that encourage autonomy, emphasize user choice, and allow opportunities for building mastery. For example, SuperBetter [59] employs SDT-based, game-based principles to intrinsically motivate users to engage with the app and experience the well-being-promoting effects of mastery (see the "Gamification and Intrinsic Motivation to Engage" section).

Figure 1. Screenshot of Smiling Mind displaying meditations.

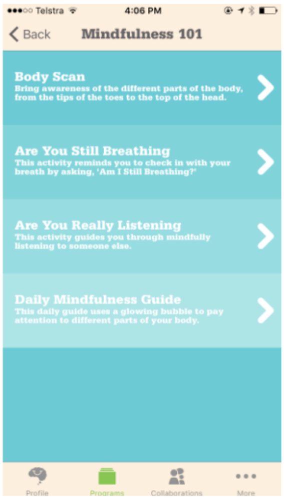
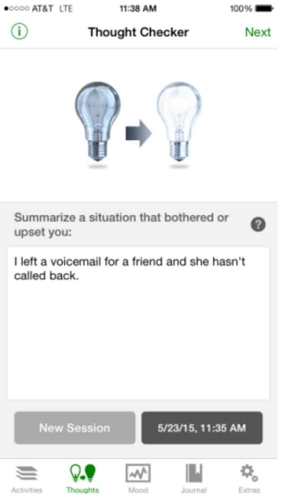


Figure 2. Screenshot of MoodKit displaying thought checker.



Address Both Anxiety and Low Mood

Emotional disorders (eg, anxiety and depression) are by far the most common psychological conditions in the community, with an estimated 20.9% of US citizens experiencing a major depressive episode and 33.7% suffering from an anxiety disorder at some point throughout their lives [75]. Emotional disorders are also the most treatable [76], but help seeking for sufferers is very low [77]. There is strong supportive evidence for CCBT as an effective therapy for reducing symptoms of the most common anxiety disorders and depression [45,46].

There is an extremely high comorbidity between anxiety and depression [78], with 85% of people diagnosed with depression problems also suffering significant anxiety and 90% of people diagnosed with anxiety disorders suffering significant depression [79]. In Australia, 25% of all general practice patients have comorbid depression and anxiety [80]; whereas in Great Britain, half of all mental illness cases are mixed anxiety and depression [81]. These two diagnoses share a few major underlying factors [82]. This raises two important considerations for MHapp self-help interventions. First, interventions designed for one disorder are likely to have some efficacy for other emotional disorders, and second, interventions that target shared underlying factors across emotional disorders will be more efficacious.

Transdiagnostic CBT (TCBT) is an effective therapeutic approach that targets the common underlying factors shared by different psychological disorders. A meta-analysis of RCTs found a large effect size (standardized mean difference = −0.79, 95% CI −1.30 to −0.27) for TCBT across different anxiety disorders [83]. Furthermore, TCBT has been found to be successful in treating depression [25]. Barlow et al's [84] Unified Protocol (UP) is a recent TCBT treatment that focuses on monitoring and adjusting maladaptive cognitive, behavioral, and emotional reactions that underlie depression and anxiety disorders. The UP has yielded very promising results across various emotional disorders, reducing psychopathology [85] and improving psychological well-being [86]. It is important to note that TCBT protocols do not imply that all emotional disorders can be treated effectively with the exact same techniques [87]. The basic structure for treating different clinical problems may be relatively uniform, but tailoring of interventions is still essential (see the "Automated Tailoring" section), and the structure of TCBT affords flexibility. For example, the UP consists of four core modules that are designed to (1) increase present-focused emotional awareness, (2) increase cognitive flexibility, (3) aid identification and prevention of patterns of emotion avoidance and maladaptive emotion-driven behaviors, and (4) promote emotion-focused exposure [88]. This enables a prescriptive approach, whereby certain modules can be focused on more than others, depending on the needs of the client or user [88]. An Internet-delivered TCBT intervention called the Wellbeing Program used a structure of 8 lessons, focusing on areas such as psychoeducation, thought-monitoring strategies, behavioral activation, and graded exposure [57]. A clinician guided users through the program and tailored the delivery of each lesson to the user's needs. An RCT supported the efficacy of this intervention across depression and anxiety disorders [57]. Although the Wellbeing Program was guided by a clinician and not via automated processes, many other self-guided CBT interventions use a transdiagnostic approach to maximize efficiency and adaptability [89], particularly in an automated Internet-delivered context [90].

Despite the success of TCBT, many MHapps are designed for the treatment of specific disorders. Some apps are marketed for anxiety and others for depression. Few apps acknowledge that the underlying CBT principles guiding self-help interventions for anxiety and mood problems are very similar; thus, broadening the target group of the app can be beneficial for all users. Combining treatments for both anxiety and depression into a single app would also reduce the commitment required for engagement. Users could consolidate their investment within a single app, instead of dividing their effort and time engaging with 2 separate apps (one for anxiety and the other for depression).

Designed for Use by Nonclinical Populations

Many apps have been designed for use with populations who have been diagnosed with a specific clinical disorder, from depression (eg, Optimism [91]) and anxiety (eg, SAM [92]) to eating disorders (eg, Recovery Record [93]) and borderline personality disorder (eg, DBT [Dialectical Behavior Therapy] Diary Card and Skills Coach [94]). Some of these clinical diagnosis apps are known to be effective for interventions [8], but they do not capitalize on one of the major advantages of smartphones: high accessibility. Smartphones are interwoven into the routines of millions of people all over the world, the majority of whom have not been diagnosed with a clinical psychological disorder but do experience unpleasant psychological distress from time to time. Targeting a specific clinical population with an MHapp automatically excludes the majority of smartphone owners from using that app. By contrast, an MHapp built for a population interested in the *prevention* of emotional mental health problems increases the number of eligible and willing users. A meta-regression of 34 studies found that self-help interventions were significantly more effective when recruitment occurred in nonclinical settings (effect size I^2=0.66) than in clinical settings (effect size I^2=0.22) [48]. The field would therefore benefit from more MHapps with preventative applications that are widely marketable, rigorous, and effective.

An MHapp market saturated with clinical diagnosis apps also has the potential to be harmful for help seekers. Users who are experiencing low-level symptoms of a disorder may feel labeled by an app that assumes that they have a clinical diagnosis [95]. Self-stigma from this labeling can be harmful, lowering self-esteem and self-efficacy [96]. Initiatives that acknowledge the continuum of mental health and the importance of well-being promotion may reduce stigma and increase help seeking for mental health problems [97]. Programs such as Opening Minds [98] aim to reduce mental illness stigma by adopting a nonjudgmental, nondiagnostic, and nonclinical CBT-based stance to mental health problems. MHapps that focus on nonclinical mental health, psychological well-being, or coping abilities may therefore avoid the harmful effects of labeling mental illness [99].

CBT is built on the foundation that mental health is a continuum [89] and that supporting individuals in coping with nonclinical psychological distress can prevent symptoms from reaching clinical significance [100]. Furthermore, CBT-based support can help prevent relapse [101], expand an individual's coping skills repertoire [102], and assist individuals experiencing psychological distress to avoid developing a clinical disorder [103]. Building a CBT-based MHapp that acknowledges the continuum of mental health can be used by both clinical and nonclinical populations.

CBT treatment adopts a formulation-based approach rather than a diagnosis-based approach [54,104]; as such, a diagnosis is not necessary for support to be given. Formulation involves exploring the predisposing, precipitating, perpetuating, and protective factors connected to a psychological problem, and then building these factors into a causal model [105]. Conversely, diagnosis relies on detection of symptoms and fulfillment of criteria statistically linked to a particular disorder [106]. In many cases, a formal diagnostic label is not important for informing real-world treatment, and it does not specify the causal factors contributing to an individual's unique psychological problems. Formulation is much more useful because it can inform exactly which precipitating and perpetuating factors are contributing to an individual's unique psychological problem, and which psychological techniques can produce optimal solutions [107]. Hofmann [108] proposed a cognitive behavioral approach for classifying clinical psychological problems that avoids diagnostic labeling, which is better at informing CBT-based support because it is based on formulation. MHapp developers are encouraged to explore formulation-based approaches to CBT to inform the development of CBT-based MHapps.

Designing MHapps for nonclinical support may mean adopting a preventative framework. There are generally three types of preventative intervention: universal (ie, delivered to everyone in the community), selective (ie, delivered to at-risk groups), and indicated (ie, delivered to individuals with preclinical symptoms) [109]. The flexibility of MHapps means that a single app could theoretically adapt to any of these three intervention models, providing a universal intervention as default, and tailoring to a selective or indicated approach if a user's responses suggest that they are at risk of a certain condition.

Some mobile interventions that have been validated and trialed experimentally were built for personal digital assistants (PDAs) and not for modern smartphones [7,110]. This severely limits their nonclinical use and introduces other barriers to routine engagement that are not experienced by smartphone apps. However, evidence and principles from PDA-based studies should be considered when designing smartphone apps.

Automated Tailoring

An advantage of eHealth interventions over other self-help interventions is their capacity for tailoring [90,111]. Tailoring in this context refers to the adjustment of technology-delivered self-help programs to suit the user's needs, characteristics, and comorbidities or case formulation [112]. Tailored CCBT interventions have been shown to be more efficacious than rigid self-help interventions across a range of depressive and anxiety disorders [112-115].

Formulation-based tailoring improves the functionality of an intervention and provides targeted solutions to a user's psychological problems. There is a large range of different self-help mental health interventions available, and selecting the right intervention can be a challenging and overwhelming process [15]. The complexity of choices can be simplified or reduced by building an app capable of automated tailoring, which combines elements of a large number of different interventions and deploys them strategically depending on the needs of individual users. A review of currently available MHapps reveals, however, that many apps aim to provide a service but do not service a need [116]. For example, many apps provide guided meditation, but do not guide users toward meditation when they are feeling anxious. With tailoring, the app can recommend users specific solutions to their specific problems.

Automated tailoring requires the collection of data to identify the needs of users and develop a functional analysis or case formulation. This can be achieved in three main ways. First, self-report measures can be deployed to elicit in-depth responses about symptoms and characteristics. Second, data from a user's self-monitoring (see "Reporting of Thoughts, Feelings, and Behaviors" section) can be used to predict the types of interventions that are well suited to an individual user. Third, an app's behavioral usage data can be used to predict which features of that app a user is using most. If these second and third data sources are correctly utilized, tailoring can be carried out seamlessly, without any additional input from the user, which decreases users' required effort to use the app and thereby increases app functionality [3].

CBT includes a very wide range of evidence-based techniques that may be selectively employed by an MHapp depending on automated tailoring data. For example, if data sources suggest that the user is experiencing significant physiological arousal, rather than overwhelming worry or other anxiety-related problems, CBT techniques such as breathing relaxation may be recommended over others, based on the available evidence [117]. Ideally, these therapeutic techniques would be employed by the MHapp that actually performs the automated tailoring, but restrictions may mean that the MHapp must rely on referring users to other apps. This is not ideal, as it may disrupt the user's engagement with the MHapp. However, if necessary, any referrals should be based on a thorough review of the other existing apps and their supporting evidence [116].

Reporting of Thoughts, Feelings, or Behaviors

Clients who record their own thoughts, feelings, and behaviors as part of a CBT-based intervention are able to reflect on their reports and exercise self-monitoring [118]. Self-monitoring is a core feature of many evidence-based psychological therapeutic techniques, including CBT [119,120], mindfulness exercises [121], emotion-focused therapy [122], DBT [123], and acceptance and commitment therapy (ACT) [124]. Self-monitoring can be used to restructure maladaptive anxiety responses [125,126], challenge perpetuating factors of depression [127], and sufficiently treat a small but significant proportion of posttraumatic stress disorder sufferers [128,129].

Self-monitoring is particularly suitable for CBT-based interventions that aim to change behavior, with self-monitoring-only treatment conditions showing benefits for problem drinking [130] and sleep hygiene [131]. Furthermore, self-monitoring is a feature of successful weight loss interventions [132]. Encouraging MHapp users to report their thoughts, feelings, or behaviors in an objective way should therefore help promote accurate, beneficial self-monitoring.

Self-monitoring of mood can boost overall emotional self-awareness (ESA) [133], which can in turn lead to improvements in emotional self-regulation [134]. Emotional self-regulation is valuable for individuals in preventing distress from spiraling out of control and thereby culminating in clinical problems [135]. Poor emotional awareness is a common underlying factor for both anxiety and depression [136]. The ability to differentiate and understand personal emotions, an integral process in ESA, is positively related to adaptive regulation of emotions [137] and positive mental health outcomes [138]. Self-reflection and insight correlate positively with levels of positive affect and the use of cognitive reappraisal, and negatively with levels of negative affect and the use of expressive suppression [139]. Explicit emotion labeling shares neurocognitive mechanisms with implicit emotion regulation ability, suggesting that increasing ESA through practicing labeling of personal emotions will lead to improvements in emotional regulation and adaptation [140].

Some self-monitoring interventions are limited by problems related to recall biases. Self-reflection at the end of a day or in a time and place removed from normal stressors can be inaccurate [141]. One of the benefits of MHapps is that smartphones are capable of ecological momentary assessment (EMA) and experience sampling methods (ESM), which involve measuring experiences and behavior in real time [142]. MHapp users can record self-monitoring data on their smartphones while they are participating in their usual daily routines, undergoing challenges, or directly experiencing stressors [143]. This can help reduce bias in self-monitoring [141], thereby improving the accuracy of users' reflections.

Increasing ESA should lead to greater help seeking, because factors preventing help seeking include low emotional competence [144] and low self-awareness [77]. Using technology for self-monitoring can increase help seeking, particularly if there is a capacity to contact health professionals built in to the service [145] (see the "Links to Crisis Support Services" section).

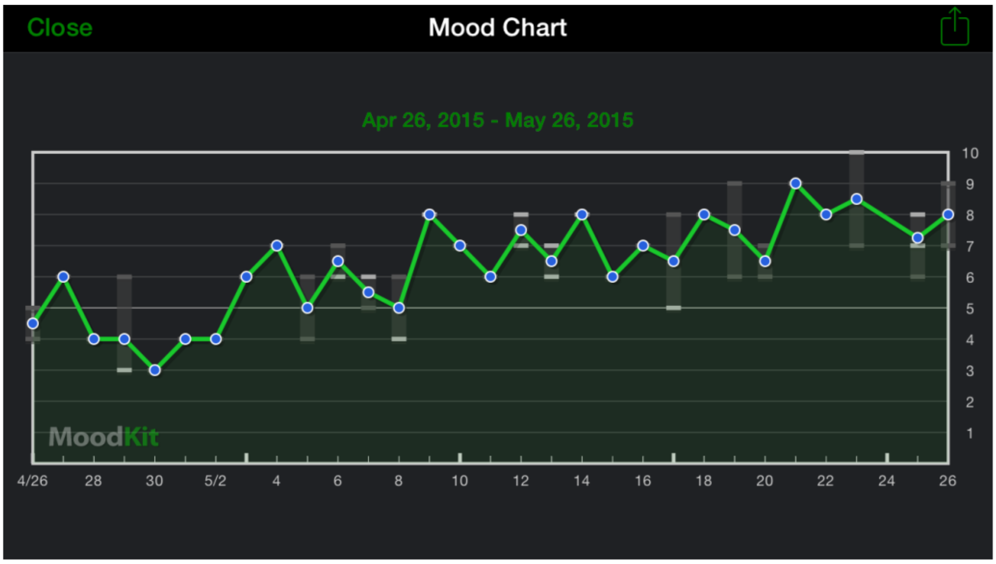
Self-monitoring via traditional means might also be less effective for very busy individuals who do not have the time to complete monitoring entries [118]. MHapps can reduce monitoring demands by automating some parts of the monitoring process, such as shifting the burden of some of the more administrative parts of self-monitoring (eg, entering dates and times, formatting monitoring entries) from the user to the smartphone [5]. Using smartphone apps also allows for more frequent and broader opportunities for recording reflections, such as while waiting or traveling on public transport.

Keeping all self-reports structured and objective can help users report quickly and in a format that facilitates data analysis by the MHapp. It may also reduce some of the barriers to self-monitoring: for instance, some depressed clients may find the demands of open-ended self-monitoring overwhelming, whereas perfectionistic or obsessive clients may spend too much time and effort on their monitoring [146]. MHapps with highly structured reporting in a simple interface (see "Simple and Intuitive Interface and Interactions" section) may be able to remedy this by limiting the amount of information necessary for logs, simplifying the monitoring process, reducing the demands on users, and increasing engagement in the app [5].

Several studies support the efficacy of using app-based interventions to increase ESA. Morris et al [147] developed an app that prompted users to report their moods several times a day. Users reported increases in their ESA, and upon reflection of their ratings, some were able to recognize patterns of dysfunction and interrupt these patterns through modification of routines. Kauer et al [133] used a mobile phone self-monitoring program to prompt users to report their emotional state several times throughout the day. Participants who reported on their emotional state showed increased ESA and decreased depressive symptoms compared with controls. Both of these monitoring systems were, however, quite simple and offered little constructive feedback to users about their mood history. They were also trialed on small samples of individuals who had reported psychological distress. There is, therefore, a need to further investigate the impact of smartphone-based mood reporting on ESA and associated mental health outcomes, using an app that gives better feedback and is relevant to nonclinical users.

The reporting required for self-monitoring can also enable feedback and evaluation of therapeutic progress. In psychological therapy, therapeutic outcomes can be enhanced by providing clients and clinicians with feedback concerning treatment progress [148,149]. These positive effects have been substantiated via a literature review [150] and a meta-analysis, which found a notable effect size (d=0.10, 95% CI 0.01-0.19) [151]. MHapps may be able to provide feedback by presenting a user's own reporting data back to them, but reframed in context with the user's treatment goal. For example, the mood feedback provided by MoodKit [62] can displayed as a chart, as shown in Figure 3. This type of feedback-focused progress tracking relates also to gamification (see the "Gamification and Intrinsic Motivation to Engage" section) and keeping a log of past app engagement (see the "Log of Past App Use" section).

Figure 3. Screenshot of MoodKit displaying mood chart.



Recommend Activities

CBT aims to engage clients in a range of activities that are congruent with its core principles (ie, context engagement, attention change, and cognitive change) [58]. This represents a shift away from passive interventions toward ones that actively engage clients. CBT-based activities that can be recommended to MHapp users can be summarized into the following categories: (1) exercise and direct mood improvement, (2) behavioral activation, and (3) coping skills training.

Activities That Directly Enhance Mood Improvement

A range of activities might target mood directly. For example, it is well established that increasing physical activity and promoting exercise can reduce depressive symptoms [152-154] and anxiety [155], and improve psychological well-being [156,157]. A meta-analysis of 39 RCTs examined the effects of exercise on people diagnosed with a mental illness, and found large effect sizes for depressive symptoms (standardized mean difference=0.80, 95% CI 0.47-1.13) and schizophrenia symptoms (standardized mean difference=1.0, 95% CI 0.37-1.64), and a moderate effect size for quality of life (standardized mean difference=0.64, 95% CI 0.35-0.92) [158]. Effective smartphone apps that promote physical exercise have already been developed [7], but lack an explicit link to mental health that mental-health-focused users may need to justify their use. Motivating MHapp users to engage in physical exercise can have a broad range of mental health benefits.

Another activity that has been directly linked to mood improvement is music listening. Music can be a powerful tool for evoking emotion [159]. Furthermore, relaxing music can challenge emotional recall biases [160] and decrease anxiety [161]. Over 68% of users listen to music on their smartphones [1], and many users use music to reach specific emotional goals [162,163]. An MHapp that includes music listening activities could help users with emotional regulation.

Behavioral Activation

Behavioral activation (BA) is a key CBT technique that involves encouraging individuals to engage in physiologically activating and psychologically rewarding activities [164]. A meta-analysis of 17 RCTs reported that BA for clinical depression outperformed control conditions (standardized mean difference=−0.70, 95% CI −1.00 to −0.39) and was as effective as CBT-as-usual (standardized mean difference=0.08, 95% CI −0.14 to 0.30) [165]. There is also evidence that BA can help relieve anxiety [166]. BA aims to (1) encourage the planning of activities and the setting of goals so that clients move away from relying on mood-dependent behaviors; (2) break cycles of avoidance behavior; and (3) develop skills that focus attention on the present moment to enable engagement in activities and associated experiences of pleasure [167]. Motivating MHapp users to complete BA activities is therefore a simple and effective way to improve mental health and well-being outcomes.

Inactivity perpetuates itself via a vicious cycle of low mood: inactivity can lead to decreased opportunities to experience pleasure or gain a sense of mastery, which in turn leads to an increase in negative thinking. This leads to decreased mood, which again leads to greater inactivity, and so forth [168]. BA helps to break this cycle by scheduling activities and reducing escape and avoidance behaviors [167]. Selecting activities that involve mastery and promote positive feelings of self-worth is recommended [168], as such activities can boost motivation via factors related to SDT as well as self-efficacy [100]. Classifying activities as routine, pleasurable, or necessary can be useful, as each has different motivations and benefits to performing [169]. To maximize the likelihood that a recommended behavior will actually be performed by a smartphone user, the behavioral economics of the situation need to be considered [5].

Using a framework such as Fogg's [170] behavior model, which has been specifically designed with app users in mind, can help in the selection of short, tangible, and universal activities that will maximize user engagement. Fogg's behavior model states that three factors determine the likelihood of a target behavior occurring: behavior triggers, elements of motivation, and elements of simplicity. Most relevant to selecting BA activities are elements of simplicity, which affect a user's ability to easily perform the behavior, and include factors such as time, money, physical effort, mental effort, social deviance, and routine. Feedback and self-reflection (see the "Reporting of Thoughts, Feelings, or Behaviors" section) can be an important part of behavioral activation [169]. An app that promotes reflective learning by encouraging an activity and then prompting reflection on the experience immediately after can promote self-discovery [171].

Coping Skills Training

Coping skills training is the most direct way of improving self-efficacy [172,173]. Coping self-efficacy (CSE) is a type of self-efficacy reflecting an individual's perceived ability to effectively cope with adversity and distress [174]. Individuals with high CSE have confidence in their ability to cope with adversity [175] and engage in more active coping strategies [176]. Having greater CSE is associated with better mental health outcomes, including lower likelihoods of depression [177] and anxiety [174], lower overall psychological distress [178-180], and greater psychological thriving [181]. Furthermore, CSE can decrease the negative effect of stressful events on physical health [182]. The greater an individual's CSE, the less likely they will also be to avoid anxiety-provoking situations [174]. Avoidance plays a key role in the development of anxiety, depression, and many other psychological disorders [183], so interventions that boost CSE by encouraging participation in psychologically beneficial activities will both reduce day-to-day distress and help prevent disorders from developing.

The development of coping skills is a central component in CBT-based practices, and such skills can help clients reduce distress that can trigger problematic maintenance cycles [54,100,104,184]. For example, a core exercise in the treatment of anxiety is the development of relaxation skills, and a meta-analysis of 27 RCTs found a medium to large effect size for relaxation training on anxiety (d=0.57, 95% CI 0.52-0.68) [117]. Relaxation training not only develops skills to reduce physiological arousal, but also builds self-efficacy and confidence in coping ability [185,186]. CBT for depression also involves exploration of activities that can reduce distress and improve self-efficacy [187,188]. Research in positive psychology stresses that development of a coping skills repertoire is not only beneficial for those vulnerable to anxiety or depression, but also important for individuals to function well emotionally and achieve their full potential [189]. Offering a range of different strategies and thereby allowing a client to choose which one fits them best can boost self-efficacy and perceived control [190,191]. Furthermore, according to SDT, this choice and control can feed intrinsic motivation toward self-improvement [70].

Unfortunately, there is currently a lack of technology-based interventions designed to develop CSE in relation to mental health. A comparison of 2 Web-based interventions for diabetes management, one involving coping skills training and the other focusing on education, showed that although both interventions had a positive effect on diabetes self-efficacy, only the coping skills (ie, active) intervention showed significant increases in primary control coping behaviors and decreases in perceived stress [192]. Other studies have found no advantage of coping skills training over educational interventions [193-195], but none has investigated the impact of the type of real-time engagement that smartphone apps offer. Many of the coping skills interventions investigated are limited to a series of educational sessions about potential coping strategies. By contrast, smartphone approaches to coping skills interventions could motivate participants to try a number of different coping strategies in real-time as they go about their lives and respond to stressors. This high level of engagement and interactivity could yield substantial improvements in CSE and psychological well-being.

Mental Health Information

Psychoeducation, an integral part of CBT, presents clients with mental health information in an attempt to teach them about the psychological processes underlying their distress and inform them of resources available to manage it [196]. A meta-analysis of 25 RCTs reported that the "Coping with Depression" psychoeducational intervention, developed by Lewinsohn et al [197], was effective at treating depression, albeit with a small effect size (d=0.28, 95% CI 0.18-0.38) [102]. Participants who completed the preventative version of the intervention were 38% less likely to develop clinical depression [102]. Psychoeducation can also improve mental health outcomes on a community-wide scale. A meta-analysis of 15 studies concluded that the Mental Health First Aid program, developed by Kitchener and Jorm [198], improved participants' knowledge (Glass's Δ=0.56, 95% CI 0.38-0.74), attitudes (Glass's Δ=0.28, 95% CI 0.22-0.35), and supportive behaviors (Glass's Δ=0.25, 95% CI 0.12-0.38) with regard to mental health [199].

MHapps are well positioned to deliver psychoeducation, as they can engage users with a range of multimedia and audiovisual tools to aid understanding of mental health concepts. A meta-analysis of 4 RCTs reported a small effect size (d=0.20, 95% CI 0.01-0.40) for passive psychoeducation including brief audiovisual sources and information presented via the Internet, demonstrating that even this minimal form of psychoeducation is effective at reducing depressive symptoms and psychological distress [200]. Another meta-analysis of 19 studies found a significant but small effect size of psychoeducation on stress (standardized mean difference=0.27, 95% CI 0.14-0.40); in a follow-up moderator analysis, this study showed that shorter interventions were significantly more effective than were longer interventions (P<.05, B=−0.020, 95% CI −0.024 to −0.016) [201]. Smartphones are well equipped to deliver this kind of brief, passive psychoeducation, and MHapps can offer links to websites for more in-depth information where required [202].

Psychoeducation topics that have greater relevance to the user's reported problems are of greater use to the user, so MHapps should tailor psychoeducation to individual users (see the "Automated Tailoring" section) [111]. For example, if a user reports feelings of anxiety, delivery of information about the physiological responses of anxiety and their relationship with thoughts and behaviors would be more appropriate than would delivery of information about the physiological symptoms of depression. Relevance and engagement may also be enhanced by adopting a collaboratively empirical approach [64], whereby users are encouraged to apply concepts learned through psychoeducation to their own circumstances through hypothesis testing. An app that engages users in a process of experimentation-based self-discovery may enhance psychoeducational outcomes.

Presenting mental health information and engaging individuals in psychoeducation can lead to boosts in mental health literacy (MHL) [203]. MHL has been defined as "knowledge and beliefs about mental disorders which aid their recognition, management or prevention" [204]. Greater MHL is associated with a reduction in stigmatizing beliefs about those with mental illness [205] and with greater and more appropriate help seeking [144,206,207]. Known factors preventing young people from seeking help for mental health issues include poor MHL, preference for self-reliance in problem management, and perceived stigma of mental illness [77].

Mental health information can also increase treatment credibility, thereby motivating users to engage with a given treatment [208], and can provide evidence-based justifications for performing recommended activities (see the "Recommend Activities" section). Notably, users have a tendency to perceive health information on the Internet as being credible [209], so this raises the ethical imperative of ensuring that all information is strictly evidence based. Providing links to sources of evidence may satisfy the needs of scientifically minded users and mental health experts. The wealth of mental health resources already available online [210,211] could be utilized by MHapps. Improving MHL may simply be a case of providing easy access to these resources through the app.

Christensen et al [212] compared 2 Web-based interventions aimed at promoting mental health. BluePages, a psychoeducation site, and MoodGYM, a self-guided CBT site, both led to decreases in users' depression symptoms. MoodGYM reduced users' dysfunctional thinking, whereas BluePages failed to do this. However, BluePages improved users' knowledge of treatments for depression beyond what MoodGYM achieved. This evidence suggests that both psychoeducation and self-guided CBT interventions are needed to generate the most substantial and stable gains in mental health and well-being. A successful app-based intervention would combine elements of both psychoeducation and self-guided CBT.

Real-Time Engagement

The high engagement potential of smartphones means that users are able to seek help for psychological challenges in the moment they are experiencing them or soon after. MHapps that have not been designed to be used in real time will fail to capitalize on valuable opportunities to engage with users.

Many CBT-based therapy programs utilize in vivo exposure and between-session (homework) activities to help clients resolve maladaptive anxiety responses in ecologically valid settings [65,105]. The advantages of between-session interventions are wide ranging [66] and have already been covered in this paper under Recommendation 1 "Cognitive Behavioral Therapy Based." Some therapy programs have even utilized virtual reality to harness the power of real-time engagement [213,214]. These interventions acknowledge the benefits of engaging with clients in real-world contexts in real time.

The rationale behind real-time engagement includes basic behavioral principles of learning. It enhances the generalization of learned skills to new settings, and can encourage practice of behaviors to maintain therapeutic gains [215]. Real-time engagement opens up more opportunities for learning and applying coping strategies in ecologically valid contexts. Of the MHapps that aim to increase users' coping abilities, few utilize the real-time capabilities of smartphones [8,216]. Most deliver long-running interventions designed to increase users' overall resilience or optimism, such as SuperBetter [59]. The MHapps that do provide users with in vivo coping strategies, such as MindShift, are very clinically focused, which restricts their reach (see the "Designed for Nonclinical, Nondiagnostic Support" section). Engaging users to attempt coping strategies in real time improves the functionality of the MHapp and increases opportunities for learning.

Heron and Smyth [217] call health apps that use real-time engagement "ecological momentary interventions," and they present evidence for the efficacy of such apps in psychosocial applications. Depp et al [110] developed and trialed a mobile intervention called PRISM that used real-time data to prompt individuals with bipolar disorder to engage in self-management behaviors. The results from this study were promising, but this rather clinically focused intervention was built for PDAs rather than for smartphones, and therefore was unlikely to be as unobtrusive in daily life as smartphone interventions.

Activities Explicitly Linked to Specific Reported Mood Problems

Linking recommended activities to specific psychological challenges helps trigger engagement with an intervention. Eyal [3] emphasizes the need for successful apps to have triggers that fulfill an immediate and obvious need, using the metaphor of vitamins and painkillers. Vitamin-like products do not satisfy immediate needs but are espoused as beneficial, whereas painkiller-like products give users immediate benefits. MHapps like SuperBetter [59] and Happify [218] require users to engage with the app regularly and encourage them to do so by reminding them of the benefits offered by the app. However, the activities recommended by these apps are not directly linked to any specific mood problems that users may be experiencing. Using specific problems as triggers can strengthen engagement [3] and can help in the learning of targeted coping strategies.

Utilizing habit formation can be a very effective way of guaranteeing repeated engagement with an app, which in the case of MHapps, should lead to mental health benefits. Habits are repeated behaviors that are triggered by cues [5]. To generate a habit that involves using an MHapp, a cue must be selected to associate with app use through the processes of conditioning [3]. Using mood problems as cues can drive real-time engagement (see the "Real-time Engagement" section). For example, an MHapp that is designed to be used when a user is feeling low or anxious is better suited to habit formation processes than is an MHapp that offers no cues for engagement and expects users to engage with it randomly throughout the day. Habit formation will also be driven if an MHapp is linked to activities that decrease psychological distress, increase self-efficacy, or reward users in some other way [5].

Encourage Nontechnology-Based Activities

When designing interventions for smartphones, it may be tempting to build the therapeutic activities into the app's interface. However, this goes against the ethos of CBT-based practice, which emphasizes the important role of activities and interventions outside of contact with a practitioner, computer program, or self-help guide [120]. Encouraging users to engage in real-world activities, off the device they are using, respects that ethos and fosters the environmentally valid application of skills.

In this context, it is also of note that depression and lower psychological well-being are correlated with Internet use, especially among introverts with low levels of social support [219]. However, this role is moderated by the function of Internet use—for instance, Internet use for communication has been found to be related to lower levels of depression, whereas Internet use for noncommunication purposes has been found to be related to greater depression and social anxiety symptoms [220]. Internet use and Internet addiction have also been associated with social anxiety [221], and positive correlations have been found between avoidance coping and Internet use [222,223]. This may also apply to Internet-enabled, noncommunication-based mobile phone apps that distract users' attention away from psychological challenges. Avoidance coping has been shown to increase the likelihood of acute and chronic life stressors and depressive symptoms over long periods [224]. Providing users with nontechnology-based activities helps to balance MHapp-based technology use with positive behavior change strategies and limits use of avoidance coping strategies.

Technology can allow greater multimodal learning by combining text with spoken language, sounds, and graphics that are closer representations of learning in an applied setting [225]. For example, blended learning, which involves blending the use of technology with applied learning in the classroom [226,227], has been shown to deliver superior learning outcomes to traditional teaching methods [228,229]. It has been recommended that technology be used to enhance real-life experiences, not replace them [230,231]. MHapps may therefore harness the power of blended, multimodal methods to effectively enhance learning of real-world coping strategies.

Some available MHapps encourage users to engage in nontechnology-based activities. SuperBetter motivates users to engage in regular nontechnology-based resilience-building activities [232]. Preliminary results from an RCT suggest that SuperBetter is effective for reducing symptoms of depression [233]: specifically, SuperBetter users experienced a reduction in the equivalent of 5 symptoms of depression, and waitlist participants experienced a reduction in just 2.

Gamification and Intrinsic Motivation to Engage

The therapist plays an instrumental role in promoting clients' motivation to engage in psychotherapy and undertake homework activities [65]. This means that self-help CBT may be of limited use if the user suffers from low motivation and volition, which is common among those with mood disorders [234]. Gamification is a novel solution that may help counteract problems with motivation and yield additional well-being outcomes.

To "gamify" something does not mean to turn it into a digital game. Gamification is instead the use of "game-based mechanics, aesthetics, and game thinking to engage people, motivate action, promote learning, and solve problems" [17]. Many apps have employed the principles of gamification to motivate users to pursue various goals, but such goals are likely to be most motivating if they originate from the users themselves [235]. Gamification can enhance a user's motivation to pursue an existing goal, but it does not, in itself, create new goals for users. These goals may require the formation of new routines, and gamification excels at motivating people to repeat tasks until new habits are formed [3]. Some examples include Nike+ Running [236] and other fitness tracking apps that award points for reaching fitness goals, and Smiling Mind [60], which tallies minutes spent meditating and awards badges for specific meditation-related achievements, as seen in Figure 4.

Figure 4. Screenshot of Smiling Mind displaying achievements.

Games are abstracted, simplified versions of reality, so gamification can help users reduce reality's complexity into a more easily understood operating model [17]. This helps users to quickly learn cause-and-effect inferences, without complex extraneous factors detracting from their motivation to make change. Gamification is also based on the principle that making something goal oriented can increase the positive feelings associated with it and drive intrinsic motivation [232]. In this context, gamification is an applied expression of the concepts proposed by SDT [17] (see the "Cognitive Behavioral Therapy Based" section).

Gamification is a means of making intrinsic rewards more obvious and tangible. Alternate reality games (ARGs) link online or app-based events and achievements to real-world ones [237]. By tracking and quantifying the progress of real-world goals, users are able to reflect on their competency and experience mastery. Gamification also helps to break larger, more abstract goals down into smaller, more tangible and concrete tasks. For example, if a user's goal is to build resilience and recover from depression, the MHapp and ARG SuperBetter is able to break that goal down into daily tasks of activating 3 power-ups, battling 1 bad guy, and doing 3 quests [59]. Although many regular electronic games are attractive because they are escapist [238], ARGs are antiescapist, motivating users to deal with real-world challenges and increasing the likelihood of them obtaining intrinsic rewards.

Individuals tend to choose more challenging activities when these activities are framed as games and imbued with intrinsic motivation [239,240], and making activities goal-directed further enhances enjoyment of their challenges [241]. When building points and award systems for gamified solutions, it is best to introduce users by awarding them some points or rewards on sign-up or early on. The endowed progress effect means that starting with some points rather than zero increases effort and motivation to engage [242].

Although fun is the primary reward in electronic games, self-efficacy is the primary reward in well-structured gamified solutions [235]. Gamification principles can amplify achievements by offering immediate reflections of intrinsic rewards, thereby boosting self-efficacy. Badges, points, and other gamification rewards remind users that they have achieved something by quantifying their success and allowing users to reflect on their own growth [232]. Even apparent failure can be rewarding in a gamified environment, if the right animation or interaction—namely, one that maintains the user's feelings of competency—is used [17].

One study found that the reward- and motivation-related neurotransmitter dopamine was released during a simple, goal-directed game-based task, presenting neurological evidence for why game-based mechanics may yield positive well-being effects [243]. A meta-analysis of 10 RCTs found that electronic-game-based depression interventions had a moderate effect on depressive symptoms (d=−0.47, 95% CI −0.69 to −0.24) [244].

Apps allow constant improvement through updates and Web-delivered content [245], and this is very important for a successful gamified solution. Not only should the gamified structures be tweaked until users are being optimally engaged, but also novel and untried features should be introduced to motivate users to maintain their engagement with the app. Apps that sustain variability throughout use can maintain user interest with the promise of new and interesting content [3].

Log of Past App Use

Gamification relies on users having the ability to record and review their achievements. Thus, having a well-presented log of past app use can potentially raise intrinsic motivation and increase users' investment in the app. Logs of past use can also enable automated tailoring (see the "Automated Tailoring" section). If a log is being recorded for this purpose, then making it accessible to the user should not present coding difficulties.

Narratives in games can link discrete, seemingly unrelated tasks [232]. Narrative framework embedded into an app's use can motivate users to do small tasks to work toward an overall goal. Using a log that provides users with useful feedback about their successes and challenges can provide this narrative framework.

For example, many mental health boosting activities, such as exercise, relaxation, and cognitive reframing, appear to be unrelated. However, embedding them into a narrative that has an end goal related to boosting mental health can help users make sense of the tasks, thereby boosting users' motivation to achieve these goals.

Wilson's [246] story-editing technique can be applied to apps to enhance engagement [5]. According to Wilson's theory, reinterpretation of a self-narrative can affect future behavior. Past failings can be reinterpreted as learning opportunities, and other actions can be framed as preparations for a specific goal. Altering self-narrative in this way helps users see "themselves as someone for whom the action is a natural, normal extension of who they are" [5]. For example, fitness trackers and apps that count a user's steps, such as the Jawbone UP [247], show users that they have already been exercising, but may need to increase their level slightly to achieve their goals.

The addition of more storyline-based game principles, such as avatars with experience points, can further reinforce a sense of narrative [17]. Avatars are characters within a game that are representations of the user [248]. Bandura's [249] social cognitive theory states that the relatability and similarity of a model will increase the likelihood of a learned behavior being performed. Fox and Bailenson [250] substantiated this in a digital environment, with participants exercising more when they were shown an exercising avatar that resembled them than when the avatar did not resemble them. Furthermore, users who are given taller avatars act more confidently and aggressively than do those who are given shorter avatars, both virtually and face-to-face [251,252]. This indicates that the narrative elements used in a gamified solution can translate to behavioral changes in the real world. If users are capable of exercising autonomy and customizing their avatars so that these avatars better resemble users' ideal state, the likelihood of behavioral modification should be improved.

Importantly, users must also be aware of the cognitive or behavioral work they have completed. Investment through labor and work increases engagement and enjoyment [253]. Understood through SDT, this may be a reflection of a user's desire to build competency and mastery [254]. Therefore, users who can log the extent of their app use and receive feedback on how much they have done or invested are more likely to have greater, more enjoyable engagement with the app.

To maintain a log of app-based activity, users may have to create an account to synchronize their app progress with a server. This would allow users to use multiple devices and help them avoid losing their progress if their app were deleted or they changed devices. Many apps use a social networking site login, such as Facebook, for easy account creation, but this can trigger privacy-related anxieties in users [255], so it may be best to avoid this when creating an MHapp that collects potentially sensitive data. Other ethical and privacy concerns arise when recording app data to a server [256], so the integrity of storage sites should be thoroughly evaluated, especially with regard to obtaining users' informed permission to record and access their personal data [116].

Reminders to Engage

Some of the most successful guided self-help Web-based treatments for anxiety and depression use email or telephone reminders to maintain user engagement [10]. Reminders can increase adherence and reduce dropout from self-help CBT interventions [24]. Push notifications are alerts that can be sent via the Internet to apps on mobile devices [257]. MHapps that use push notifications are similar to Internet interventions that use short message service (SMS) reminders in that they prompt users throughout their day to engage in the intervention. Previous studies have demonstrated that interventions with SMS reminders can be effective for diabetes management [258], smoking cessation [259], and weight loss [260].

Although external triggers can be useful to remind users of an app, too many annoying or interruptive reminders can lead to disengagement. SDT stipulates that anything that quashes a sense of autonomy, such as a series of insistent reminders, can reduce intrinsic motivation to engage [71]. Eyal [3] distinguishes internal and external triggers of engagement, extoling the long-term benefits of the former over the latter. External triggers may help to initiate the engagement processes, but internal triggers are more reliable drivers of long-term habits. Eyal cites the example of social image-sharing app Instagram, which uses the internal trigger "I want to share this experience with others." However, if Instagram reminded users every day to post an image, it is likely that using it would soon be perceived as a chore with no intrinsic reward.

Although some reminders can restrict a sense of autonomy, others can encourage it. A recent meta-analysis of 42 studies found that phrases that emphasize an individual's right to refuse, such as "But you are free to accept or refuse," increase the likelihood of people agreeing to requests, with an overall effect size of r=0.13 [261]. External reminders should be framed within an SDT context to grant autonomy and respect intrinsic motivators. Chaiken's [262] heuristic-systematic processing theory can further inform the design of reminder communications. Framing reminders to satisfy the commitment and consistency, liking, authority, or scarcity heuristics can aid user engagement [263].

Simple and Intuitive Interface and Interactions

The simplicity of a program's interface and ease of navigation significantly influence user perceptions of quality in Web-based mental health interventions [264,265]. User satisfaction and perceptions of credibility directly influence engagement and therapeutic benefit [208]. Building an enjoyable app with good graphic design and a slick, intuitive, and satisfying interface is necessary for an effective intervention [5,266]. Simplicity also reduces the likelihood of technical difficulties that may dissuade users from engaging [267].

Fogg's behavior model (ie, the model of technology-based behavior change [268] discussed in the "Recommend Activities" section) emphasizes that simplicity reduces demands for initiating behavior outcomes, and increases the likelihood of a behavior occurring. A simpler interface decreases the ability required to engage with the app, and increases the likelihood of successful engagement [3].

No-action default (or "opt out") options have enormous influence over the use of a product or service [269]. For example, countries that have presumed consent organ donation policies have 25-30% higher donation rates after all other factors that influence rates are accounted for [270]. It has been argued that making organ donation as the no-action default option for Australian citizens could significantly raise donation rates and save many lives [271]. No-action defaults both preserve autonomous decision-making and influence behavior toward goals [272], so MHapps are well positioned to capitalize on these effects to guide users toward beneficial outcomes. App settings should be customizable to allow for autonomous use and tailoring, but come with recommended default options preset. For example, the default option for reminders should be set to "on," and at a frequency that is not overwhelming for the user (see the "Reminders to Engage and External Triggers" section).

The language used in the delivery of a mental health intervention, particularly a self-help intervention, can also have a major impact on engagement [273]. The language needs to be simple, concrete, confident, and hopeful for users to understand and engage with interventions. Language should also be inclusive of all sexual orientations and lifestyles [274] and be nonclinical, nonpsychopathological, and nondiagnostic to avoid stigma [57,99]. The literacy of intended users must be considered, just as it is for different newspapers [275]. The length of sentences and paragraphs is not only limited by the constraints of a smartphone screen, but also by the working memory of users. Making information meaningful to users can help its consolidation into memorable chunks, easing the demands on memory [276]. Using illustrations, such as faces, for emotions, can also improve the efficiency of understanding [277]. Decreasing load on memory is all the more important for users suffering from symptoms of depression or anxiety, which can restrict working memory function [278].

Although keeping information simple is necessary for initial understanding, enabling exploration of more in-depth information is important to satisfy some users [202]. Building a feature such as a "learn more" or "help" button into an MHapp can enable users to access more information about certain content or features. Furthermore, navigation around an app can be key to maintaining a sense of autonomy and competency. An app that limits a user's freedom of navigation may be frustrating and not intrinsically rewarding to use. Features such as an ever-present button that navigates the user back to the home screen can remedy this.

Links to Crisis Support Services

Crisis support services are valuable resources for vulnerable individuals undergoing acute psychological distress [279]. Suicidal callers to crisis hotlines experience significant decreases in suicidality, hopelessness, and psychological pain [280]. Developing and utilizing these services has consequently become a key area for promoting public mental health care [281,282]. However, barriers to help seeking can prevent troubled individuals from utilizing these supports.

Building links to crisis support services into MHapps may overcome some of these barriers. Furthermore, an MHapp that records a user's mood (see the "Reporting of Thoughts, Feelings, or Behaviors" section) may be able to unobtrusively detect indicators of depressive episodes and prompt contact of the relevant supports. Negative attitudes toward seeking help can be a major barrier to engagement [77]. However, if an app presents support options in an attractive and easy-to-access way, accessing those supports is more likely to be perceived as acceptable and appealing [269]. Lack of awareness of service availability, or the nature of support offered, can also prevent help seeking [203], as can the belief that support is rarely available and will not help anyway [283]. An MHapp that enables access to information about how support services operate and how they can help could reduce these barriers. According to the Fogg's behavior model [268], accessing crisis support services through technology should be made straightforward to reduce barriers to action and increase the likelihood of service contact being made.

Importantly, Internet supports are preferred to telephone helplines in some populations, including young people [284]. Organizations such as Lifeline have an online crisis support chat facility [285], so where these are available, links should be offered on mobile devices. There is also growing support for the effectiveness of online chat options [286], which may be better suited to how some individuals who use digital devices tend to communicate [287].

Experimental Trials to Establish Efficacy

A major shortcoming of currently available MHapps is the lack of RCT evidence for their efficacy. Although many apps use evidence-based frameworks, like CBT, only a handful have been experimentally trialed. Donker et al [8] conducted a systematic review of the literature, searching for evidence of effective MHapps; only 8 papers were identified as providing scientific support for MHapps, and in these papers, only 5 separate MHapps were described. Just 1 of these 5 was a self-contained app, with the other 4 requiring input from a mental health professional. Frustratingly for those who might benefit from these apps, none of them is currently available on the iOS or Android app stores.

This lack of controlled outcome research in the field is unexpected, given the ease of collecting data using mobile and Internet technologies [90]. Although validation of other psychological interventions requires time-consuming assessments, MHapps are capable of reliably, quickly, and automatically collecting a myriad of self-report and behavioral usage data [288].

When starting with a product vision for an app, target outcomes should be well defined in concrete, objective, and measurable terms [5]. These overarching goals guide development and enable a definition of success for the app. There are three main types of data that can be used to assess the target outcomes of MHapps: (1) assessment tools administered before and after a set period of app use, (2) EMA techniques to administer multiple brief self-report questionnaires throughout app use, and (3) app usage data. A thorough assessment of an MHapp should attempt to use all three data sources.

Assessment Tools Administered Before and After a Set Period of App Use

Wendel [5] stresses that, where possible, target outcomes for apps should avoid user "states of mind," such as emotions and other internal, psychological variables, as these are problematic to measure. However, the main goal of MHapps is to alter the user's state of mind. This means the tools used to measure the MHapp's target outcomes should be selected carefully, keeping in mind the ease of administration via a smartphone, the ease of integration into an MHapp's interface, the licensing of the assessment tool, and the validity and reliability of the measure.

Outcome measures for MHapps should contain a suitable assessment of emotional well-being and mental health. For example, the 9-item Patient Health Questionnaire (PHQ-9) [289] is a brief, self-administered, valid, and reliable measure with 88% specificity and 88% sensitivity for major depression. It is licensed to be used freely, and existing apps have successfully adapted it for a smartphone interface [290]. The 7-item Generalized Anxiety Disorder scale (GAD-7) [291] is a similar measure for anxiety, and using both the PHQ-9 and GAD-7 together can give a balanced assessment of emotional psychopathology [292]. To assess the languishing-flourishing dimension of mental health, the 14-Likert-item Warwick-Edinburgh Mental Well-Being Scale could be used, as it is a brief, reliable, and valid tool [293].

Secondary to mental health outcome measures are measures of the MHapp's intervention targets. For example, a self-monitoring MHapp should aim to assess the degree to which insight and ESA are being enhanced by the self-monitoring intervention (see the "Reporting of Thoughts, Feelings, or Behaviors" section). To validate their MHapp, Kauer et al [133] used a short survey, delivered by phone, called the ESA Scale. This tool comprises 33 items, all rated on a scale from 0 (never) to 4 (a lot), and was adapted from the 20-item Self-Reflection and Insight Scale [294], the 10-item Ruminative Response Scale [295], and the 12-item Meta-Evaluation Scale [296]. MHapps that aim to boost CSE (see the "Recommend Activities" section) could use the Coping Self-Efficacy Scale [175], which is a short questionnaire that can be administered via a smartphone. MHapps that utilize elements of psychoeducation may require assessments of MHL (see the "Mental Health Information" section). There is no standardized assessment tool for MHL, but it is often measured using self-report questionnaires and vignettes [204], which can be adapted for smartphone-based assessment. However, vignettes tend to be long and cumbersome forms of assessment, and are not well-suited to the restrictions of smartphone screens and interfaces. A well-validated, standardized, brief assessment tool for MHL would benefit the development of many self-help interventions, including MHapps.

It is recommended that follow-up data are collected at several different time points throughout the MHapp intervention and after its use has been concluded. An RCT on the mindfulness meditation app Headspace [297] found that it led to increases in positive affect and decreases in depression, but had no effects for measures of negative affect, satisfaction with life, or flourishing. This failure to uncover effects may be attributable to the limited time course of the research, as the intervention only lasted for 10 days and there was only one postintervention measurement [298].

Ecological Momentary Assessment

Using EMA, brief self-report questionnaires can be prompted at various periods throughout a user's day [143], with the precise time of survey completion accurately recorded. EMA can reduce bias in self-report data [142] and enables study of ecologically valid contexts [141]. As described in the "Reporting of Thoughts, Feelings, or Behaviors" section, EMA can also be a valuable part of interventions.

It is important to adopt an EMA design that is most appropriate for the types of data being collected and for the MHapp being trialed. EMA questionnaires should be brief enough for smartphone users to feel capable of completing them without too much interruption to their day. The aim of EMA is to obtain an ecologically valid measurement, so limiting disruption maximizes validity [217]. The design of EMAs can be event-based or time-based, depending on whether responses are collected following a specific event, such as an app-based interaction, or triggered at a given time point [141]. The choice in design should also be well thought-out and justified. For example, if a time-based EMA collects measurements at the exact same time every day, it may not accurately capture changes in the user's state experienced throughout the rest of the day. Event-based EMA should be used in an MHapp that recommends activities (see the "Recommend Activities" section) and requests a user to rate their mood before and after performance of the activity (see the "Reporting of Thoughts, Feelings, or Behaviors" section).

App Usage Data

Ongoing monitoring of client data is valuable to the validation of CBT-based interventions [142], and ongoing data collection should be a seamless and constant background process on smartphone apps. App usage data are often collected continuously by app developers to analyze user behavior and improve app functionality. The range of data capable of being collected in this way is very large, including measurements such as time spent using specific features of an app, number of times the app is used in day, and what times in the day features on the app are being used.

Data collected via EMA and other assessment tools may also provide insight into user variables that affect patterns of app usage. For example, it may be found that a specific feature is used most when users are highly distressed. This is an important information to consider, for both the development of psychological theories and the development of MHapps, as it may be appropriate to display a link to crisis services on the app's interface when a specific feature is being used.

Program adherence is easily assessed with usage data, and app design can be concurrently altered to increase adherence [24]. Although there is no doubt that these data are already being used by developers to improve individual MHapps, there has seemingly been a lack of academic transparency to validate those MHapps and aid in the development of others.

Strength of Evidence for Recommendations

Each recommendation explored in this review is supported by a different rank of evidence. Table 2 summarizes the 16 recommendations and ranks each according to evidence strength. The strongest level listed includes recommendations that are demonstrably effective, as shown by the numerous meta-analyses and RCTs of interventions previously cited in this review. However, more research in the form of RCTs is needed for such MHapps. The next rank of evidence pertains to recommendations that are probably effective according to available evidence but still require more research in the MHapp field. The rank under this includes recommendations that appear to be promising according to the evidence, but, again, must be researched in more depth to validate their stated principles in self-help interventions, including MHapps.

Discussion

MHapps offer exciting new opportunities to improve and manage the mental health of smartphone users. This review has generated 16 recommendations to be considered in the development of future MHapps. In summary, MHapps should aim to prevent emotional mental health problems by employing a wide array of CBT-based techniques that are tailored to an individual's needs and delivered via a simple, interactive design. Structures of gamification and habit formation should be used to maximize engagement in the app's interventions. The app itself should be experimentally validated, and user data should be utilized for its ongoing improvement.

It is highly recommended that MHapp developers familiarize themselves with the literature, both in the field of self-help CBT and in the field of app-based behavior change, before embarking on any MHapp projects. Respecting the value of both of these research fields should enable the reliable, engaging delivery of an evidence-based mental health intervention. This review may help developers get started with this familiarization process, but further reading is strongly advised. Furthermore, a multidisciplinary team consisting of experts in app usability engineering, programming, data collection and analysis, industry and health care sector applications, clinical psychological interventions, and any other relevant fields is strongly advisable.

The Mobile Application Rating Scale (MARS) is a recently developed measure enabling objective, multidimensional rating and comparison of mobile health apps [299]. Tools such as this will be essential for the future of MHapp development, and will enable clinicians and consumers to make more informed decisions about their choice of smartphone-based support.

There is a risk of researchers developing MHapps primarily for research needs rather than to meet the needs of end users. When an MHapp is released to the public, it is a self-contained product and must operate efficiently in the user's daily routine. For MHapp research to be ecologically valid, MHapp developers must create self-contained apps that still function outside of a research setting. Several RCTs have been conducted on MHapps that are not publically available [52]. This prevents researchers and intervention developers from analyzing and exploring existing evidence-based MHapps. It also blocks help seekers from finding evidence-based MHapps and benefiting from effective support.

Table 2. Recommendations for future mental health apps.

Evidence	Recommendation	Details
Demonstrably effective, but more research needed in MHapp field	1. Cognitive behavioral therapy based	Start with an evidence-based framework to maximize effectiveness
	2. Address both anxiety and low mood	Increases accessibility and addresses comorbidity between anxiety and depression. Also compatible with transdiagnostic theories of anxiety and depression
Probably effective, but more research needed in MHapp field	3. Designed for use by nonclinical populations	Avoiding diagnostic labels reduces stigma, increases accessibility, and enables preventative use
	4. Automated tailoring	Tailored interventions are more efficacious than is rigid self-help
	5. Reporting of thoughts, feelings, or behaviors	Self-monitoring and self-reflection to promote psychological growth and enable progress evaluation
	6. Recommend activities	Behavioral activation to boost self-efficacy and repertoire of coping skills
	7. Mental health information	Develop mental health literacy
	8. Real-time engagement	Allows users to use in moments in which they are experiencing distress for optimum benefits of coping behaviors and relaxation techniques
Supported by theory and indirect evidence but focused research needed	9. Activities explicitly linked to specific reported mood problems	Enhances understanding of cause-and-effect relationship between actions and emotions
	10. Encourage nontechnology-based activities	Helps to avoid potential problems with attention, increase opportunities for mindfulness, and limit time spent on devices
	11. Gamification and intrinsic motivation to engage	Encourage use of the app via rewards and internal triggers, and positive reinforcement and behavioral conditioning. Also links with flourishing
	12. Log of past app use	Encourage use of the app through personal investment. Internal triggers for repeated engagement
	13. Reminders to engage	External triggers for engagement
	14. Simple and intuitive interface and interactions	Reduce confusion and disengagement in users
	15. Links to crisis support services	Helps users who are in crisis to seek help
Necessary for validation of principles	16. Experimental trials to establish efficacy	It is important to establish the app's own efficacy before recommending it as an effective intervention

A behavioral plan is a "detailed 'story' of how the user progresses from being a neophyte to accomplishing the action while using the product" [5]. Any app should be designed from the foundation of a comprehensive behavioral plan [5]. This means that it may not be possible to incorporate all 16 recommendations listed herein into a single MHapp. To guide development of behavioral plans and interactive frameworks, it would be helpful to focus on specific foundations. Three of the recommendations listed can be used as foundations for intervention development, as they aim to target specific psychological constructs, such as ESA, MHL, and CSE. The "Reporting of Thoughts, Feelings, or Behaviors" section details mood reporting, self-monitoring, and improving ESA. MHapps that use this as a foundation could be referred to as "reflection-focused." The "Recommend Activities" section relates to engaging users in activities to improve their CSE. MHapps that use this as a foundation could be referred to as "goal-focused." The "Mental Health Information" section relates to mental health information, psychoeducation, and improving MHL. MHapps that use this as a foundation could be referred to as "education-focused." More research is needed to investigate the different effects of reflection-focused, education-focused, and goal-focused MHapp designs on mental health, and whether different users obtain different benefits from each design.

Each recommendation explored in this review could be the target of an RCT. RCTs that compare identical MHapps with or without specific features could provide evidence for or against these features in future MHapps. However, it is important to acknowledge the influence of the overall behavioral plan on the MHapp's effectiveness. Some features may work better in one MHapp's behavioral plan than in another's, and simply including more recommended features may not improve the overall intervention. Future MHapp and eHealth RCTs should aim to validate underlying theories and principles for intervention improvement [21].

The World Health Organization [300] predicts that depression will become the global leading cause of disease burden by 2030. There is an enormous worldwide need for better preventative mental health, and MHapps that target emotional well-being are set to provide exciting new opportunities in the field. The evidence-based recommendations discussed herein are important for all MHapp developers to acknowledge if better interventions are to be developed to meet this rising demand in the future.

Conflicts of Interest

None declared.

References

1. Google. Our mobile planet: United States of America. 2013. URL: http://services.google.com/fh/files/misc/omp-2013-us-en.pdf [accessed 2015-07-17] [WebCite Cache ID 6a5EeTpp5]
2. Meeker M, Wu L. Internet trends D11 conference. 2014. URL: http://www.slideshare.net/kleinerperkins/kpcb-internet-trends-2013 [accessed 2015-07-21] [WebCite Cache ID 6aAzuuSTv]
3. Eyal N. Hooked: How to Build Habit-Forming Products. New York, NY: Sunshine Business Dev; 2014.
4. Oulasvirta A, Rattenbury T, Ma L, Raita E. Habits make smartphone use more pervasive. Pers Ubiquit Comput 2012 Jan 01;16:105-114. [doi: 10.1007/s00779-011-0412-2]
5. Wendel S. Designing for Behavior Change: Applying Psychology and Behavioral Economics. Sebastopol, CA: O'Reilly Media, Inc; 2013.
6. Free C, Phillips G, Galli L, Watson L, Felix L, Edwards P, et al. The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: a systematic review. PLoS Med 2013 Jan 15;10(1):e1001362 [FREE Full text] [doi: 10.1371/journal.pmed.1001362] [Medline: 23349621]
7. Fanning J, Mullen SP, McAuley E. Increasing physical activity with mobile devices: A meta-analysis. J Med Internet Res 2012 Nov 21;14:e161 [FREE Full text] [doi: 10.2196/jmir.2171] [Medline: 23171838]
8. Donker T, Petrie K, Proudfoot J, Clarke J, Birch M, Christensen H. Smartphones for smarter delivery of mental health programs: A systematic review. J Med Internet Res 2013 Nov 15;15(11):e247 [FREE Full text] [doi: 10.2196/jmir.2791] [Medline: 24240579]
9. Proudfoot J, Parker G, Hadzi PD, Manicavasagar V, Adler E, Whitton A. Community attitudes to the appropriation of mobile phones for monitoring and managing depression, anxiety, and stress. J Med Internet Res 2010;12(5):e64 [FREE Full text] [doi: 10.2196/jmir.1475] [Medline: 21169174]
10. Simon GE, Ludman EJ. It's time for disruptive innovation in psychotherapy. Lancet 2009 Aug 22;374(9690):594-595. [doi: 10.1016/S0140-6736(09)61415-X] [Medline: 19699995]
11. Watts SE, Andrews G. Internet access is NOT restricted globally to high income countries: So why are evidenced based prevention and treatment programs for mental disorders so rare? Asian J Psychiatr 2014 Aug;10:71-74. [doi: 10.1016/j.ajp.2014.06.007] [Medline: 25042956]
12. Mojtabai R, Olfson M, Mechanic D. Perceived need and help-seeking in adults with mood, anxiety, or substance use disorders. Arch Gen Psychiatry 2002 Jan;59(1):77-84. [Medline: 11779286]
13. Collin PJ, Metcalf AT, Stephens-Reicher JC, Blanchard ME, Herrman HE, Rahilly K, et al. ReachOut.com: The role of an online service for promoting help-seeking in young people. Advances in Mental Health 2014 Dec 17;10(1):39-51. [doi: 10.5172/jamh.2011.10.1.39]
14. Wilson CJ, Rickwood DJ, Bushnell JA, Caputi P, Thomas SJ. The effects of need for autonomy and preference for seeking help from informal sources on emerging adults' intentions to access mental health services for common mental disorders and suicidal thoughts. Advances in Mental Health 2014 Dec 17;10(1):29-38. [doi: 10.5172/jamh.2011.10.1.29]
15. Martinez R, Williams C. Matching clients to CBT self-help resources. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions. 1st edition. Oxford, UK: Oxford University Press; 2010.
16. Whittaker R, McRobbie H, Bullen C, Borland R, Rodgers A, Gu Y. Mobile phone-based interventions for smoking cessation. Cochrane Database Syst Rev 2012;11:CD006611. [doi: 10.1002/14651858.CD006611.pub3] [Medline: 23152238]
17. Kapp KM. The Gamification of Learning and Instruction: Game-based Methods and Strategies for Training and Education. 1st edition. San Francisco, CA: Pfeiffer; 2012.
18. Moses T. Self-labeling and its effects among adolescents diagnosed with mental disorders. Soc Sci Med 2009 Feb;68(3):570-578. [doi: 10.1016/j.socscimed.2008.11.003] [Medline: 19084313]
19. APA Presidential Task Force on Evidence-Based Practice. Evidence-based practice in psychology. Am Psychol 2006;61(4):271-285. [doi: 10.1037/0003-066X.61.4.271] [Medline: 16719673]
20. Aarons GA, Hurlburt M, Horwitz SM. Advancing a conceptual model of evidence-based practice implementation in public service sectors. Adm Policy Ment Health 2011 Jan;38(1):4-23 [FREE Full text] [doi: 10.1007/s10488-010-0327-7] [Medline: 21197565]
21. Tomlinson M, Rotheram-Borus MJ, Swartz L, Tsai AC. Scaling up mHealth: Where is the evidence? PLoS Med 2013;10(2):e1001382 [FREE Full text] [doi: 10.1371/journal.pmed.1001382] [Medline: 23424286]
22. Jorm AF, Griffiths KM, Christensen H, Parslow RA, Rogers B. Actions taken to cope with depression at different levels of severity: A community survey. Psychol Med 2004 Feb;34(2):293-299. [Medline: 14982135]
23. Leboff G. Stickier Marketing: How to Win Customers in a Digital Age. 2nd edition. London, UK: Kogan Page; 2014.

24. Cavanagh K. Turn on, tune in and (don't) drop out: Engagement, adherence, attrition, and alliance with internet-based interventions. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions, 1st edition. Oxford, UK: Oxford University Press; 2010:227-223.
25. Payne LA, Ellard KK, Farchione TJ, Fairholme CP, Barlow DH. Emotional disorders: A unified transdiagnostic protocol. In: Barlow DH, editor. Clinical Handbook of Psychological Disorders: A Step-by-Step Treatment Manual. 5th edition. New York, NY: The Guilford Press; 2014:237-274.
26. Hofmann SG, Asnaani A, Vonk IJJ, Sawyer AT, Fang A. The efficacy of cognitive behavioral therapy: A review of meta-analyses. Cognit Ther Res 2012 Oct 1;36(5):427-440 [FREE Full text] [doi: 10.1007/s10608-012-9476-1] [Medline: 23459093]
27. Jorm AF, Morgan AJ, Hetrick SE. Relaxation for depression. Cochrane Database Syst Rev 2008(4):CD007142. [doi: 10.1002/14651858.CD007142.pub2] [Medline: 18843744]
28. Tolin DF. Is cognitive-behavioral therapy more effective than other therapies? A meta-analytic review. Clin Psychol Rev 2010 Aug;30(6):710-720. [doi: 10.1016/j.cpr.2010.05.003] [Medline: 20547435]
29. Cuijpers P, Sijbrandij M, Koole S, Huibers M, Berking M, Andersson G. Psychological treatment of generalized anxiety disorder: a meta-analysis. Clin Psychol Rev 2014 Mar;34(2):130-140. [doi: 10.1016/j.cpr.2014.01.002] [Medline: 24487344]
30. Gil PJM, Carrillo FXM, Meca JS. Psychol Spain. 2001. Effectiveness of cognitive-behavioural treatment in social phobia: A meta-analytic review URL: http://psycnet.apa.org/psycinfo/2003-04139-003 [accessed 2016-01-20] [WebCite Cache ID 6egCivics]
31. Olatunji BO, Kauffman BY, Meltzer S, Davis ML, Smits JAJ, Powers MB. Cognitive-behavioral therapy for hypochondriasis/health anxiety: A meta-analysis of treatment outcome and moderators. Behav Res Ther 2014 Jul;58:65-74. [doi: 10.1016/j.brat.2014.05.002] [Medline: 24954212]
32. Haby MM, Donnelly M, Corry J, Vos T. Cognitive behavioural therapy for depression, panic disorder and generalized anxiety disorder: A meta-regression of factors that may predict outcome. Aust N Z J Psychiatry 2006 Jan;40(1):9-19. [doi: 10.1111/j.1440-1614.2006.01736.x] [Medline: 16403033]
33. Bisson J, Andrew M. Psychological treatment of post-traumatic stress disorder (PTSD). Cochrane Database Syst Rev 2007(3):CD003388. [doi: 10.1002/14651858.CD003388.pub3] [Medline: 17636720]
34. Eddy KT, Dutra L, Bradley R, Westen D. A multidimensional meta-analysis of psychotherapy and pharmacotherapy for obsessive-compulsive disorder. Clin Psychol Rev 2004 Dec;24(8):1011-1030. [doi: 10.1016/j.cpr.2004.08.004] [Medline: 15533282]
35. Hofmann SG, Smits JAJ. Cognitive-behavioral therapy for adult anxiety disorders: A meta-analysis of randomized placebo-controlled trials. J Clin Psychiatry 2008 Apr;69(4):621-632 [FREE Full text] [Medline: 18363421]
36. Saini M. A meta-analysis of the psychological treatment of anger: Developing guidelines for evidence-based practice. J Am Acad Psychiatry Law 2009;37(4):473-488. [Medline: 20018996]
37. Okajima I, Komada Y, Inoue Y. A meta-analysis on the treatment effectiveness of cognitive behavioral therapy for primary insomnia. Sleep Biol Rhythms 2011 Jan 01;9(1):24-34. [doi: 10.1111/j.1479-8425.2010.00481.x]
38. Leung KS, Cottler LB. Treatment of pathological gambling. Curr Opin Psychiatry 2009 Jan;22(1):69-74. [doi: 10.1097/YCO.0b013e32831575d9] [Medline: 19122538]
39. Tolin DF, Frost RO, Steketee G, Muroff J. Cognitive behavioral therapy for hoarding disorder: A meta-analysis. Depress Anxiety 2015 Mar;32(3):158-166. [doi: 10.1002/da.22327] [Medline: 25639467]
40. Li L, Xiong L, Zhang S, Yu Q, Chen M. Cognitive-behavioral therapy for irritable bowel syndrome: A meta-analysis. J Psychosom Res 2014 Jul;77(1):1-12. [doi: 10.1016/j.jpsychores.2014.03.006] [Medline: 24913335]
41. Hutton P, Taylor PJ. Cognitive behavioural therapy for psychosis prevention: A systematic review and meta-analysis. Psychol Med 2014 Feb;44(3):449-468. [doi: 10.1017/S0033291713000354] [Medline: 23521867]
42. Richardson KM, Rothstein HR. Effects of occupational stress management intervention programs: A meta-analysis. J Occup Health Psychol 2008 Jan;13(1):69-93. [doi: 10.1037/1076-8998.13.1.69] [Medline: 18211170]
43. Marks IM, Kenwright M, McDonough M, Whittaker M, Mataix-Cols D. Saving clinicians' time by delegating routine aspects of therapy to a computer: A randomized controlled trial in phobia/panic disorder. Psychol Med 2004 Jan;34(1):9-17. [Medline: 14971623]
44. McCrone P, Knapp M, Proudfoot J, Ryden C, Cavanagh K, Shapiro DA, et al. Cost-effectiveness of computerised cognitive-behavioural therapy for anxiety and depression in primary care: Randomised controlled trial. Br J Psychiatry 2004 Jul;185:55-62 [FREE Full text] [Medline: 15231556]
45. Grist R, Cavanagh K. Computerised Cognitive Behavioural Therapy for Common Mental Health Disorders, What Works, for Whom Under What Circumstances? A Systematic Review and Meta-analysis. J Contemp Psychother 2013 Sep 4;43(4):243-251. [doi: 10.1007/s10879-013-9243-y]
46. Andrews G, Cuijpers P, Craske MG, McEvoy P, Titov N. Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: A meta-analysis. PLoS One 2010;5(10):e13196 [FREE Full text] [doi: 10.1371/journal.pone.0013196] [Medline: 20967242]

47. Carlbring P, Nordgren LB, Furmark T, Andersson G. Long-term outcome of Internet-delivered cognitive-behavioural therapy for social phobia: A 30-month follow-up. Behav Res Ther 2009 Oct;47(10):848-850. [doi: 10.1016/j.brat.2009.06.012] [Medline: 19631312]
48. Gellatly J, Bower P, Hennessy S, Richards D, Gilbody S, Lovell K. What makes self-help interventions effective in the management of depressive symptoms? Meta-analysis and meta-regression. Psychol Med 2007 Sep;37(9):1217-1228. [doi: 10.1017/S0033291707000062] [Medline: 17306044]
49. Pennant ME, Loucas CE, Whittington C, Creswell C, Fonagy P, Fuggle P, et al. Computerised therapies for anxiety and depression in children and young people: A systematic review and meta-analysis. Behav Res Ther 2015 Apr;67:1-18. [doi: 10.1016/j.brat.2015.01.009] [Medline: 25727678]
50. Watts S, Mackenzie A, Thomas C, Griskaitis A, Mewton L, Williams A, et al. CBT for depression: A pilot RCT comparing mobile phone vs. computer. BMC Psychiatry 2013;13:49 [FREE Full text] [doi: 10.1186/1471-244X-13-49] [Medline: 23391304]
51. Kristjánsdóttir OB, Fors EA, Eide E, Finset A, Stensrud TL, van DS, et al. A smartphone-based intervention with diaries and therapist-feedback to reduce catastrophizing and increase functioning in women with chronic widespread pain: randomized controlled trial. J Med Internet Res 2013;15(1):e5 [FREE Full text] [doi: 10.2196/jmir.2249] [Medline: 23291270]
52. Dagöö J, Asplund RP, Bsenko HA, Hjerling S, Holmberg A, Westh S, et al. Cognitive behavior therapy versus interpersonal psychotherapy for social anxiety disorder delivered via smartphone and computer: A randomized controlled trial. J Anxiety Disord 2014 May;28(4):410-417. [doi: 10.1016/j.janxdis.2014.02.003] [Medline: 24731441]
53. Heffner JL, Vilardaga R, Mercer LD, Kientz JA, Bricker JB. Feature-level analysis of a novel smartphone application for smoking cessation. Am J Drug Alcohol Abuse 2015 Jan;41(1):68-73. [doi: 10.3109/00952990.2014.977486] [Medline: 25397860]
54. Bakker G. Practical CBT: Using Functional Analysis and Standardised Homework in Everyday Therapy. Bowen Hills, Queensland: Australian Academic Press; 2008.
55. Moorey S. The six cycles maintenance model: Growing a "vicious flower" for depression. Behav Cogn Psychother 2010 Mar;38(2):173-184. [doi: 10.1017/S1352465809990580] [Medline: 19925693]
56. Gyani A, Shafran R, Layard R, Clark DM. Enhancing recovery rates: lessons from year one of IAPT. Behav Res Ther 2013 Sep;51(9):597-606 [FREE Full text] [doi: 10.1016/j.brat.2013.06.004] [Medline: 23872702]
57. Titov N, Dear BF, Schwencke G, Andrews G, Johnston L, Craske MG, et al. Transdiagnostic internet treatment for anxiety and depression: A randomised controlled trial. Behav Res Ther 2011 Aug;49(8):441-452. [doi: 10.1016/j.brat.2011.03.007] [Medline: 21679925]
58. Mennin DS, Ellard KK, Fresco DM, Gross JJ. United we stand: Emphasizing commonalities across cognitive-behavioral therapies. Behav Ther 2013 Jun;44(2):234-248. [doi: 10.1016/j.beth.2013.02.004] [Medline: 23611074]
59. SuperBetter Inc. SuperBetter [mobile application software], Version 1.1.2. 2015. URL: https://itunes.apple.com/au/app/superbetter/id536634968?mt=8 [accessed 2015-07-22] [WebCite Cache ID 6aChtbPCA]
60. Smiling Mind Pty Ltd. Smiling Mind [mobile application software], Version 2.1.6. 2015. URL: https://itunes.apple.com/au/app/smiling-mind/id560442518?mt=8 [accessed 2015-07-22] [WebCite Cache ID 6aCj4lEHD]
61. Gross JJ. Emotion regulation: affective, cognitive, and social consequences. Psychophysiology 2002 May;39(3):281-291. [Medline: 12212647]
62. Thriveport LLC. MoodKit - Mood Improvement Tools [mobile application software], Version 3.0. 2015. URL: https:/ /itunes.apple.com/au/app/moodkit-mood-improvement-tools/id427064987?mt=8 [accessed 2015-10-16] [WebCite Cache ID 6cKhbLFvM]
63. Persons J. The Case Formulation Approach to Cognitive-Behavior Therapy (Guides to Individualized Evidence-Based Treatment). New York, NY: The Guilford Press; 2008.
64. Tee J, Kazantzis N. Collaborative empiricism in cognitive therapy: A definition and theory for the relationship construct. Clin Psychol Sci Pract 2011 Mar 01;18:47-61. [doi: 10.1111/j.1468-2850.2010.01234.x]
65. Kazantzis N, MacEwan J, Dattilio FM. A guiding model for practice. In: Kazantzis N, Deane FP, Ronan KR, L'Abate L, editors. Using Homework Assignments In Cognitive Behavior Therapy. New York, NY: Routledge; 2005:359-407.
66. Kazantzis N, Whittington C, Dattilio F. Meta-analysis of homework effects in cognitive and behavioral therapy: A replication and extension. Clin Psychol Sci Pract 2010;17:144-156. [doi: 10.1111/j.1468-2850.2010.01204.x]
67. happtic Pty Ltd. Behavioral Experiments - CBT [mobile application software], Version 1.0. 2015. URL: https://itunes.apple.com/us/app/behavioral-experiments-cbt/id547492686?mt=8 [accessed 2015-10-16] [WebCite Cache ID 6cKfn0RJ0]
68. Bennett-Levy J, Westbrook D, Fennell M, Cooper M, Rouf K, Hackmann A. Behavioural experiments: Historical and conceptual underpinnings. In: Bennett-Levy J, Butler G, Fennell M, Hackmann A, Mueller M, Westbrook D, editors. Oxford Guide to Behavioural Experiments in Cognitive Therapy. Oxford, UK: Oxford University Press; 2004:1-20.
69. McMillan D, Lee R. A systematic review of behavioral experiments vs. exposure alone in the treatment of anxiety disorders: A case of exposure while wearing the emperor's new clothes? Clin Psychol Rev 2010 Jul;30(5):467-478. [doi: 10.1016/j.cpr.2010.01.003] [Medline: 20381224]

70. Gagné M, Deci EL. The history of self-determination theory in psychology and management. In: Gagné M, editor. The Oxford Handbook of Work Engagement, Motivation, and Self-Determination Theory. Oxford, UK: Oxford University Press; 2014.
71. Ryan RM, Deci EL. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. Am Psychol 2000 Jan;55(1):68-78. [Medline: 11392867]
72. Deci EL, Ryan RM. Intrinsic Motivation and Self-determination in Human Behavior. Boston, MA: Springer; 1985.
73. Bandura A. Self-efficacy: The Exercise of Control. New York, NY: W.H. Freeman; 1997.
74. Vallerand R, Reid G. On the causal effects of perceived competence on intrinsic motivation: A test of cognitive evaluation theory. J Sport Psychol 1984;6:94-102.
75. Kessler RC, Petukhova M, Sampson NA, Zaslavsky AM, Wittchen H. Twelve-month and lifetime prevalence and lifetime morbid risk of anxiety and mood disorders in the United States. Int J Methods Psychiatr Res 2012 Sep;21(3):169-184 [FREE Full text] [doi: 10.1002/mpr.1359] [Medline: 22865617]
76. Layard R, Clark D. Thrive: The Power of Evidence-Based Psychological Therapies. London, UK: Penguin; 2014.
77. Gulliver A, Griffiths KM, Christensen H. Perceived barriers and facilitators to mental health help-seeking in young people: A systematic review. BMC Psychiatry 2010;10:113 [FREE Full text] [doi: 10.1186/1471-244X-10-113] [Medline: 21192795]
78. Sartorius N, Ustün TB, Lecrubier Y, Wittchen HU. Depression comorbid with anxiety: Results from the WHO study on psychological disorders in primary health care. Br J Psychiatry Suppl 1996 Jun(30):38-43. [Medline: 8864147]
79. Gorman JM. Comorbid depression and anxiety spectrum disorders. Depress Anxiety 1996;4(4):160-168. [doi: 10.1002/(SICI)1520-6394(1996)4:4<160::AID-DA2>3.0.CO;2-J] [Medline: 9166648]
80. Tiller JW. Depression and anxiety. Med J Aust 2013 Sep 16;199(6 Suppl):S28-S31. [Medline: 25370281]
81. Das-Munshi J, Goldberg D, Bebbington PE, Bhugra DK, Brugha TS, Dewey ME, et al. Public health significance of mixed anxiety and depression: Beyond current classification. Br J Psychiatry 2008 Mar;192(3):171-177 [FREE Full text] [doi: 10.1192/bjp.bp.107.036707] [Medline: 18310574]
82. Barlow DH, Allen LB, Choate ML. Toward a unified treatment for emotional disorders. Behavior Therapy 2004 Mar;35(2):205-230. [doi: 10.1016/S0005-7894(04)80036-4]
83. Reinholt N, Krogh J. Efficacy of transdiagnostic cognitive behaviour therapy for anxiety disorders: A systematic review and meta-analysis of published outcome studies. Cogn Behav Ther 2014;43(3):171-184. [doi: 10.1080/16506073.2014.897367] [Medline: 24646219]
84. Barlow DH, Farchione TJ, Fairholme CP, Ellard KK, Boisseau CL, Allen LB, et al. Unified Protocol for Transdiagnostic Treatment of Emotional Disorders: Therapist Guide. Oxford, UK: Oxford University Press; 2010.
85. Farchione TJ, Fairholme CP, Ellard KK, Boisseau CL, Thompson-Hollands J, Carl JR, et al. Unified protocol for transdiagnostic treatment of emotional disorders: A randomized controlled trial. Behav Ther 2012 Sep;43(3):666-678 [FREE Full text] [doi: 10.1016/j.beth.2012.01.001] [Medline: 22697453]
86. Gallagher MW, Sauer-Zavala SE, Boswell JF, Carl JR, Bullis J, Farchione TJ, et al. The impact of the Unified Protocol for Emotional Disorders on quality of life. Int J Cogn Ther 2013 Mar 1;6(1) [FREE Full text] [doi: 10.1521/ijct.2013.6.1.57] [Medline: 24358405]
87. Hofmann SG, Barlow DH. Evidence-based psychological interventions and the common factors approach: The beginnings of a rapprochement? Psychotherapy (Chic) 2014 Dec;51(4):510-513. [doi: 10.1037/a0037045] [Medline: 25111379]
88. Ellard KK, Fairholme CP, Boisseau CL, Farchione TJ, Barlow DH. Unified Protocol for the transdiagnostic treatment of emotional disorders: Protocol development and initial outcome Data. Cognitive and Behavioral Practice 2010 Feb;17(1):88-101. [doi: 10.1016/j.cbpra.2009.06.002]
89. White J. The STEPS model: A high volume, multi-level, multi-purpose approach to address common mental health problems. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions. 1st edition. Oxford , UK: Oxford University Press; 2010:35-52.
90. Christensen H. Increasing access effectiveness: Using the internet to deliver low intensity CBT. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions. Oxford, UK: Oxford University Press; 2010:53-67.
91. Optimism Apps Pty Ltd. Optimism [mobile application software], Version 2.5.8. URL: https://itunes.apple.com/au/app/optimism/id352262677?mt=8 [accessed 2015-07-21] [WebCite Cache ID 6aBIi2rmb]
92. University of the West of England. Self-help for Anxiety Management [mobile application software], Version 1.2.7. 2015. URL: https://itunes.apple.com/au/app/self-help-for-anxiety-management/id666767947?mt=8 [accessed 2015-07-21] [WebCite Cache ID 6aBIrHCO1]
93. Recovery Record Inc. Recovery Record [mobile application software], Version 4.7.7. 2015. URL: https://itunes.apple.com/au/app/recovery-record-eating-disorder/id457360959?mt=8 [accessed 2015-07-21] [WebCite Cache ID 6aBJ0tvBa]
94. Durham DBT Inc. DBT Diary Card and Skills Coach [mobile application software], Version 2.9. 2015. URL: https://itunes.apple.com/au/app/dbt-diary-card-skills-coach/id479013889?mt=8 [accessed 2015-07-21] [WebCite Cache ID 6aBJ4cixc]
95. Rosenfield S. Labeling mental illness: The effects of received services and perceived stigma on life satisfaction. Am Sociol Rev 1997 Aug;62(4):660. [doi: 10.2307/2657432]

96. Corrigan PW, Watson AC, Barr L. The self-stigma of mental illness: Implications for self-esteem and self-efficacy. J Soc Clin Psychol 2006 Oct;25(8):875-884. [doi: 10.1521/jscp.2006.25.8.875]
97. Herrman H. The need for mental health promotion. Aust N Z J Psychiatry 2001 Dec;35(6):709-715. [Medline: 11990880]
98. Mental Health Commission of Canada. Opening Minds: Program Overview. Calgary, Alberta, Canada: Mental Health Commission of Canada; 2012. URL: http://www.mentalhealthcommission.ca/English/system/files/private/document/Stigma_Opening_Minds_Overview_ENG.pdf [accessed 2015-11-20] [WebCite Cache ID 6aFUC49vr]
99. Corrigan PW. How clinical diagnosis might exacerbate the stigma of mental illness. Soc Work 2007 Jan;52(1):31-39. [Medline: 17388081]
100. Dobson D, Dobson KS. Evidence-Based Practice of Cognitive-Behavioral Therapy. 1st edition. New York, NY: The Guilford Press; 2009.
101. Vittengl JR, Clark LA, Dunn TW, Jarrett RB. Reducing relapse and recurrence in unipolar depression: A comparative meta-analysis of cognitive-behavioral therapy's effects. J Consult Clin Psychol 2007 Jun;75(3):475-488 [FREE Full text] [doi: 10.1037/0022-006X.75.3.475] [Medline: 17563164]
102. Cuijpers P, Muñoz RF, Clarke GN, Lewinsohn PM. Psychoeducational treatment and prevention of depression: The "Coping with Depression" course thirty years later. Clin Psychol Rev 2009 Jul;29(5):449-458. [doi: 10.1016/j.cpr.2009.04.005] [Medline: 19450912]
103. Rohde P, Stice E, Shaw H, Brière FN. Indicated cognitive behavioral group depression prevention compared to bibliotherapy and brochure control: Acute effects of an effectiveness trial with adolescents. J Consult Clin Psychol 2014 Feb;82(1):65-74 [FREE Full text] [doi: 10.1037/a0034640] [Medline: 24099432]
104. Cronin TJ, Lawrence KA, Taylor K, Norton PJ, Kazantzis N. Integrating between-session interventions (homework) in therapy: The importance of the therapeutic relationship and cognitive case conceptualization. J Clin Psychol 2015 May;71(5):439-450. [doi: 10.1002/jclp.22180] [Medline: 25809713]
105. Westbrook D, Kennerley H, Kirk J. An Introduction to Cognitive Behaviour Therapy: Skills and Applications. 2nd edition. Los Angeles, CA: Sage Publications Ltd; 2011.
106. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders, (DSM-5). Washington DC: American Psychiatric Association; 2013.
107. Goldfried MR, Wolfe BE. Toward a more clinically valid approach to therapy research. J Consult Clin Psychol 1998 Feb;66(1):143-150. [Medline: 9489268]
108. Hofmann SG. Toward a cognitive-behavioral classification system for mental disorders. Behav Ther 2014 Jul;45(4):576-587 [FREE Full text] [doi: 10.1016/j.beth.2014.03.001] [Medline: 24912469]
109. Rickwood D. Pathways of recovery: Preventing Further Episodes of Mental Illness (monograph). Canberra, Australia: Department of Health and Ageing; 2006.
110. Depp CA, Mausbach B, Granholm E, Cardenas V, Ben-Zeev D, Patterson TL, et al. Mobile interventions for severe mental illness: design and preliminary data from three approaches. J Nerv Ment Dis 2010 Oct;198(10):715-721 [FREE Full text] [doi: 10.1097/NMD.0b013e3181f49ea3] [Medline: 20921861]
111. Jorm AF, Morgan AJ, Malhi GS. The future of e-mental health. Aust N Z J Psychiatry 2013 Feb;47(2):104-106. [doi: 10.1177/0004867412474076] [Medline: 23382504]
112. Carlbring P, Maurin L, Törngren C, Linna E, Eriksson T, Sparthan E, Marquez von Hage Christian, et al. Individually-tailored, Internet-based treatment for anxiety disorders: A randomized controlled trial. Behav Res Ther 2011 Jan;49(1):18-24. [doi: 10.1016/j.brat.2010.10.002] [Medline: 21047620]
113. Johansson R, Sjöberg E, Sjögren M, Johnsson E, Carlbring P, Andersson T, et al. Tailored vs. standardized internet-based cognitive behavior therapy for depression and comorbid symptoms: A randomized controlled trial. PLoS One 2012;7(5):e36905 [FREE Full text] [doi: 10.1371/journal.pone.0036905] [Medline: 22615841]
114. Nordgren LB, Hedman E, Etienne J, Bodin J, Kadowaki A, Eriksson S, et al. Effectiveness and cost-effectiveness of individually tailored Internet-delivered cognitive behavior therapy for anxiety disorders in a primary care population: A randomized controlled trial. Behav Res Ther 2014 Aug;59:1-11 [FREE Full text] [doi: 10.1016/j.brat.2014.05.007] [Medline: 24933451]
115. Silfvernagel K, Carlbring P, Kabo J, Edström S, Eriksson J, Månson L, et al. Individually tailored internet-based treatment for young adults and adults with panic attacks: Randomized controlled trial. J Med Internet Res 2012;14(3):e65 [FREE Full text] [doi: 10.2196/jmir.1853] [Medline: 22732098]
116. Su WC. A Preliminary Survey of Knowledge Discovery on Smartphone Applications (apps): Principles, Techniques and Research Directions for E-health. Taipei, Taiwan: ICME International Conference on Complex Medical Engineering; 2014. URL: http://arxiv.org/abs/1407.7314 [accessed 2015-10-16] [WebCite Cache ID 6cJLSX04G]
117. Manzoni GM, Pagnini F, Castelnuovo G, Molinari E. Relaxation training for anxiety: A ten-years systematic review with meta-analysis. BMC Psychiatry 2008;8:41 [FREE Full text] [doi: 10.1186/1471-244X-8-41] [Medline: 18518981]
118. Heidt JM, Mark BP. Self-monitoring as a treatment vehicle. In: O'Donohue WT, Fisher JE, editors. Cognitive Behavior Therapy: Applying Empirically Supported Techniques in Your Practice. 2nd edition. Hoboken, NJ: John Wiley & Sons; 2009:361-367.

119. Cohen JS, Edmunds JM, Brodman DM, Benjamin CL, Kendall PC. Using self-monitoring: Implementation of collaborative empiricism in cognitive-behavioral therapy. Cogn Behav Prac 2013 Nov;20(4):419-428. [doi: 10.1016/j.cbpra.2012.06.002]
120. Kazantzis N, Deane FP, Ronan KR, Lampropoulos GK. Empirical foundations. In: Deane FP, Ronan KR, L'Abate L, Kazantzis N, editors. Using Homework Assignments In Cognitive Behavior Therapy. New York, NY: Routledge; 2005:29-49.
121. Erisman SM, Roemer L. A preliminary investigation of the effects of experimentally induced mindfulness on emotional responding to film clips. Emotion 2010 Feb;10(1):72-82 [FREE Full text] [doi: 10.1037/a0017162] [Medline: 20141304]
122. Paivio SC. Essential processes in emotion-focused therapy. Psychotherapy (Chic) 2013 Sep;50(3):341-345. [doi: 10.1037/a0032810] [Medline: 24000848]
123. Feldman G, Harley R, Kerrigan M, Jacobo M, Fava M. Change in emotional processing during a dialectical behavior therapy-based skills group for major depressive disorder. Behav Res Ther 2009 Apr;47(4):316-321. [doi: 10.1016/j.brat.2009.01.005] [Medline: 19232571]
124. Hayes SC, Strosahl KD, Wilson KG. Acceptance and Commitment Therapy: The Process and Practice of Mindful Change. 2nd edition. New York: Guilford Press; 2011.
125. Başoğlu M, Marks IM, Sengün S. A prospective study of panic and anxiety in agoraphobia with panic disorder. Br J Psychiatry 1992 Jan;160:57-64. [Medline: 1347481]
126. Huppert JD, Roth Ledley D, Foa EB. The use of homework in behavior therapy for anxiety disorders. J Psychother Integr 2006;16(2):128-139. [doi: 10.1037/1053-0479.16.2.128]
127. Jarrett RB, Nelson RO. Mechanisms of change in cognitive therapy of depression. Behav Ther 1987 Jun;18(3):227-241. [doi: 10.1016/S0005-7894(87)80017-5]
128. Ehlers A, Clark DM, Hackmann A, McManus F, Fennell M, Herbert C, et al. A randomized controlled trial of cognitive therapy, a self-help booklet, and repeated assessments as early interventions for posttraumatic stress disorder. Arch Gen Psychiatry 2003 Oct;60(10):1024-1032. [doi: 10.1001/archpsyc.60.10.1024] [Medline: 14557148]
129. Tarrier N, Sommerfield C, Reynolds M, Pilgrim H. Symptom self-monitoring in the treatment of posttraumatic stress disorder. Behav Ther 1999 Sep;30(4):597-605. [doi: 10.1016/S0005-7894(99)80027-6]
130. Kavanagh DJ, Sitharthan T, Spilsbury G, Vignaendra S. An evaluation of brief correspondence programs for problem drinkers. Behav Ther 1999 Sep;30(4):641-656. [doi: 10.1016/S0005-7894(99)80030-6]
131. Todd J, Mullan B. The role of self-monitoring and response inhibition in improving sleep behaviours. Int J Behav Med 2014 Jun;21(3):470-477. [doi: 10.1007/s12529-013-9328-8] [Medline: 23813124]
132. Latner JD, Wilson GT, Stunkard AJ, Jackson ML. Self-help and long-term behavior therapy for obesity. Behav Res Ther 2002 Jul;40(7):805-812. [Medline: 12074374]
133. Kauer SD, Reid SC, Crooke Alexander Hew Dale, Khor A, Hearps Stephen John Charles, Jorm AF, et al. Self-monitoring using mobile phones in the early stages of adolescent depression: Randomized controlled trial. J Med Internet Res 2012;14(3):e67 [FREE Full text] [doi: 10.2196/jmir.1858] [Medline: 22732135]
134. Hill Christina L M, Updegraff JA. Mindfulness and its relationship to emotional regulation. Emotion 2012 Feb;12(1):81-90. [doi: 10.1037/a0026355] [Medline: 22148996]
135. Gross JJ, Levenson RW. Hiding feelings: The acute effects of inhibiting negative and positive emotion. J Abnorm Psychol 1997 Feb;106(1):95-103. [Medline: 9103721]
136. Suveg C, Hoffman B, Zeman JL, Thomassin K. Common and specific emotion-related predictors of anxious and depressive symptoms in youth. Child Psychiatry Hum Dev 2009 Jun;40(2):223-239. [doi: 10.1007/s10578-008-0121-x] [Medline: 19039662]
137. Barrett LF, Gross J, Christensen TC, Benvenuto M. Knowing what you're feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. Cogn Emot 2001 Nov;15(6):713-724. [doi: 10.1080/02699930143000239]
138. O'Toole MS, Jensen MB, Fentz HN, Zachariae R, Hougaard E. Emotion differentiation and emotion regulation in high and low socially anxious individuals: An experience-sampling study. Cogn Ther Res 2014 Mar 13;38(4):428-438. [doi: 10.1007/s10608-014-9611-2]
139. Haga SM, Kraft P, Corby E. Emotion regulation: Antecedents and well-being outcomes of cognitive reappraisal and expressive suppression in cross-cultural samples. J Happiness Stud 2007 Nov 23;10(3):271-291. [doi: 10.1007/s10902-007-9080-3]
140. Burklund LJ, Creswell JD, Irwin MR, Lieberman MD. The common and distinct neural bases of affect labeling and reappraisal in healthy adults. Front Psychol 2014;5:221 [FREE Full text] [doi: 10.3389/fpsyg.2014.00221] [Medline: 24715880]
141. Shiffman S, Stone AA, Hufford MR. Ecological momentary assessment. Annu Rev Clin Psychol 2008;4:1-32. [Medline: 18509902]
142. Proudfoot J, Nicholas J. Monitoring evaluation in low intensity CBT interventions. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, editors. Oxford Guide to Low Intensity CBT Interventions. Oxford, UK: Oxford University Press; 2010.
143. Randall WM, Rickard NS. Development and Trial of a Mobile Experience Sampling Method (m-ESM) for Personal Music Listening. Music Percept 2013 Dec;31(2):157-170. [doi: 10.1525/mp.2013.31.2.157]

144. Rickwood D, Deane FP, Wilson CJ, Ciarrochi J. Young people's help-seeking for mental health problems. Adv Ment Health 2005 Dec;4(3):218-251. [doi: 10.5172/jamh.4.3.218]
145. Lau AY, Proudfoot J, Andrews A, Liaw S, Crimmins J, Arguel A, et al. Which bundles of features in a Web-based personally controlled health management system are associated with consumer help-seeking behaviors for physical and emotional well-being? J Med Internet Res 2013;15(5):e79 [FREE Full text] [doi: 10.2196/jmir.2414] [Medline: 23649790]
146. Hollon SD, Kendall PC. In vivo assessment techniques for cognitive-behavioural interventions. In: Kendall PC, Hollon SD, editors. Assessment Strategies for Cognitive-Behavioral Interventions. New York: Academic Press; 1981:319-362.
147. Morris ME, Kathawala Q, Leen TK, Gorenstein EE, Guilak F, Labhard M, et al. Mobile therapy: Case study evaluations of a cell phone application for emotional self-awareness. J Med Internet Res 2010;12(2):e10 [FREE Full text] [doi: 10.2196/jmir.1371] [Medline: 20439251]
148. Hawkins EJ, Lambert MJ, Vermeersch DA, Slade KL, Tuttle KC. The therapeutic effects of providing patient progress information to therapists and patients. Psychother Res 2004 Sep 01;14(3):308-327. [doi: 10.1093/ptr/kph027]
149. Simon W, Lambert MJ, Harris MW, Busath G, Vazquez A. Providing patient progress information and clinical support tools to therapists: Effects on patients at risk of treatment failure. Psychother Res 2012 Nov;22(6):638-647. [doi: 10.1080/10503307.2012.698918] [Medline: 22755547]
150. Carlier Ingrid V E, Meuldijk D, Van Vliet Irene M, Van FE, Van der Wee Nic J A, Zitman FG. Routine outcome monitoring and feedback on physical or mental health status: Evidence and theory. J Eval Clin Pract 2012 Feb;18(1):104-110. [doi: 10.1111/j.1365-2753.2010.01543.x] [Medline: 20846319]
151. Knaup C, Koesters M, Schoefer D, Becker T, Puschner B. Effect of feedback of treatment outcome in specialist mental healthcare: Meta-analysis. Br J Psychiatry 2009 Jul;195(1):15-22 [FREE Full text] [doi: 10.1192/bjp.bp.108.053967] [Medline: 19567889]
152. Cooney GM, Dwan K, Greig CA, Lawlor DA, Rimer J, Waugh FR, et al. Exercise for depression. Cochrane Database Syst Rev 2013;9:CD004366. [doi: 10.1002/14651858.CD004366.pub6] [Medline: 24026850]
153. Craft LL, Perna FM. The benefits of exercise for the clinically depressed. Prim Care Companion J Clin Psychiatry 2004;6(3):104-111 [FREE Full text] [Medline: 15361924]
154. Josefsson T, Lindwall M, Archer T. Physical exercise intervention in depressive disorders: Meta-analysis and systematic review. Scand J Med Sci Sports 2014 Apr;24(2):259-272. [doi: 10.1111/sms.12050] [Medline: 23362828]
155. Anderson E, Shivakumar G. Effects of exercise and physical activity on anxiety. Front Psychiatry 2013;4:27 [FREE Full text] [doi: 10.3389/fpsyt.2013.00027] [Medline: 23630504]
156. Alexandratos K, Barnett F, Thomas Y. The impact of exercise on the mental health and quality of life of people with severe mental illness: A critical review. Br J Occup Ther 2012 Feb 01;75(2):48-60. [doi: 10.4276/030802212X13286281650956]
157. Folkins CH, Sime WE. Physical fitness training and mental health. Am Psychol 1981 Apr;36(4):373-389. [Medline: 7023304]
158. Rosenbaum S, Tiedemann A, Sherrington C, Curtis J, Ward PB. Physical activity interventions for people with mental illness: A systematic review and meta-analysis. J Clin Psychiatry 2014 Sep;75(9):964-974. [doi: 10.4088/JCP.13r08765] [Medline: 24813261]
159. Juslin PN, Liljeström S, Västfjäll D, Lundqvist LO. How does music evoke emotions? Exploring the underlying mechanisms. In: Juslin PN, Sloboda J, editors. Handbook of Music and Emotion: Theory, Research, Applications. Oxford, UK: Oxford University Press; 2011:605-642.
160. Rickard NS, Wong WW, Velik L. Relaxing music counters heightened consolidation of emotional memory. Neurobiol Learn Mem 2012 Feb;97(2):220-228. [doi: 10.1016/j.nlm.2011.12.005] [Medline: 22207009]
161. Knight WE, Rickard NS. Relaxing music prevents stress-induced increases in subjective anxiety, systolic blood pressure, and heart rate in healthy males and females. J Music Ther 2001;38(4):254-272. [Medline: 11796077]
162. McFerran KS, Saarikallio S. Depending on music to feel better: Being conscious of responsibility when appropriating the power of music. The Arts in Psychotherapy 2014 Feb;41(1):89-97. [doi: 10.1016/j.aip.2013.11.007]
163. Randall WM, Rickard NS, Vella-Brodrick DA. Emotional outcomes of regulation strategies used during personal music listening: A mobile experience sampling study. Musicae Scientiae 2014 Aug 20;18(3):275-291. [doi: 10.1177/1029864914536430]
164. Dimidjian S, Martell CR, Herman-Dunn R, Hubley CP. Behavioral activation for depression. In: Barlow D, editor. Clinical Handbook of Psychological Disorders: A Step-by-Step Treatment Manual. New York: Guilford Press; 2014:353-393.
165. Ekers D, Richards D, Gilbody S. A meta-analysis of randomized trials of behavioural treatment of depression. Psychol Med 2008 May;38(5):611-623. [doi: 10.1017/S0033291707001614] [Medline: 17903337]
166. Hopko DR, Robertson SMC, Lejuez CW. Behavioral activation for anxiety disorders. The Behavior Analyst Today 2006;7(2):212-232. [doi: 10.1037/h0100084]
167. Martell CR, Dimidjian S, Lewinsohn PM. Behavioral activation therapy. In: Kazantzis N, Reinecke MA, Freeman A, editors. Cognitive and Behavioral Theories in Clinical Practice. New York: Guilford Press; 2010:198-223.
168. Beck JS. Cognitive Behavior Therapy: Basics and Beyond. 2nd edition. New York, NY: The Guilford Press; 2011.
169. Richards D. Behavioural activation. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions. 1st edition. Oxford, UK: Oxford University Press; 2010:142-150.

170. Fogg BJ. A behavior model for persuasive design. In: Proceedings of the 4th International Conference on Persuasive Technology. 2009 Presented at: 4th International Conference on Persuasive Technology; April 26-29; New York, USA p. 1-40. [doi: 10.1145/1541948.1541999]
171. Brockbank A, McGill I. Facilitating Reflective Learning in Higher Education. 2nd edition. New York, NY: Open University Press; 2007.
172. Chesla CA, Chun KM, Kwan CM, Mullan JT, Kwong Y, Hsu L, et al. Testing the efficacy of culturally adapted coping skills training for Chinese American immigrants with type 2 diabetes using community-based participatory research. Res Nurs Health 2013 Aug;36(4):359-372. [doi: 10.1002/nur.21543] [Medline: 23606271]
173. Dubow EF, Schmidt D, McBride J, Edwards S, Merk FL. Teaching children to cope With stressful experiences: Initial implementation and evaluation of a primary prevention program. J Clin Child Psychol 1993 Dec;22(4):428-440. [doi: 10.1207/s15374424jccp2204_3]
174. Bandura A. Perceived self-efficacy in cognitive development and functioning. Educational Psychologist 1993 Mar;28(2):117-148. [doi: 10.1207/s15326985ep2802_3]
175. Chesney MA, Neilands TB, Chambers DB, Taylor JM, Folkman S. A validity and reliability study of the coping self-efficacy scale. Br J Health Psychol 2006 Sep;11(Pt 3):421-437 [FREE Full text] [doi: 10.1348/135910705X53155] [Medline: 16870053]
176. Thorne KJ, Andrews JJ, Nordstokke D. Relations among children's coping strategies and anxiety: the mediating role of coping efficacy. J Gen Psychol 2013;140(3):204-223. [doi: 10.1080/00221309.2013.792235] [Medline: 24837655]
177. Philip EJ, Merluzzi TV, Zhang Z, Heitzmann CA. Depression and cancer survivorship: Importance of coping self-efficacy in post-treatment survivors. Psychooncology 2013 May;22(5):987-994 [FREE Full text] [doi: 10.1002/pon.3088] [Medline: 22573371]
178. Benka J, Nagyova I, Rosenberger J, Macejova Z, Lazurova I, Van der Klink J, et al. Is coping self-efficacy related to psychological distress in early and established rheumatoid arthritis patients? J Dev Phys Disabil 2013 Dec 22. [doi: 10.1007/s10882-013-9364-y]
179. Pritchard C, Gow K. Coping self-efficacy and psychological distress in flood victims. In: Gow K, Celinski MJ, editors. Individual Trauma: Recovering from Deep Wounds and Exploring the Potential for Renewal. Hauppauge, NY: Nova Science; 2012:207-219.
180. Smith AJ, Benight CC, Cieslak R. Social support and postdeployment coping self-efficacy as predictors of distress among combat veterans. Mil Psychol 2013;25(5):452-461. [doi: 10.1037/mil0000013]
181. Sirois FM, Hirsch JK. Associations of psychological thriving with coping efficacy, expectations for future growth, and depressive symptoms over time in people with arthritis. J Psychosom Res 2013 Sep;75(3):279-286. [doi: 10.1016/j.jpsychores.2013.06.004] [Medline: 23972419]
182. Denton FN, Rostosky SS, Danner F. Stigma-related stressors, coping self-efficacy, and physical health in lesbian, gay, and bisexual individuals. J Couns Psychol 2014 Jul;61(3):383-391. [doi: 10.1037/a0036707] [Medline: 25019542]
183. Hayes SC, Wilson KG, Gifford EV, Follette VM, Strosahl K. Experimental avoidance and behavioral disorders: A functional dimensional approach to diagnosis and treatment. J Consult Clin Psychol 1996 Dec;64(6):1152-1168. [Medline: 8991302]
184. Craske MG, Barlow DH. Panic disorder and agoraphobia. In: Barlow D, editor. Clinical Handbook of Psychological Disorders: A Step-by-Step Treatment Manual. New York: The Guilford Press; 2014:1-61.
185. Long BC, Haney CJ. Coping strategies for working women: Aerobic exercise and relaxation interventions. Behav Ther 1988 Dec;19(1):75-83. [doi: 10.1016/S0005-7894%2888%2980057-1]
186. Manzoni G, Gorini A, Preziosa A, Pagnini F, Castelnuovo G, Molinari E, et al. New technologies and relaxation: An explorative study on obese patients with emotional eating. J Cybertherapy Rehabil 2008;1(2):182-192.
187. Besenius C, Beirne K, Grogan S, Clark-Carter D. Cognitive Behavioral Therapy (CBT) in a Depression/Alcohol Use Disorder Group: A Qualitative Study. AlcoholTreat Q 2013 Jan;31(1):50-66. [doi: 10.1080/07347324.2013.746613]
188. Nash VR, Ponto J, Townsend C, Nelson P, Bretz MN. Cognitive behavioral therapy, self-efficacy, and depression in persons with chronic pain. Pain Manag Nurs 2013 Dec;14(4):e236-e243. [doi: 10.1016/j.pmn.2012.02.006] [Medline: 23273826]
189. Park N, Peterson C, Brunwasser SM. Positive psychology and therapy. In: Kazantzis N, Reinecke MA, Freeman A, editors. Cognitive and Behavioral Theories in Clinical Practice. New York: Guilford Press; 2010:198-223.
190. Rokke PD, al'Absi M. Matching pain coping strategies to the individual: A prospective validation of the cognitive coping strategy inventory. J Behav Med 1992 Dec;15(6):611-625. [Medline: 1484383]
191. Rokke PD, Lall R. The role of choice in enhancing tolerance to acute pain. Cogn Ther Res 1992 Feb;16(1):53-65. [doi: 10.1007/BF01172956]
192. Whittemore R, Jaser SS, Jeon S, Liberti L, Delamater A, Murphy K, et al. An internet coping skills training program for youth with type 1 diabetes: Six-month outcomes. Nurs Res 2012;61(6):395-404 [FREE Full text] [doi: 10.1097/NNR.0b013e3182690a29] [Medline: 22960587]
193. Grey M, Whittemore R, Jaser S, Ambrosino J, Lindemann E, Liberti L, et al. Effects of coping skills training in school-age children with type 1 diabetes. Res Nurs Health 2009 Aug;32(4):405-418 [FREE Full text] [doi: 10.1002/nur.20336] [Medline: 19488997]

194. Schmitz JM, Spiga R, Rhoades HM, Fuentes F, Grabowski J. Smoking cessation in women with cardiac risk: A comparative study of two theoretically based therapies. Nicotine Tob Res 1999 Mar;1(1):87-94. [Medline: 11072392]
195. Velsor-Friedrich B, Militello LK, Richards MH, Harrison PR, Gross IM, Romero E, et al. Effects of coping-skills training in low-income urban African-American adolescents with asthma. J Asthma 2012 May;49(4):372-379. [doi: 10.3109/02770903.2012.660296] [Medline: 22352813]
196. Macrodimitris SD, Hamilton KE, Backs-Dermott BJ, Mothersill KJ. CBT basics: A group approach to teaching fundamental cognitive-behavioral skills. J Cogn Psychother 2010 May 01;24(2):132-146. [doi: 10.1891/0889-8391.24.2.132]
197. Lewinsohn PM, Steinmetz JL, Antonuccio D, Teri L. Int J Ment Health. 1984. Group therapy for depression: The coping with depression course URL: http://www.jstor.org/stable/41344359?seq=1 [accessed 2015-07-22] [WebCite Cache ID 6aCeBM47d]
198. Kitchener BA, Jorm AF. Mental health first aid training for the public: Evaluation of effects on knowledge, attitudes and helping behavior. BMC Psychiatry 2002 Oct 1;2:10 [FREE Full text] [Medline: 12359045]
199. Hadlaczky G, Hökby S, Mkrtchian A, Carli V, Wasserman D. Mental Health First Aid is an effective public health intervention for improving knowledge, attitudes, and behaviour: A meta-analysis. Int Rev Psychiatry 2014 Aug;26(4):467-475. [doi: 10.3109/09540261.2014.924910] [Medline: 25137113]
200. Donker T, Griffiths KM, Cuijpers P, Christensen H. Psychoeducation for depression, anxiety and psychological distress: A meta-analysis. BMC Med 2009;7:79 [FREE Full text] [doi: 10.1186/1741-7015-7-79] [Medline: 20015347]
201. Van Daele T, Hermans D, Van Audenhove C, Van den Bergh O. Stress reduction through psychoeducation: A meta- analytic review. Health Educ Behav 2012 Aug;39(4):474-485. [doi: 10.1177/1090198111419202] [Medline: 21986242]
202. Whitehead L, Proudfoot J. Standards and operating guidelines for Internet interventions. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions. 1st edition. Oxford, UK: Oxford University Press; 2010:247-252.
203. Jorm AF. Mental health literacy: Empowering the community to take action for better mental health. Am Psychol 2012 Apr;67(3):231-243. [doi: 10.1037/a0025957] [Medline: 22040221]
204. Jorm AF, Korten AE, Jacomb PA, Christensen H, Rodgers B, Pollitt P. "Mental health literacy": A survey of the public's ability to recognise mental disorders and their beliefs about the effectiveness of treatment. Med J Aust 1997 Feb 17;166(4):182-186. [Medline: 9066546]
205. Hansson L, Markström U. The effectiveness of an anti-stigma intervention in a basic police officer training programme: A controlled study. BMC Psychiatry 2014;14:55 [FREE Full text] [doi: 10.1186/1471-244X-14-55] [Medline: 24568685]
206. Goldney RD, Fisher LJ, Wilson DH, Cheok F. Mental health literacy of those with major depression and suicidal ideation: An impediment to help seeking. Suicide Life Threat Behav 2002;32(4):394-403. [Medline: 12501964]
207. Lauber C, Nordt C, Falcato L, Rössler W. Do people recognise mental illness? Factors influencing mental health literacy. Eur Arch Psychiatry Clin Neurosci 2003 Oct;253(5):248-251. [doi: 10.1007/s00406-003-0439-0] [Medline: 14504994]
208. Ritterband L, Thorndike F, Vasquez D, Saylor D. Treatment credibility and satisfaction with Internet interventions. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions. 1st edition. Oxford, UK: Oxford University Press; 2010:235-245.
209. Eastin MS. Credibility assessments of online health information: The effects of source expertise and knowledge of content. J Comput-Mediat Commun 2001;6. [doi: 10.1111/j.1083-6101.2001.tb00126.x]
210. beyondblue. beyondblue. 2015. URL: https://www.beyondblue.org.au/ [accessed 2015-07-22] [WebCite Cache ID 6aChSwddx]
211. headspace. headspace. 2015. URL: http://headspace.org.au/ [accessed 2015-07-22] [WebCite Cache ID 6aChZ8JaX]
212. Christensen H, Griffiths KM, Jorm AF. Delivering interventions for depression by using the internet: randomised controlled trial. BMJ 2004 Jan 31;328(7434):265 [FREE Full text] [doi: 10.1136/bmj.37945.566632.EE] [Medline: 14742346]
213. Opriş D, Pintea S, García-Palacios A, Botella C, Szamosközi Ş, David D. Virtual reality exposure therapy in anxiety disorders: A quantitative meta-analysis. Depress Anxiety 2012 Feb;29(2):85-93. [doi: 10.1002/da.20910] [Medline: 22065564]
214. Rothbaum BO, Anderson P, Zimand E, Hodges L, Lang D, Wilson J. Virtual reality exposure therapy and standard (in vivo) exposure therapy in the treatment of fear of flying. Behav Ther 2006 Mar;37(1):80-90. [doi: 10.1016/j.beth.2005.04.004] [Medline: 16942963]
215. Kazantzis N, L'Abate L. Theoretical foundations. In: Kazantzis N, Deane FP, Ronan KR, L'Abate L, editors. Using Homework Assignments In Cognitive Behavior Therapy. New York, NY: Routledge; 2005.
216. Harrison V, Proudfoot J, Wee PP, Parker G, Pavlovic DH, Manicavasagar V. Mobile mental health: Review of the emerging field and proof of concept study. J Ment Health 2011 Dec;20(6):509-524. [doi: 10.3109/09638237.2011.608746] [Medline: 21988230]
217. Heron KE, Smyth JM. Ecological momentary interventions: Incorporating mobile technology into psychosocial and health behaviour treatments. Br J Health Psychol 2010 Feb;15(Pt 1):1-39 [FREE Full text] [doi: 10.1348/135910709X466063] [Medline: 19646331]
218. Happify Inc. Happify [mobile application software], Version 1.16. URL: https://itunes.apple.com/au/app/happify/id730601963?mt=8 [accessed 2015-07-22] [WebCite Cache ID 6aCi63OBO]

219. Kraut R, Kiesler S, Boneva B, Cummings J, Helgeson V, Crawford A. Internet Paradox Revisited. J Social Issues 2002 Jan;58(1):49-74. [doi: 10.1111/1540-4560.00248]
220. Selfhout M, Branje SJ, Delsing M, ter Bogt TF, Meeus WH. Different types of Internet use, depression, and social anxiety: The role of perceived friendship quality. J Adolesc 2009 Aug;32(4):819-833. [doi: 10.1016/j.adolescence.2008.10.011] [Medline: 19027940]
221. Weinstein A, Dorani D, Elhadif R, Bukovza Y, Yarmulnik A, Dannon P. Internet addiction is associated with social anxiety in young adults. Ann Clin Psychiatry 2015 Feb;27(1):4-9. [Medline: 25696775]
222. Milani L, Osualdella D, Di BP. Quality of interpersonal relationships and problematic Internet use in adolescence. Cyberpsychol Behav 2009 Dec;12(6):681-684. [doi: 10.1089/cpb.2009.0071] [Medline: 19788382]
223. Seepersad S. Coping with loneliness: Adolescent online and offline behavior. Cyberpsychol Behav 2004 Feb;7(1):35-39. [doi: 10.1089/109493104322820093] [Medline: 15006167]
224. Holahan CJ, Moos RH, Holahan CK, Brennan PL, Schutte KK. Stress generation, avoidance coping, and depressive symptoms: A 10-year model. J Consult Clin Psychol 2005 Aug;73(4):658-666 [FREE Full text] [doi: 10.1037/0022-006X.73.4.658] [Medline: 16173853]
225. Jewitt C. Technology, Literacy and Learning: A Multimodal Approach. New York, NY: Routledge; 2006.
226. Means B, Toyama Y, Murphy R, Bakia M, Jones K. Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies.: US Department of Education; 2009. URL: http://eric.ed.gov/?id=ED505824 [accessed 2015-07-22] [WebCite Cache ID 6aCiMDkSI]
227. Garrison D, Kanuka H. Blended learning: Uncovering its transformative potential in higher education. Internet High Educ 2004 Apr;7(2):95-105. [doi: 10.1016/j.iheduc.2004.02.001]
228. Bernard RM, Borokhovski E, Schmid RF, Tamim RM, Abrami PC. A meta-analysis of blended learning and technology use in higher education: From the general to the applied. J Comput High Educ 2014 Feb 9;26(1):87-122. [doi: 10.1007/s12528-013-9077-3]
229. Means B, Toyama Y, Murphy R, Baki M. Teachers College Record. 2013. The effectiveness of online and blended learning: A meta-analysis of the empirical literature URL: http://www.sri.com/sites/default/files/publications/effectiveness_of_online_and_blended_learning.pdf [accessed 2015-07-22] [WebCite Cache ID 6aCid92vV]
230. Byron T. Safer children in a digital world: The report of the Byron review. 2008. URL: http://webarchive.nationalarchives.gov.uk/20130401151715/http://www.education.gov.uk/publications/eOrderingDownload/DCSF-00334-2008.pdf [accessed 2015-07-22] [WebCite Cache ID 6aCikqtOA]
231. Howard-Jones P, Demetriou S, Bogacz R, Yoo J, Leonards U. Toward a science of learning games. Mind Brain Educ 2011 Mar 01:5-41. [doi: 10.1111/j.1751-228X.2011.01108.x]
232. McGonigal J. Reality Is Broken: Why Games Make Us Better and How They Can Change the World. New York: Penguin (Non-Classics); 2011.
233. The University of Pennsylvania, SuperBetter Labs LLC. A randomized controlled trial: The effects of SuperBetter on depression. 2014. URL: https://annmarieroepke.files.wordpress.com/2013/08/superbetter-study-results-bulletin-3-23-14.pdf [accessed 2015-07-22] [WebCite Cache ID 6aCiqwJgC]
234. Krämer LV, Helmes AW, Bengel J. Understanding activity limitations in depression. Eur Psychol 2014 Jan;19(4):278-288. [doi: 10.1027/1016-9040/a000205]
235. Burke B. Gamify: How Gamification Motivates People To Do Extraordinary Things. Brookline, MA: Bibliomotion; 2014.
236. Nike Inc. Nike+ Running [mobile application software], Version 4.8. 2015. URL: https://itunes.apple.com/au/app/nike+-running/id387771637?mt=8 [accessed 2015-07-22] [WebCite Cache ID 6aCj03BHP]
237. Kim J, Allen J, Lee E. Alternate reality gaming. Commun ACM 2008 Feb 01;51(2):36-42. [doi: 10.1145/1314215.1314222]
238. Yee N. Motivations for play in online games. Cyberpsychol Behav 2006 Dec;9(6):772-775. [doi: 10.1089/cpb.2006.9.772] [Medline: 17201605]
239. Harter S. Pleasure Derived from Challenge and the Effects of Receiving Grades on Children's Difficulty Level Choices. Child Development 1978 Sep;49(3):788-799. [doi: 10.2307/1128249]
240. Koestner R, Zuckerman M, Koestner J. Praise, involvement, and intrinsic motivation. J Pers Soc Psychol 1987;53(2):383-390. [doi: 10.1037/0022-3514.53.2.383]
241. Abuhamdeh S, Csikszentmihalyi M. The importance of challenge for the enjoyment of intrinsically motivated, goal-directed activities. Pers Soc Psychol Bull 2012 Mar;38(3):317-330. [doi: 10.1177/0146167211427147] [Medline: 22067510]
242. Nunes J, Drèze X. The Endowed Progress Effect: How artificial advancement increases effort. J Consum Res 2006 Mar;32(4):504-512. [doi: 10.1086/500480]
243. Koepp MJ, Gunn RN, Lawrence AD, Cunningham VJ, Dagher A, Jones T, et al. Evidence for striatal dopamine release during a video game. Nature 1998 May 21;393(6682):266-268. [doi: 10.1038/30498] [Medline: 9607763]
244. Li J, Theng YL, Foo S. Game-based digital interventions for depression therapy: A systematic review and meta-analysis. Cyberpsychol Behav Soc Netw 2014 Aug;17(8):519-527. [doi: 10.1089/cyber.2013.0481] [Medline: 24810933]
245. Rodrigues JJPC, Oliveira M, Vaidya B. New trends on ubiquitous mobile multimedia applications. EURASIP J Wirel Commun Netw 2010;2010(1):689517. [doi: 10.1155/2010/689517]

246. Wilson T. Redirect: The Surprising New Science of Psychological Change. New York, NY: Little, Brown and Company; 2011.
247. Jawbone. UP by JawboneTM – Free Fitness Tracker, Step Counter, Count Calories, Weight Loss, Diet, Recipes [mobile application software], Version 4.6. URL: https://itunes.apple.com/au/app/up-by-jawbone-free-fitness/id916240764?mt=8 [accessed 2015-07-22] [WebCite Cache ID 6aCjS7hDg]
248. Cacioli J, Mussap AJ. Avatar body dimensions and men's body image. Body Image 2014 Mar;11(2):146-155. [doi: 10.1016/j.bodyim.2013.11.005] [Medline: 24394638]
249. Bandura A. Social cognitive theory of mass communication. Media Psychology 2001 Aug;3(3):265-299. [doi: 10.1207/S1532785XMEP0303_03]
250. Fox J, Bailenson JN. Virtual self-modeling: The effects of vicarious reinforcement and identification on exercise behaviors. Media Psychology 2009 Mar 05;12(1):1-25. [doi: 10.1080/15213260802669474]
251. Yee N, Bailenson J. The Proteus Effect: The effect of transformed self-representation on behavior. Human Comm Res 2007 Jul;33(3):271-290. [doi: 10.1111/j.1468-2958.2007.00299.x]
252. Yee N, Bailenson JN, Ducheneaut N. The Proteus Effect: Implications of transformed digital self-representation on online and offline behavior. Commun Res 2009 Jan 22;36(2):285-312. [doi: 10.1177/0093650208330254]
253. Norton MI, Mochon D, Ariely D. The IKEA effect: When labor leads to love. J Consum Psychol 2012 Jul;22(3):453-460. [doi: 10.1016/j.jcps.2011.08.002]
254. Mochon D, Norton MI, Ariely D. Bolstering and restoring feelings of competence via the IKEA effect. Int J Res Mark 2012 Dec;29(4):363-369. [doi: 10.1016/j.ijresmar.2012.05.001]
255. Young AL, Quan-Haase A. Privacy protection strategies on Facebook. Inf Commun Soc 2013 May;16(4):479-500. [doi: 10.1080/1369118X.2013.777757]
256. Buchanan EA, Hvizdak EE. Online survey tools: Ethical and methodological concerns of human research ethics committees. J Empir Res Hum Res Ethics 2009 Jun;4(2):37-48. [doi: 10.1525/jer.2009.4.2.37] [Medline: 19480590]
257. Apple Inc. Local and push notifications. 2015. URL: https://developer.apple.com/notifications/ [accessed 2015-07-22] [WebCite Cache ID 6aCjtwchT]
258. Kim HS, Yoo YS, Shim HS. Effects of an Internet-based intervention on plasma glucose levels in patients with type 2 diabetes. J Nurs Care Qual 2005;20(4):335-340. [Medline: 16177585]
259. Rodgers A, Corbett T, Bramley D, Riddell T, Wills M, Lin R, et al. Do u smoke after txt? Results of a randomised trial of smoking cessation using mobile phone text messaging. Tob Control 2005 Aug;14(4):255-261 [FREE Full text] [doi: 10.1136/tc.2005.011577] [Medline: 16046689]
260. Patrick K, Raab F, Adams MA, Dillon L, Zabinski M, Rock CL, et al. A text message-based intervention for weight loss: Randomized controlled trial. J Med Internet Res 2009;11(1):e1 [FREE Full text] [doi: 10.2196/jmir.1100] [Medline: 19141433]
261. Carpenter CJ. A meta-analysis of the effectiveness of the "But You Are Free" compliance-gaining technique. Commun Stud 2013 Jan;64(1):6-17. [doi: 10.1080/10510974.2012.727941]
262. Chaiken S. Heuristic versus systematic information processing and the use of source versus message cues in persuasion. J Pers Soc Psychol 1980;39(5):752-766. [doi: 10.1037/0022-3514.39.5.752]
263. Walji MF, Zhang J. Human-centered design of persuasive appointment reminders. In: Proceedings of the 41st Hawaii International Conference on System Sciences. 2008 Presented at: 41st Hawaii International Conference on System Sciences; Jan 7-10, 2008; Hawaii p. 236. [doi: 10.1109/HICSS.2008.194]
264. Kenardy J, McCafferty K, Rosa V. Internet-delivered indicated prevention for anxiety disorders: Six-month follow-up. Clin Psychol 2006 Mar 01:10-42. [doi: 10.1080/13284200500378746]
265. Kerr C, Murray E, Stevenson F, Gore C, Nazareth I. Internet interventions for long-term conditions: Patient and caregiver quality criteria. J Med Internet Res 2006;8(3):e13 [FREE Full text] [doi: 10.2196/jmir.8.3.e13] [Medline: 16954123]
266. Fling B. Mobile Design and Development: Practical Concepts and Techniques for Creating Mobile Sites and Web Apps. Sebastopol, CA: O'Reilly Media Inc; 2009.
267. Crabb RM, Cavanagh K, Proudfoot J, Learmonth D, Rafie S, Weingardt KR. Is computerized cognitive-behavioural therapy a treatment option for depression in late-life? A systematic review. Br J Clin Psychol 2012 Nov;51(4):459-464. [doi: 10.1111/j.2044-8260.2012.02038.x] [Medline: 23078214]
268. Fogg BJ. BJ Fogg's Behavior Model. 2011. URL: http://www.behaviormodel.org/index.html [accessed 2015-07-22] [WebCite Cache ID 6aCvOQMc7]
269. Brown CL, Krishna A. The skeptical shopper: A metacognitive account for the effects of default options on choice. J Consum Res 2004 Dec;31(3):529-539. [doi: 10.1086/425087]
270. Abadie A, Gay S. The impact of presumed consent legislation on cadaveric organ donation: A cross-country study. J Health Econ 2006 Jul;25(4):599-620. [doi: 10.1016/j.jhealeco.2006.01.003] [Medline: 16490267]
271. Rockloff M, Hanley C. The default option: Why a system of presumed consent may be effective at increasing rates of organ donation. Psychol Health Med 2014;19(5):580-585. [doi: 10.1080/13548506.2013.841967] [Medline: 24083828]
272. Dinner I, Johnson EJ, Goldstein DG, Liu K. Partitioning default effects: Why people choose not to choose. J Exp Psychol Appl 2011 Dec;17(4):332-341. [doi: 10.1037/a0024354] [Medline: 21707203]

273. Williams C, Morrison J. A new language for CBT: New ways of working require new thinking, as well as new words. In: Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide to Low Intensity CBT Interventions. 1st edition. Oxford, UK: Oxford University Press; 2010:69-83.
274. Rozbroj T, Lyons A, Pitts M, Mitchell A, Christensen H. Assessing the applicability of e-therapies for depression, anxiety, and other mood disorders among lesbians and gay men: Analysis of 24 web- and mobile phone-based self-help interventions. J Med Internet Res 2014;16(7):e166 [FREE Full text] [doi: 10.2196/jmir.3529] [Medline: 24996000]
275. Martinez R, Whitfield G, Dafters R, Williams C. Can people read self-help manuals for depression? A challenge for the stepped care model and book prescription schemes. Behav Cognit Psychother 2007 Dec 18;36(01). [doi: 10.1017/S1352465807004067]
276. Smith F. Understanding Reading: A Psycholinguistic Analysis of Reading and Learning to Read. Mahwah, NJ: Routledge; 2004.
277. Carney RN, Levin JR. Pictorial illustrations still improve students' learning from text. Educ Psychol Rev 2002 Mar 01;14:5-26. [doi: 10.1023/A:1013176309260]
278. Richards JM, Gross JJ. Emotion regulation and memory: The cognitive costs of keeping one's cool. J Pers Soc Psychol 2000 Sep;79(3):410-424. [Medline: 10981843]
279. Lifeline Research Foundation. 2013 research report. 2014. URL: https://www.lifeline.org.au/ArticleDocuments/122/Lifeline_AnnualReport_2014.pdf [accessed 2015-07-22] [WebCite Cache ID 6aCvpR3nA]
280. Gould MS, Kalafat J, Harrismunfakh JL, Kleinman M. An evaluation of crisis hotline outcomes. Part 2: Suicidal callers. Suicide Life Threat Behav 2007 Jun;37(3):338-352. [doi: 10.1521/suli.2007.37.3.338] [Medline: 17579545]
281. Australian Government Department of Health and Ageing. E-mental health strategy for Australia. 2012. URL: http://www.health.gov.au/internet/main/publishing.nsf/Content/7C7B0BFEB985D0EBCA257BF0001BB0A6/$File/emstrat.pdf [accessed 2015-01-21] [WebCite Cache ID 6aCvvNsxU]
282. World Health Organization. Preventing suicide: A global imperative. 2014. URL: http://apps.who.int/iris/bitstream/10665/131056/1/9789241564779_eng.pdf?ua=1&ua=1 [accessed 2015-01-21] [WebCite Cache ID 6aCw1iKbW]
283. Fox JC, Blank M, Rovnyak VG, Barnett RY. Barriers to help seeking for mental disorders in a rural impoverished population. Community Ment Health J 2001 Oct;37(5):421-436. [Medline: 11419519]
284. Burns J, Morey C, Lagelée A, Mackenzie A, Nicholas J. Reach Out! Innovation in service delivery. Med J Aust 2007 Oct 1;187(7 Suppl):S31-S34. [Medline: 17908022]
285. Lifeline. Crisis chat. 2015. URL: https://www.lifeline.org.au/Get-Help/Online-Services/crisis-chat [accessed 2015-07-22] [WebCite Cache ID 6aCwBPE3Q]
286. Dowling M, Rickwood D. Online counseling and therapy for mental health problems: A systematic review of individual synchronous interventions using chat. J Technol Hum Serv 2013 Jan;31(1):1-21. [doi: 10.1080/15228835.2012.728508]
287. Bradford S, Rickwood D. Young people's views on electronic mental health assessment: Prefer to type than talk? J Child Fam Stud 2015;24(5):1213-1221 [FREE Full text] [doi: 10.1007/s10826-014-9929-0] [Medline: 25960628]
288. Raento M, Oulasvirta A, Eagle N. Smartphones: An emerging tool for social scientists. Sociol Methods Res 2009 Feb 01;37(3):426-454. [doi: 10.1177/0049124108330005]
289. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: Validity of a brief depression severity measure. J Gen Intern Med 2001 Sep;16(9):606-613 [FREE Full text] [Medline: 11556941]
290. Austin Physician Productivity LLC. STAT Depression Screening PHQ-9 [mobile application software], Version 1.7. 2013. URL: https://itunes.apple.com/us/app/stat-depression-screening/id348793894?mt=8 [accessed 2015-07-22] [WebCite Cache ID 6aCwRKABg]
291. Spitzer RL, Kroenke K, Williams Janet B W, Löwe B. A brief measure for assessing generalized anxiety disorder: The GAD-7. Arch Intern Med 2006 May 22;166(10):1092-1097. [doi: 10.1001/archinte.166.10.1092] [Medline: 16717171]
292. Kroenke K, Spitzer RL, Williams JBW, Löwe B. The Patient Health Questionnaire Somatic, Anxiety, and Depressive Symptom Scales: A systematic review. Gen Hosp Psychiatry 2010;32(4):345-359. [doi: 10.1016/j.genhosppsych.2010.03.006] [Medline: 20633738]
293. Tennant R, Hiller L, Fishwick R, Platt S, Joseph S, Weich S, et al. The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Development and UK validation. Health Qual Life Outcomes 2007;5:63 [FREE Full text] [doi: 10.1186/1477-7525-5-63] [Medline: 18042300]
294. Grant AM, Franklin J, Langford P. The Self-Reflection and Insight Scale: A new measure of private self-consciousness. Soc Behav Pers 2002 Jan 01;30(8):821-835. [doi: 10.2224/sbp.2002.30.8.821]
295. Treynor W, Gonzalez R, Nolen-Hoeksema S. Rumination reconsidered: A psychometric analysis. Cogn Ther Res 2003 Jun 01;27:247-259. [doi: 10.1023/A:1023910315561]
296. Mayer JD, Stevens AA. An emerging understanding of the reflective (meta-) experience of mood. J Res Personal 1994 Sep;28(3):351-373. [doi: 10.1006/jrpe.1994.1025]
297. Headspace Meditation Limited. Headspace: Meditation techniques for mindfulness, stress relief & peace of mind [mobile application software], Version 2.4. 2015. URL: https://itunes.apple.com/au/app/headspace-meditation-techniques/id493145008?mt=8 [accessed 2015-11-20] [WebCite Cache ID 6dAp4YEeX]

298. Howells A, Ivtzan I, Eiroa-Orosa FJ. Putting the "app" in happiness: A randomised controlled trial of a smartphone-based mindfulness intervention to enhance wellbeing. J Happiness Stud 2014 Oct 29. [doi: 10.1007/s10902-014-9589-1]
299. Hides L, Kavanagh D, Stoyanov S, Zelenko O, Tjondronegoro D, Mani M. Mobile application rating scale (MARS). Abbotsford, Victoria, AUS: Young and Well Cooperative Research Centre; 2014. URL: http://www.youngandwellcrc.org.au/wp-content/uploads/2015/03/MARS-REPORT_FINAL_181214.pdf [accessed 2015-11-20] [WebCite Cache ID 6dAonlMIo]
300. World Health Organization. Global burden of mental disorders and the need for a comprehensive, coordinated response from health and social sectors at the country level: Report by the secretariat. 2011. URL: http://apps.who.int/gb/ebwha/pdf_files/EB130/B130_9-en.pdf [accessed 2015-07-22] [WebCite Cache ID 6aCxA7cp9]

Abbreviations

ACT: acceptance and commitment therapy
ARG: alternate reality game
BA: behavioral activation
CBT: cognitive behavioral therapy
CCBT: computerized cognitive behavioral therapy
CE: collaborative empiricism
CSE: coping self-efficacy
DBT: dialectical behavior therapy
EMA: ecological momentary assessment
ESA: emotional self-awareness
ESM: experience sampling method
GAD-7: 7-item Generalized Anxiety Disorder Scale
MARS: Mobile App Rating Scale
MHapp: mental health app
MHL: mental health literacy
PDA: personal digital assistant
PHQ-9: 9-item Patient Health Questionnaire
RCT: randomized controlled trial
SDT: self-determination theory
TCBT: transdiagnostic cognitive behavioral therapy
UP: unified protocol

Edited by G Eysenbach; submitted 04.08.15; peer-reviewed by Z Lv, WC Su, J Martin; comments to author 09.10.15; revised version received 18.10.15; accepted 16.11.15; published 01.03.16

Please cite as:
Bakker D, Kazantzis N, Rickwood D, Rickard N
Mental Health Smartphone Apps: Review and Evidence-Based Recommendations for Future Developments
JMIR Mental Health 2016;3(1):e7
URL: http://mental.jmir.org/2016/1/e7/
doi:10.2196/mental.4984
PMID:26932350

CHAPTER 2: GENERAL APPROACH OF THESIS

This chapter outlines the general aims, approach, and methods used for the remainder of this thesis. Chapter 1's literature review concluded that more research was needed on the use of self-contained, fully-automated MHapps in naturalistic contexts. Furthermore, work was needed to investigate the effects of different MHapps that use different features and focus on different mechanisms of change. The recommendations outlined for future MHapps provided guidance for pursuing research using newly developed MHapps in this thesis. The research aims of this thesis are summarised in Table 1.

Consumer-focussed app development is a process of iteration and experimentation (Fling, 2009). Versions of the app are created and then tested, either by developers or intended users. The feedback data collected about the user's experience is used to guide improvements to the app (Baron, Duffecy, Reid, Begale, & Caccamo, 2018; Werner-Seidler et al., 2017; Winslow et al., 2016). Such data are often referred to as usability data, as they assess the overall usability of an automated intervention. Given these factors, it is important to treat the development process of MHapps as a unique form of research. These processes are documented in Chapters 3 and 5 for MoodPrism and MoodMission respectively.

Table 1

Summary of Thesis Aims

	MHapp	
Phase	Reflection-focussed: MoodPrism	Problem-focussed: MoodMission
Development.	Develop a self-monitoring, mood-tracking app. (Chapter 3)	Develop an app for providing cognitive behavioural therapy (CBT) strategies. (Chapter 5)
Effectiveness of naturalistic use.	Explore the relationships between app engagement and mental health and wellbeing outcomes. (Chapter 4)	Explore the relationships between app engagement and mental health and wellbeing outcomes. (Chapter 6)
Mechanisms of effectiveness.	Examine whether emotional self-awareness (ESA) mediates the relationships between app engagement and mental health and wellbeing. (Chapter 4)	Examine whether coping self-efficacy (CSE) mediates the relationships between app engagement and mental health and wellbeing. (Chapter 6)
Efficacy in a randomised controlled trial (RCT).	Compare MoodPrism, MoodMission, and one established MHapp to a waitlist control group. (Chapter 7)	
Mechanisms of efficacy.	Examine whether ESA mediates the effects found in the RCT. (Chapter 7)	Examine whether CSE mediates the effects found in the RCT. (Chapter 7)

There is a distinction between studies that investigate an intervention's *effectiveness* and those that investigate intervention *efficacy*. While effectiveness of an intervention is established through investigation of the naturalistic, real-world effects, efficacy is established through comparison to a control group, such as in a RCT (Arean et al., 2016; Stoll, Pina, Gary, & Amresh, 2017). Both categories of evidence are important to collect and review, as each makes a unique contribution to the understanding of the intervention's utility. Effectiveness studies of MHapps reveal the likelihood of mental health improvement if an individual naturalistically finds, downloads, and engages with an app. Alternatively, RCTs guide participants within a formal research context and compare the effects of using an intervention against an alternative, control condition. While this may reduce the influence of placebo effects and increase clarity of efficacy (Torous & Firth, 2016), it introduces biases like the Hawthorne effect, artificially increasing participant engagement in interventions and biasing them to report favourable outcomes to experimenters (McCambridge, Witton, & Elbourne, 2014).

Although naturalistic effectiveness studies lack a control group for comparison, methods can be used to bring control to the study design. One approach used in MHapp research involves assessing participants' engagement with the intervention so the relationship between engagement and outcomes can be investigated (Carpenter et al., 2016). This can reveal the effects of engaging with an intervention, rather than just downloading a MHapp. If the MHapp is effective, there should be a positive relationship between app engagement and mental health benefits. This approach was used in the effectiveness investigations of MoodPrism and MoodMission, detailed in Chapters 4 and 6 respectively.

Chapter 1 recommended that in addition to investigating MHapp effects on mental health and wellbeing outcomes, research should explore mechanisms underlying the effects generated by MHapps. Three psychological constructs were proposed as mechanisms for change; ESA (Kauer et al., 2012), CSE (Chesney, Neilands, Chambers, Taylor, & Folkman, 2006), and mental health literacy (MHL; Jorm, 2012). To achieve this investigation for MoodPrism and MoodMission, mediation analyses were used to determine which of the three possible mechanisms each app was utilising. ESA, CSE, and MHL were investigated as mediators between app engagement and each mental health outcome measure. The same analyses were used for each app in both Chapter 4 and 6 to enable comparison.

Participants and Recruitment

The age of participants was restricted to 13 years and older for all studies. The apps were designed for a wide range of ages, and inclusion of adolescents was deemed important, as this demographic have high smartphone usage rates and MHapps can encourage help-seeking (Bradford & Rickwood, 2015). While MoodPrism and MoodMission are now available on both Android phones and iPhones, two studies were restricted to participants using iPhones. At the time of usability testing, MoodMission had not been developed for Android, so Chapter 3's study reports data from iPhone users only. One of the apps used in Chapter 7's RCT, MoodKit, was only available on iPhone, so all participants recruited for this study were iPhone users.

The studies reported in this thesis used three different recruitment strategies. Firstly, the development studies detailed in Chapters 3 and 5 used participants who had agreed to test a prototype MHapp and provide feedback. This included contacts of the researchers and other involved parties, for example, individuals who had pledged support to MoodMission's crowdfunding campaign. This enabled collection of constructive quantitative and qualitative data from willing individuals. The second recruitment strategy involved collecting data from all individuals who had downloaded MoodPrism or MoodMission to their smartphone. Participants were not actively recruited for these studies, reported in Chapters 4 and 6, but instead consented to provide access to their data for research purposes. This provided highly naturalistic data for investigation of intervention effectiveness. The third recruitment strategy was used for the RCT, whereby interested participants signed up to the study by providing their email address on a webpage. Participants were then randomised to a condition and sent instructions on how to proceed with the study. This is similar to most RCTs of digital interventions.

Due to deidentification of data, participants were not tracked through all studies to ensure that they were only providing data to one study. Therefore, it is possible that, for example, an individual could have participated in both development and effectiveness studies. However, participants in the RCT were excluded if they had used MHapps other than the one they were allocated, and MoodMission and MoodPrism were promoted independently, so it is unlikely that individuals provided data to multiple studies.

Materials

As several studies aimed to measure the same constructs, and each app included surveys for built-in data collection, similar measures were utilised across the effectiveness and efficacy studies. Measures were chosen based on: a) available psychometrics; b) how pragmatically appropriate they were for delivery via smartphone; and c) freedom of licensing to allow inclusion in apps. These measures are summarised in Table 2, and details on each can be found where they are reported in the relevant chapters.

Table 2

Measures Used Across Multiple Thesis Studies

Construct	Name of Measure	Reference
ESA	Emotional Self-Awareness Scale – Revised (ESAS-R)	(Kauer et al., 2012)
MHL	Mental Health Literacy Questionnaire (MHLQ)	No appropriate standardized MHL measure existed, so this questionnaire was developed by the researchers.
CSE	Coping Self-Efficacy Scale (CSES)	(Chesney et al., 2006)
Anxiety	Generalized Anxiety Scale, 7-item (GAD-7)	(Kroenke, Spitzer, & Williams, 2001)
Depression	Patient Health Questionnaire 9-item (PHQ-9)	
Positive Wellbeing	Warwick-Edinburgh Mental Well-being Scale (WEMWBS)	(Tennant et al., 2007)
App Feedback and Engagement[a]	Feedback Questionnaire	Adapted from the Mobile Application Rating Scale (MARS; Hides et al., 2014) by Rickard, Arjmand, Bakker and Seabrook (2016)

[a]Administered only in the 30-day follow-up surveys

Procedures

A single human ethics certificate of approval was obtained for all data collection and research conducted in this thesis (project number CF14/968 – 2014000398; see Appendix A). All effectiveness and efficacy studies used data from measures administered at baseline, when the app was first used, and again after 30 days of use. This 30 day time frame was selected because it was long enough to allow therapeutic change to occur, short enough to avoid intervention disengagement, and had been used in other MHapp studies (e.g. Enock, Hofmann, & McNally, 2014; Kauer et al., 2012; Roepke et al., 2015).

CHAPTER 3: DEVELOPMENT OF MOODPRISM AND PREPARATION FOR EVALUATION

The literature review of Chapter 1 provided guidance for developing MHapps. Following the formulation of these recommendations, development of an app that had both research and mental health aims was pursued. This app was named MoodPrism by the development team, because it converted a spectrum of inputted data into a colourful mood diary.

The initial aim for MoodPrism was to provide researchers with ecological momentary assessment (EMA) data on mood and other relevant activities, such as life events and social media use. EMA, sometimes referred to as experience sampling methodology (ESM), allows collection of ecologically valid data from participants as they continue with their daily routines. Apps used to collect EMA data often provide very limited feedback to participants in order to avoid data "contamination", so the data collected is unaffected by the methodology used to collect it (Wen, Schneider, Stone, & Spruijt-Metz, 2017). However, other unevaluated mood-tracking apps are available to consumers on the app stores, and some research had been conducted to validate the utility of using an app for this purpose (e.g. Kauer et al., 2012). Therefore, it was predicted that tailored feedback provided by a mood-tracking EMA app could be beneficial for participants, increasing both their motivation to provide EMA data and their emotional self-awareness (ESA). As suggested in Chapter 1, such MHapps could be designated as being "reflection-focussed", and the increase in ESA may lead to improvements in mental health and wellbeing.

MoodPrism was collaboratively designed and developed with the help of a commercial digital creation studio. After downloading MoodPrism, users completed a number of onboarding surveys with questions presented similarly to Figure 1. Completing all the onboarding surveys unlocked the daily mood surveys, which users could complete once a day after being notified. Daily mood surveys (see Figure 2 for example screens) opened with the prompt, "How were you feeling just before you were prompted by this app?" and assessed emotional wellbeing using 12 items rated on a five-point scale from “not at all” to “extremely”. The survey also included multiple choice items to rate the most positive and negative events that happened in the day, and for the user to report where they were and who was with them. Completing daily mood surveys created entries in the mood history, which can be seen in Figure 3.

The balancing of different research questions and interests, and the nature of the mood-tracking behavioural plan, allowed eleven of the sixteen recommendations made by Bakker, Kazantzis, Rickwood, and Rickard (2016) to be accommodated in MoodPrism. These are summarised in Table 1. The recommendations that were not accommodated concerned recommending activities to users. This was not possible because MoodPrism was designed to collect EMA mood data, and providing an “active” intervention, like engagement in coping activities, may have invalidated data that was answering specific research questions.

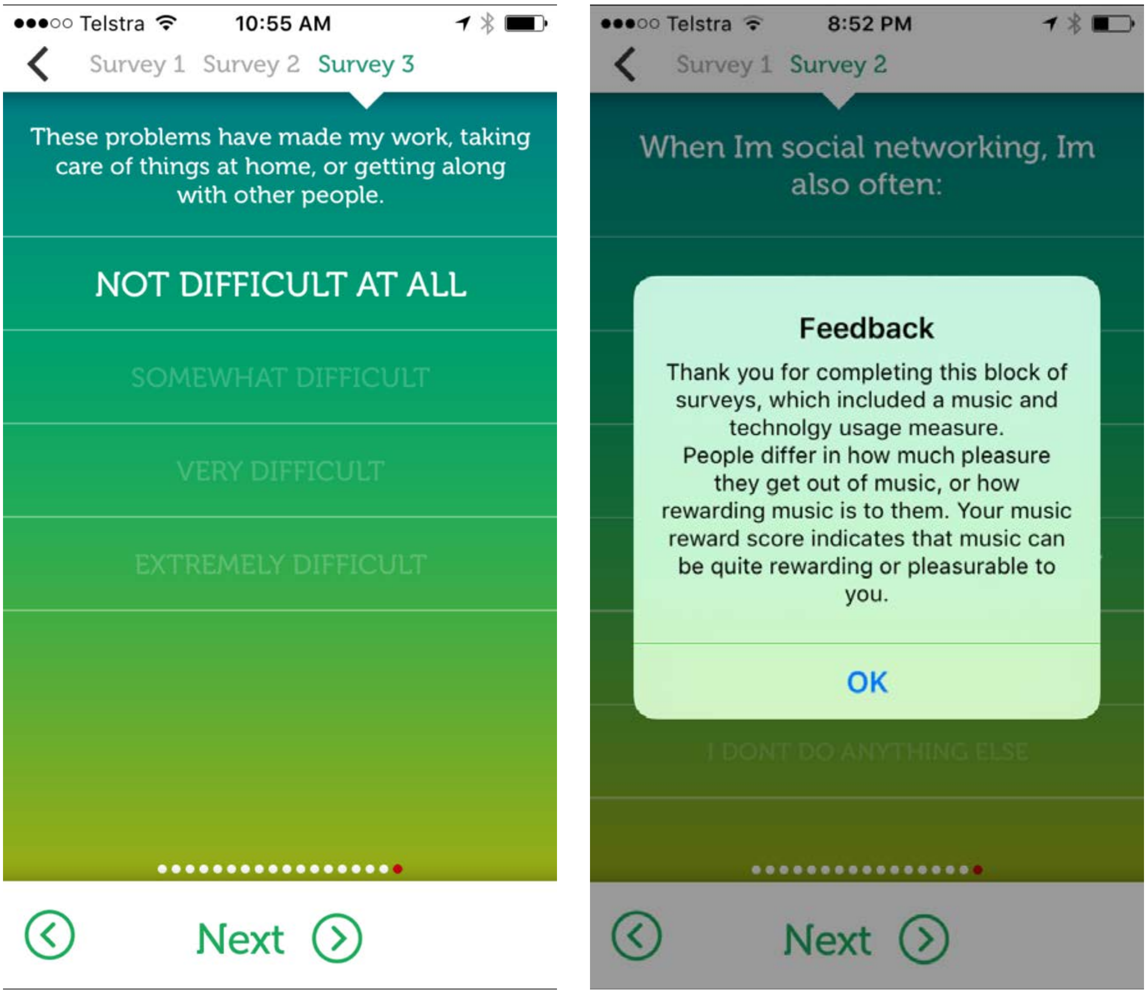


Figure 1. Example screens from onboarding surveys.

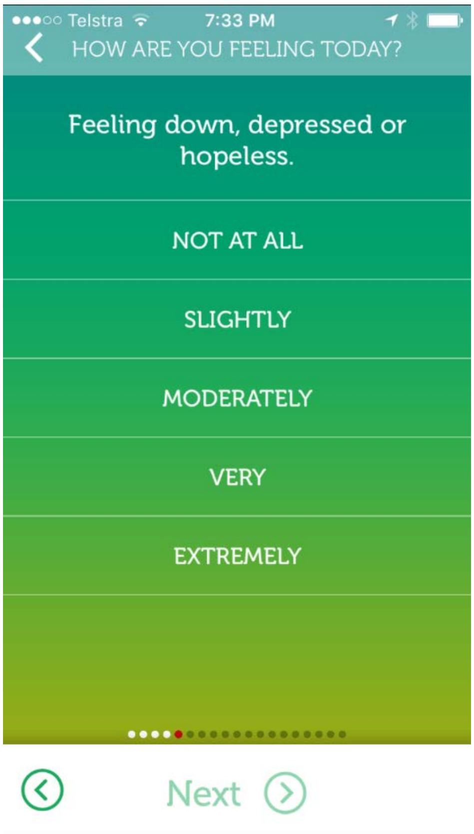


Figure 2. Example screen from daily mood surveys.

Figure 3. Example mood history screens.

Table 1

How Recommendations from Bakker et al. (2016) are Incorporated into MoodPrism

Recommendation		Use in MoodPrism
1	Cognitive behavior therapy (CBT) based	Self-monitoring of mood and activity is commonly incorporated in CBT as a decentering and cognitive reframing exercise, helping with the observation of and distancing from distressing emotions (Mennin, Ellard, Fresco, & Gross, 2013).
2	Address both anxiety and low mood	Daily mood surveys included items relevant to anxiety (e.g. “Nervous, anxious, or on edge”) and low mood (e.g. “Feeling down, depressed, or hopeless”), taken from the 4-item Patient Health Questionnaire (PHQ-4; Löwe et al., 2010).
3	Designed for use by nonclinical populations	No diagnostic labels were used, and mood feedback was able to accommodate a wide range of positive and negative states.
5	Reporting of thoughts, feelings, or behaviors	Daily mood surveys allowed users to make these reports.
7	Mental health information	Links to mental health websites and other resources were presented as part of each day’s mood feedback. Users were encouraged to tap on these links if they wished to learn more.
8	Real-time engagement	Daily mood surveys were designed to be completed in real-time, as a user carries out their daily routine.
12	Log of past app use	Presented in the Mood History.
13	Reminders to engage	Push notifications reminded users to complete their daily mood survey, and were made at a random time within a window set by the user.
14	Simple and intuitive interface and interactions	Care was taken to make all screens and interfaces clear and intuitive. For example, all questions were presented one-per-screen to avoid clutter and confusion.
15	Links to crisis support services	Links to Lifeline and other supports were available in the mood diary entries and throughout the app.
16	Experimental trials	See chapters 4 and 7.

Once a stable prototype of MoodPrism had been developed, the app was tested by a small group of participants who provided quantitative and qualitative feedback data to inform small changes and improvements. These data, along with a more detailed account of the development process, is reported in Rickard, Arjmand, Bakker, and Seabrook (2016). This paper is included in Appendix B. MoodPrism was released on the Australian iTunes and Google Play app stores in September 2015 and was promoted through a variety of channels to encourage downloads and use.

CHAPTER 4: ENGAGEMENT IN MOBILE PHONE APP FOR SELF-MONITORING OF EMOTIONAL WELLBEING PREDICTS CHANGES IN MENTAL HEALTH: MOODPRISM

Explanatory Note

The following chapter presents an original research article that first appeared online in the Journal of Affective Disorders in November 2017 and was included in the February 2018 edition of the journal. This paper reports empirical findings from data collected by the mood-tracking MHapp detailed in the previous chapter, MoodPrism. Analysis of data from 234 participants revealed relationships between app engagement and mental health benefits. Mediation analyses were also used to investigate the roles of ESA, MHL, and CSE as potential mechanisms underlying mental health effects. ESA was found to play a significant role, supporting the hypothesis of how reflection-focussed apps, like MoodPrism, can be beneficial.

This paper used an adjusted form of the ESA scale (ESAS; developed by Kauer et al., 2012), referred to as the ESAS-Revised (ESAS-R). This is included in Appendix C at the end of this thesis. The novel MHL measure, referred to as the MHL Questionnaire (MHLQ), is also included in Appendix D of this thesis.

Journal of Affective Disorders 227 (2017) 432–442

Contents lists available at ScienceDirect

Journal of Affective Disorders

journal homepage: www.elsevier.com/locate/jad

Research paper

Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism

David Bakker[a,*], Nikki Rickard[a,b]

[a] Monash Institute of Cognitive and Clinical Neurosciences and School of Psychological Sciences, Monash University, Australia
[b] Centre for Positive Psychology, University of Melbourne, Australia

ARTICLE INFO

Keywords:
Computer/Internet Technology
Anxiety
Depression
Mobile
Self-monitoring
Emotional self-awareness

ABSTRACT

Background: Mobile apps are being used increasingly for mental health purposes, but evidence of their efficacy remains limited. The mechanisms underlying any effects of such apps are also unclear. This study examined the effectiveness of a self-monitoring mobile phone app by investigating the relationships between app engagement and mental health outcomes.
Method: Participants downloaded the MoodPrism app from the iOS and Android app stores, completing in-app assessments at start of use and again 30 days later. The app prompted participants daily to complete a short mood questionnaire and formulated their responses into a mood diary. Data from 234 assessment completers (73% female; M age = 34.8 years) were analysed via hierarchical and mediation regressions.
Results: In this community sample, app engagement ratings predicted decreases in depression and anxiety, and increases in mental well-being. These effects were mediated by increases in emotional self-awareness, but only for participants who were clinically depressed or anxious at the time of the baseline assessment. Mental health literacy and coping self-efficacy did not play mediating roles.
Limitations: Findings suggest that other influential mediators may have not been measured, and future studies could verify the findings by using alternative methodologies, such as comparison with a control group.
Conclusions: Engaging with an emotional wellbeing self-monitoring app may reduce depressive and anxious symptoms, and increase mental well-being. Increases in emotional self-awareness may mediate these changes in clinical populations, and further research is needed to reveal other mechanisms that mental health apps can utilize.

1. Introduction

Depression is the leading cause of disease burden worldwide (World Health Organization, 2017). While many effective treatments have been developed, the proportion of people accessing them is disappointingly low. In Australia, where there is high mental health awareness and access to treatments compared to other parts of the world, 65% of people who experience a mental health issue do not access support (ABS, 2007). Simultaneously, smartphone ownership is extremely high, with almost 80% of Australians owning one (Deloitte, 2016) and over 2 billion owners worldwide (Statista, 2017). Smartphone apps hold immense promise as cost-effective, engaging tools for improving mental health and wellbeing (Bakker et al., 2016; Vogl et al., 2016), and can be useful support tools for depression (Callan et al., 2017), anxiety (Sucala et al., 2017), and other mental health issues (Van Ameringen et al., 2017).

A growing literature has examined the efficacy of specific smartphone apps designed to improve mental health (e.g. Kauer et al., 2012; Carpenter et al., 2016; Birney et al., 2016; Schwartz et al., 2016). However, there is a need to further investigate the mechanisms by which mental health apps (MHapps) exert their effects (Donker et al., 2013; Dubad et al., 2017; Grist et al., 2017; Huguet et al., 2016; Van Singer et al., 2015). Revealing the mechanisms underlying positive outcomes of MHapp use could help designers improve the app interventions on offer, and confer lessons to non-app-based mental health and wellbeing interventions.

Many MHapps include self-monitoring exercises, which are often based on those used in cognitive behavioural therapy (CBT; Cohen et al., 2013; Kazantzis et al., 2005). Self-monitoring can be used to restructure maladaptive anxiety responses (Başoğlu et al., 1992; Huppert et al., 2006), to challenge perpetuating factors of depression (Jarrett and Nelson, 1987), and to sufficiently treat a small but significant proportion of post-traumatic stress disorder sufferers (Ehlers et al., 2003; Tarrier et al., 1999). The novel experience sampling

* Corresponding author.
akker).

https://doi.org/10.1016/j.jad.2017.11.016
Received 11 August 2017; Received in revised form 27 September 2017; Accepted 6 November 2017
Available online 09 November 2017
0165-0327/

methods used by these MHapps can also enhance research into emotional disorders (Schwartz et al., 2016), as well as outcomes of clinical practice when used collaboratively with a mental health professional (van Os et al., 2017).

Self-monitoring is thought to improve mental health and wellbeing by increasing emotional self-awareness (ESA) (Kauer et al., 2012; O'Toole et al., 2014). ESA is an individual's ability to identify their own emotions, which can improve emotional self-regulation (Barrett et al., 2001; Hill and Updegraff, 2012). Low ESA is a common factor in both anxiety and depressive disorders (Suveg et al., 2009).

Several papers have detailed the development and evaluation of MHapp interventions that target ESA. Morris et al. (2010)'s app prompted users to record their moods several times a day. Although no psychometric measure of ESA was used, the small group of five users reported perceived increases in ESA in post-use interviews. Kauer et al. (2012) developed an app for self-monitoring of current activity, stress, mood, alcohol use, cannabis use, sleep, diet, and exercise. A randomised controlled trial (RCT) was conducted with a sample of mild to moderately depressed 14–24 year olds who were referred by their general practitioner (GP). It was found that participants using the experimental version of the app experienced greater increases in ESA and greater reductions in depressive symptoms compared to those using the control app. However, this RCT has limited ecological validity because participants were given a mobile device with the app installed, rather than downloading it to their own phones, and participants reviewed their recorded self-monitoring data at several time points with their GP. The majority of publicly available MHapps will be used on a personally owned device without GP involvement. Therefore, more research is needed to investigate self-monitoring MHapps in naturalistic self-guided applications.

In addition to ESA, it has been theorised that MHapps can exert effects on mental health and wellbeing via mental health literacy (MHL) and coping self-efficacy (CSE) (Bakker et al., 2016). MHL is the "knowledge and beliefs about mental disorders which aid their recognition, management or prevention" (p. 182, Jorm et al., 1997). MHL can be improved by giving access to mental health information and psychoeducation, which is an effective internet-based intervention in itself (Donker et al., 2009). CSE is a type of self-efficacy (Bandura, 1993) that gives individuals confidence in their own ability to cope with distress and adversity (Chesney et al., 2006), and use active coping strategies (Thorne et al., 2013). MHapps that actively focus on recommending wellbeing activities or coping strategies to users are most likely to enhance CSE (Bakker et al., 2016). While self-monitoring MHapps have been shown to increase ESA, MHapps with different intervention designs may have different effects. For example, a psychoeducation MHapp may work primarily through increasing MHL, or a coping skills MHapp may work primarily through increasing CSE. Any study of the mechanisms underlying MHapps should aim to investigate ESA, MHL, and CSE, and their mediating effects on mental health and wellbeing outcomes.

Previous research has lacked investigation into the impact of clinical status on MHapp use outcomes (Dubad et al., 2017). Studies that have used nonclinical samples, with a normal distribution of mental health status, have generally found small to no effects of MHapp use (Bidargaddi et al., 2017; Howells et al., 2014; Whittaker et al., 2017), whereas studies that used clinical samples, with participants who were experiencing a diagnosable disorder, have found much stronger effects (Kauer et al., 2012; Lauritsen et al., 2017). Baseline clinical status is therefore an important factor to take into account when examining MHapp engagement as certain benefits may be limited to people experiencing depression or anxiety (Dubad et al., 2017).

A challenge in evaluating MHapps outside of clinical trials is using a methodology that allows for meaningful measurement of the app's effect. As Torous and Firth (2016, p.100) note, there is a risk of a "digital placebo effect" with MHapps, as the simple act of installing a MHapp may bias users' responses towards favourable mental health outcomes. Carpenter et al. (2016) suggest that measuring app usage variables, such as frequency of access, can bring control to studies, and a positive relationship between app usage and mental health and wellbeing improvements indicates the effectiveness of an intervention. However, boredom, procrastination, anxiousness, desire for distraction, or high rate of general phone use may underlie a user's frequent app access. Instead, app engagement, rather than raw usage, may be a more useful measure of the app's true influence. If a positive relationship is found between therapeutic outcomes and app engagement, the MHapp has true mental health and wellbeing effects beyond placebo effects. This is comparable to the positive relationship between client engagement and treatment outcomes in psychotherapy (Holdsworth et al., 2014) or between the therapeutic relationship and treatment outcomes (Kazantzis et al., 2015; Sucala et al., 2012). Therapeutic engagement is measured by self-report surveys, such as the Client Evaluation of Self and Treatment (CEST; Joe et al., 2002). In much the same way, app engagement can be measured by questionnaire (Stoyanov et al., 2016) and correlated with mental health and wellbeing outcomes to uncover intervention effects.

Self-monitoring MHapps may be effective at improving mental health outcomes, but more controlled trials are required to confirm these effects (Versluis et al., 2016), particularly in community samples. The aim of the current study was to evaluate the effectiveness of a self-monitoring MHapp, MoodPrism' (see Rickard et al., 2016), and its underlying mechanisms. In addition to the self-monitoring features that are designed to increase ESA, MoodPrism also contains smaller sub-features that may increase MHL, such as the links to mental health websites provided in mood entries. However, this app does not contain behavioural interventions or coping strategies, so it was not designed specifically with CSE increases in mind. Considering these points and the dominant self-monitoring features of MoodPrism, an additional aim of this study was to investigate whether ESA mediated the MHapp's mental health and wellbeing effects. The mediation roles of MHL and CSE were also explored as alternative mediation pathways to ESA.

It was hypothesised that after using MoodPrism for 30 days, participant app engagement would be associated with a decrease in depression and anxiety symptomatology, and an increase in mental wellbeing. Furthermore, these predicted relationships were hypothesised to be mediated by an increase in ESA that users experienced while using MoodPrism over 30 days, rather than increases in MHL or CSE. It was hypothesised that participants who scored in the clinical range on the baseline depression and anxiety measures would experience stronger mediated effects.

2. Method

2.1. Participants

The sample was drawn from data from 1349 MoodPrism users who had completed the app's onboarding surveys, administered at the start of use, between April 2016 and May 2017. Of those, 234 had also completed at least one of the follow-up surveys, so data from these 234 participants were used in the current analysis. Age data were not recorded for 36 participants due to a technical error with the app. For the remaining 198 participants, age ranged from 13 to 69 (M = 34.8, SD = 14.2), with 52 males, 144 females, and 2 participants who selected other for gender. The majority of this sample lived in suburban Australia, and the majority had completed tertiary education (65%).

2.2. Materials

MoodPrism is an iOS and Android app, freely available on the Australian app stores, designed to: a) help users track their moods over time; and b) collect data from users regarding their emotional states over time in natural everyday contexts (Rickard et al., 2016). After completing a set of surveys to obtain baseline measurements, users are prompted at a random time throughout their day to complete a daily mood survey, which asks them 12 questions about how they are feeling, where they are, and what they have been doing. This information is formatted in a mood diary, which users can review to obtain feedback about how they have been feeling over time and in what contexts. After 30 days users are prompted to complete a second set of follow-up surveys, enabling collection of data to evaluate the effectiveness of the app. The surveys involved with this study are listed below:

2.2.1. Patient Health Questionnaire 9–Item (PHQ-9)

The PHQ-9 (Kroenke et al., 2001) is a nine item measure of depressive symptomatology requiring responders to identify the frequency that they experienced certain depressive symptoms over the past 2 weeks on a 5 point scale from Not At All (0) to Nearly Every Day (4). Example items include “little interest or pleasure in doing things” and “poor appetite or overeating”. The PHQ-9 has high internal reliability, Cronbach's $\alpha = .89$, and scores over 10 have good sensitivity (88%) and specificity (88%) for diagnosis of major depression by interview (Kroenke et al., 2001).

2.2.2. Generalised Anxiety Disorder Scale 7-Item (GAD-7)

The GAD-7 (Spitzer et al., 2006) is a seven item scale developed as a brief measure for generalised anxiety symptoms and clinically assessing Generalised Anxiety Disorder (GAD). It uses the same response scale as the PHQ-9, Not At All (0) to Nearly Every Day (4) over the past 2 weeks. Example items include “not being able to stop or control worrying” and “feeling afraid as if something awful might happen”. The GAD-7 has high internal reliability, Cronbach's $\alpha = .92$, and scores over 10 have good sensitivity (89%) and specificity (82%) for diagnosis of GAD by interview (Spitzer et al., 2006).

2.2.3. Warwick-Edinburgh Mental Well-being Scale (WEMWBS)

The WEMWBS (Stewart-Brown and Janmohamed, 2008) is a fourteen item scale developed to measure the mental wellbeing of UK adults. It requires respondents to report the frequency of positive psychological experiences over the past 2 weeks on a five point scale from None Of The Time (1) to All Of The Time (5). Example items include “I've been feeling useful” and “I've been feeling cheerful”. The WEMWBS has high internal reliability, Cronbach's $\alpha = .91$, and shares high correlations with measures of life satisfaction and other measures of wellbeing (Tennant et al., 2007).

2.2.4. Emotional Self-Awareness Scale – Revised (ESAS-R)

Kauer et al.’s (2012) 33 item ESA Scale (ESAS) was revised to 30 items to remove duplication of concepts, and the five point response scale was changed from Never to A lot, to Strongly Disagree (0) to Strongly Agree (4). Items for each of the five subscales of the ESAS, including Recognition (e.g. “I frequently take time to reflect on how I feel”), Identification (e.g. “It's important to me to understand what my feelings mean”), Communication (e.g. “Expressing emotion is easy”), Contextualisation (e.g. “I usually know why I feel the way I do”), and Decision-Making (e.g. “I examined my feelings and then decided what to do”) were included in the ESAS-R. Responses from 1327 MoodPrism users revealed that the reliability of this revised scale was very high, Cronbach's $\alpha = .90$, and higher than that of the original scale reported by Kauer et al. (2012; Cronbach's $\alpha = .83$)).

2.2.5. Mental Health Literacy Questionnaire (MHLQ)

As no standardised measure of MHL exists, a questionnaire was developed using elements from measures used in the literature. The final MHLQ incorporated two short vignettes, one depicting a male with social phobia and the other depicting a female with depression, from an Australian government report (Reavley and Jorm, 2011). Respondents rated eight different supports (e.g. Visiting a chemist, Vitamins and minerals or herbal tonics, Contacting a psychologist) from Most Harmful to Most Helpful and selected what they thought the problem was for the person in the vignette. In addition to these vignettes, seven multiple choice questions were included (e.g. What is the most common mental condition in Australia? Is anger a normal human emotion?). A copy of the survey was distributed to 32 mental health clinicians, including eight clinical psychologists, who were treated as a sample with high mental health literacy. Responses were reviewed by the experimenters to determine appropriate scoring for the items.

2.2.6. Coping Self-Efficacy Scale (CSES)

The CSES (Chesney et al., 2006) is a well validated measure that requires respondents to rate 26 their confidence of in their ability to do certain actions (e.g. Talk positively to yourself, Keep from feeling sad) on an 11 point scale from Cannot Do At All to Certain Can Do. The CSES has high internal reliability, Cronbach's $\alpha = .95$, and good validity is indicated by significant relationships with psychological distress and wellbeing measures (Chesney et al., 2006).

2.2.7. App Engagement Scale

A feedback questionnaire, based on items and themes from the Mobile Application Rating Scale (MARS; Stoyanov et al., 2016), was developed for users to complete in the final assessment (Rickard et al., 2016). The 7 items most strongly related to app engagement were extracted and scores summed to create the measure of app engagement (see Appendix A). This App Engagement Scale had good internal reliability, Cronbach's $\alpha = .839$, which could not be improved by removing any more items.

2.2.8. Social Desirability Scale (SDS)

The Marlowe-Crowne SDS Short Form C (Reynolds, 1982) was administered to users as a measure of truthful and considerate responding. High scores on this measure suggest dishonest or rushed responding, as the items require careful attention when reading. This particular SDS has acceptable reliability, $r_{KR\text{-}20} = .76$, and very good concurrent validity with the longer Marlowe-Crowne SDS, $r = .93$.

2.3. Procedure

As detailed in Rickard et al. (2016), MoodPrism was developed and released on the Australian iTunes and Google Play app stores. The app was promoted via a multitude of means, including posts on Facebook and Twitter, advertising on Facebook, and events at Victorian schools and universities.

Participants downloaded the app, provided informed consent as part of the app's onboarding, and completed the baseline assessment. Although the full results and scores of the assessment were not made available to participants, they did receive select feedback messages based on their responses. For example, “Your score on our measure of positive mental health was in the lower range of positive heath scores (lower than 75% of people)”. Upon completion of the baseline assessment, MoodPrism's mood tracking features were unlocked. Participants were prompted via push notifications at a random time throughout their days to complete subsequent daily mood reports. After 30 days of use, MoodPrism prompted users to complete the final assessment.

2.4. Design and analyses

Participants who scored over 8 on the SDS were excluded from analysis, as this indicated non-serious or dishonest responding. Some limited data were missing for some participants due to technical errors. Missing data were not replaced, and analyses were conducted excluding participants with missing data in a listwise fashion. Each analysis therefore lists the degrees of freedom or number of participants included. However, the missing age data for 36 participants were replaced with the mean age to avoid loss of otherwise valid data that controlled for this potentially confounding variable. In preparation for the main analyses, potential confounding influences of Age and Gender on the outcome variables of depression, anxiety and mental wellbeing (final scores) were investigated via a series of partial correlations, with baseline depression, anxiety and mental wellbeing scores partialled out. A power analysis using G*Power 3 software and based on the indirect effect sizes reported by Kauer et al. (2012) revealed that 45 participants would be required to detect effects at ?? = .05.

Total (unmediated) effects between app engagement and outcome measures were investigated using three hierarchical regressions, with final depression, anxiety or mental wellbeing scores as the outcome variable respectively. Potential confounds identified from preparatory analyses as well as baseline depression, anxiety or mental wellbeing scores were entered in the first step, and app engagement in the second step.

The PROCESS plug-in for SPSS (Hayes, 2013) was used to conduct all mediated regression analyses, using procedures detailed in Field (2009) and Hayes and Rockwood (2016). This is the most contemporary approach to mediation, taking advantage of the bootstrap test. Based on the calculation of 95% confidence intervals, the bootstrap test has superior power to other methods, such as Sobel test or Barron and Kenny (1986)'s method. Bootstrapping using 5000 samples was performed for each analysis.

To quantify change over time between the baseline and final assessments for each mediator or outcome variable, each analysis used baseline scores as covariates and final scores as mediator or outcome variables. This is in accordance with recommendations from Hayes and Rockwood (2016) who advise against other techniques, such as the use of difference scores, to avoid "self-selection", regression to the mean, and other biases from influencing the analyses. It is of note however, that when baseline and final scores are highly correlated (as likely with the outcome variables in this study over a one month period; refer to Appendix B for correlations over time in this sample), this approach is likely to yield the same output as using difference scores (Vickers and Altman, 2001). For ease of interpretation throughout, the analyses refer to 'Depression', 'Anxiety', 'Mental Wellbeing', 'ESA', 'CSE', and 'MHL' scores, but in each case take baseline scores into account and therefore operationalize change over the 30 day app use period.

Three mediated regression models were used, each to investigate the relationship between App Engagement and each of the three outcome variables, which included Depression (PHQ-9), Anxiety (GAD-7), and Mental Wellbeing (WEMWBS). The three mediating variables used in each model were ESA measured by the ESAS-R, MHL measured by the MHLQ, and CSE measured by the CSES. As per Zhao et al. (2010)'s and Darlington and Hayes' (2016) recommendations, a significant total effect prior to addition of mediators was not a prerequisite for investigation of mediation effects. This allows the investigation of mediators, even if opposing or omitted mediators are cancelling out or masking unmediated effects (Darlington and Hayes, 2016). All Beta (β) statistics reported in the regressions are standardised effect sizes.

To establish clinical and nonclinical groups, literature on the use of the PHQ-9 and GAD-7 was investigated to find appropriate cut-off scores for acceptance into the clinical group. The creators of the PHQ-9 have warned against using a single, rigid cut-off score for determining the presence of a depressive disorder (Kroenke et al., 2010). This is partly because the measure is primarily a screening tool, so commonly used cut-offs of 10 are usually followed up with more in-depth clinical assessment. A meta-analysis of PHQ-9 validation studies recommended raising the PHQ-9 cut-off score to 15 to achieve specificity of 96% (Manea et al., 2012) when using the measure as a tool to determine clinical status. Similarly, there is debate over the most appropriate cut-off score for the GAD-7, especially in its use to detect any anxiety disorder and not just GAD (Plummer et al., 2016). Donker et al. (2011) report data from an online administration of the GAD-7 suggesting that a cut-off score of 15 gives 80% specificity for GAD and 78% specificity for any anxiety disorder. To maximise specificity and increase confidence of classification, the 'clinical group' was operationalized as a score of at least 15 on either the PHQ-9 or GAD-7. To account for those participants experiencing comorbid anxiety and depression, participants who scored over 10 on both the PHQ-9 and the GAD-7 were also included in the clinical group.

3. Results

The data were cleaned and inspected to ensure that assumptions for linear regression were met. Outlying cases ± 3SDs from the mean were excluded from each analysis. Durbin-Watson statistics were inspected for all regression models and were found to be above specified limits, suggesting the independence of errors in the models (Durbin and Watson, 1951). No multicollinearity was detected, with all variance inflation factors (VIFs) between 1.0 and 1.1, and tolerance statistics > .9 (Field, 2013). Histograms and plots of each outcome variable's residuals were generated to ensure that the assumptions of homoscedasticity and normally distributed errors were met. Correlations between scores on all baseline measures were inspected to ensure adequate independence for inclusion (see Appendix B).

3.1. Descriptive results

Means, standard deviations (SD), 95% confidence intervals (CI), and baseline-final comparison *t*-test results for the whole sample and the Clinical and Nonclinical subsamples are displayed in Table 1. App Engagement ratings for the Clinical and Nonclinical subsamples were not significantly different, $t(160) = .007$, $p = .994$. Comparison of baseline scores were made between participants who completed the final assessments and those who did not. All comparisons were non-significant ($p > .05$), except MHL scores of completers ($M = 16.59$, $SD = 2.59$) were significantly greater than those of non-completers ($M = 16.05$, $SD = 2.18$) $t(335) = 2.88$, $p = .004$.

3.2. Potential confounds

Age and gender were considered as potentially confounding variables for each of the regression analyses. Partial correlations (with baseline Depression, Anxiety or Mental Wellbeing scores partialled out respectively) revealed that Age yielded significant relationships with Depression (PHQ-9), r (154) = −.315, $p < .001$, Anxiety (GAD-7), r (154) = −.260, $p < .001$, and Mental Wellbeing (WEMWBS), r (157) = .219, $p = .006$. No significant partial correlations were observed for Gender and Depression (PHQ-9), r_{pb} (182) = .044, $p = .550$, Anxiety (GAD-7), r_{pb} (182) = .093, $p = .208$, and Mental Wellbeing (WEMWBS), r_{pb} (185) = −.024, $p = .748$. Based on these results, Age was controlled in the first step of each regression analysis.

3.3. Total (unmediated) effects

Hierarchical regressions (controlling for the age confound, and baseline scores) on the whole sample demonstrated that App Engagement significantly predicted a reduction in Depression scores, ΔF (1153) = 7.38, $p = .007$, $\Delta R^2 = .018$, and Anxiety scores, ΔF (1153) = 6.55, $p = .011$, $\Delta R^2 = .020$. App engagement also significantly predicted an increase in Mental Wellbeing scores, ΔF (1153) = 14.40, $p < .001$, $\Delta R^2 = .037$.

When split into Clinical and Nonclinical samples, App Engagement prediction of Depression scores approached significant in both samples (Clinical: ΔF (1,62) = 3.50, 95% CI [−.533, .018], $p = .066$, $\Delta R^2 = .028$; Nonclinical: ΔF (1,87) = 3.30, 95% CI [.−.352, .015], $p = .071$, $\Delta R^2 = .024$). App Engagement continued to significantly predict Anxiety scores in the Clinical sample, ΔF (1,62) = 6.13, 95% CI [−.629, −.067], $p = .016$, $\Delta R^2 = .078$. but not in the Nonclinical

Table 1
Descriptive statistics for each analysis group and results from paired samples *t*-tests comparing baseline and final scores.

	Nonclinical			Clinical			Whole sample		
	Mean (SD)	95% CI	*t*	Mean (SD)	95% CI	*t*	Mean (SD)	95% CI	*t*
PHQ-9									
Baseline	6.86 (3.43)	[6.15, 7.55]	1.28	17.01 (5.10)	[15.86, 18.19]	3.61**	11.31 (6.59)	[10.28, 12.29]	1.58
Final	7.37 (4.72)	[6.41, 8.36]		15.62 (6.58)	[14.14, 17.16]		10.99 (6.94)	[9.89, 12.03]	
GAD-7									
Baseline	4.97 (2.90)	[2.41, 3.28]	1.29	14.83 (3.71)	[14.00, 15.66]	4.15**	9.29 (5.90)	[8.37, 10.20]	2.17*
Final	5.44 (3.98)	[4.60, 6.24]		13.01 (5.20)	[11.82, 14.16]		8.76 (5.90)	[7.87, 9.72]	
WEMWBS									
Baseline	45.70 (6.68)	[44.28, 47,00]	.75	33.04 (7.52)	[31.26, 34.78]	3.41**	40.15 (9.45)	[38.66, 41.61]	2.77**
Final	46.19 (8.57)	[44.46, 47.96]		35.32 (9.86)	[33.21, 37.58]		41.43 (10.61)	[39.74, 43.13]	
ESAS									
Baseline	58.69 (11.24)	[56.39, 60.85]	.86	49.20 (11.86)	[46.75, 52.06]	.067	54.53 (12.41)	[52.57, 56.54]	.68
Final	58.47 (13.32)	[55.88, 61.17]		49.03 (12.34)	[46.32, 52.01]		54.33 (13.69)	[52.19, 56.41]	
CSES									
Baseline	157.46 (30.30)	[151.44, 163.69]	1.25	140.44 (33.70)	[131.79, 147.97]	1.09	149.97 (32.85)	[145.06, 154.73]	.16
Final	162.02 (37.17)	[155.24, 170.02]		136.41 (37.26)	[126.66, 145.42]		150.75 (39.22)	[144.62, 157.56]	
MHLQ									
Baseline	16.77 (1.91)	[16.35, 17.23]	.12	16.78 (2.04)	[16.16, 17.36]	2.18*	16.78 (1.95)	[16.44, 17.12]	1.57
Final	16.77 (2.11)	[16.31, 17.25]		16.22 (2.45)	[15.54, 16.93]		16.56 (2.26)	[16.15, 16.96]	
App engagement									
Final	26.97 (4.34)	[26.03, 27.83]		27.12 (4.15)	[26.11, 28.09]		27.03 (4.25)	[26.37, 27.68]	

* p = .05.
** p = .01.

sample, ΔF (1,87) = 1.00, 95% CI [−.246, .081], p = .320, ΔR^2 = .008. Finally, App Engagement continued to predict Mental Wellbeing scores in both Clinical, ΔF (1,62) = 8.98, 95% CI [.188, .943], p = .004, ΔR^2 = .058, and Nonclinical, $\Delta F(1,87)$ = 6.03, 95% CI [.078, .739], p = .016, ΔR^2 = .042, samples.

3.4. Mediation analyses

Mediation analyses were first performed for the whole sample (n = 114). Despite significant total effects between App engagement and outcome variables, there were no significant indirect effects through any of the three mediators (ESA, CSE or MHL) included for Depression (Fig. 1A), Anxiety (Fig. 1B) or Mental Wellbeing (Fig. 1C) scores.

Mediated regressions were then pursued independently for the Clinical (n = 43) and Nonclinical (n = 71) subsamples, despite the absence of significant total effects (as per Zhao et al., 2010). In the Nonclinical subsample, no significant total, direct, or indirect effects were observed for depression (Fig. 2A) or anxiety (Fig. 2B), despite significant relationships in the regression for anxiety between App Engagement and CSE, and between ESA and Anxiety. A significant, positive direct effect of App Engagement on Mental Wellbeing (Fig. 2C) was observed, β = .238, 95% CI [.043, .433], p = .017. However, there were no significant indirect effects, suggesting direct-only nonmediation.

In the Clinical subsample, a significant mediation effect of ESA was observed between App Engagement and Depression (Fig. 3A), with a standardized indirect effect of β = −.137, 95% CI [−.418, −.009], Anxiety (Fig. 3B); β = −.211, 95% CI [−.490, −.042], and Mental Wellbeing (Fig. 3C); β = .163, 95% CI [.018, .396]. The lack of a direct effects between App Engagement and each outcome variable suggest that ESA was involved in indirect-only mediation in each case (Zhao et al., 2010). A summary of the presence of direct and indirect effects from all regressions is presented in Table 2.

4. Discussion

The aim in this study was to assess whether engaging with the self-monitoring MHapp, MoodPrism, predicted improvements in mental health (depression and anxiety) and wellbeing. The primary finding was that app engagement ratings on the app predicted changes in depression, anxiety, and mental wellbeing ratings in a community sample. This indicates that, in general, participants who had more positive and engaging experiences using MoodPrism experienced greater decreases in depression, greater decreases in anxiety, and greater increases in mental wellbeing than those who did not rate their engagement as highly. Secondly, each of these effects were mediated by increases in ESA for participants who were depressed or anxious at the time of the baseline assessment. No such mediation was observed in participants who were not depressed or anxious at the time of the baseline assessment. In contrast, changes in MHL and CSE did not help explain the relationship between engagement with this MHapp and mental health and wellbeing outcomes.

It was found that participants who used MoodPrism for 30 days and completed the final assessments had initially higher MHL than those who started using the app and did not complete the final assessments. This suggests that individuals who already had some insight into mental health issues were more likely to use a MHapp like MoodPrism over an extended period of time. Therefore, additional efforts may be required to promote regular use of MHapps like MoodPrism to the less mental health literate, or mental health literacy interventions could be pursued before recommendation of a MHapp.

Bakker et al. (2016) suggest MHapps are commonly one of three broad types; reflection-focussed, education-focussed, and goal-focussed. Reflection-focussed MHapps are designed to improve ESA by using self-monitoring features, education-focussed MHapps are designed to improve MHL by supplying users with mental health information, and goal-focussed MHapps are designed to improve CSE by recommending activities and active coping skills. MoodPrism's self-monitoring features would classify it as a reflection-focussed app, which clarifies why the hypothesised effects involving ESA were observed. This is in contrast to apps such as Mental Health First Aid (2016) or MoodMission (2017) which are more explicitly designed to be education focussed or goal focussed, respectively.

Kauer et al. (2012) found that increases in ESA mediated an observed reduction in depression levels in a sample of participants referred for mental health issues. The current study used a general

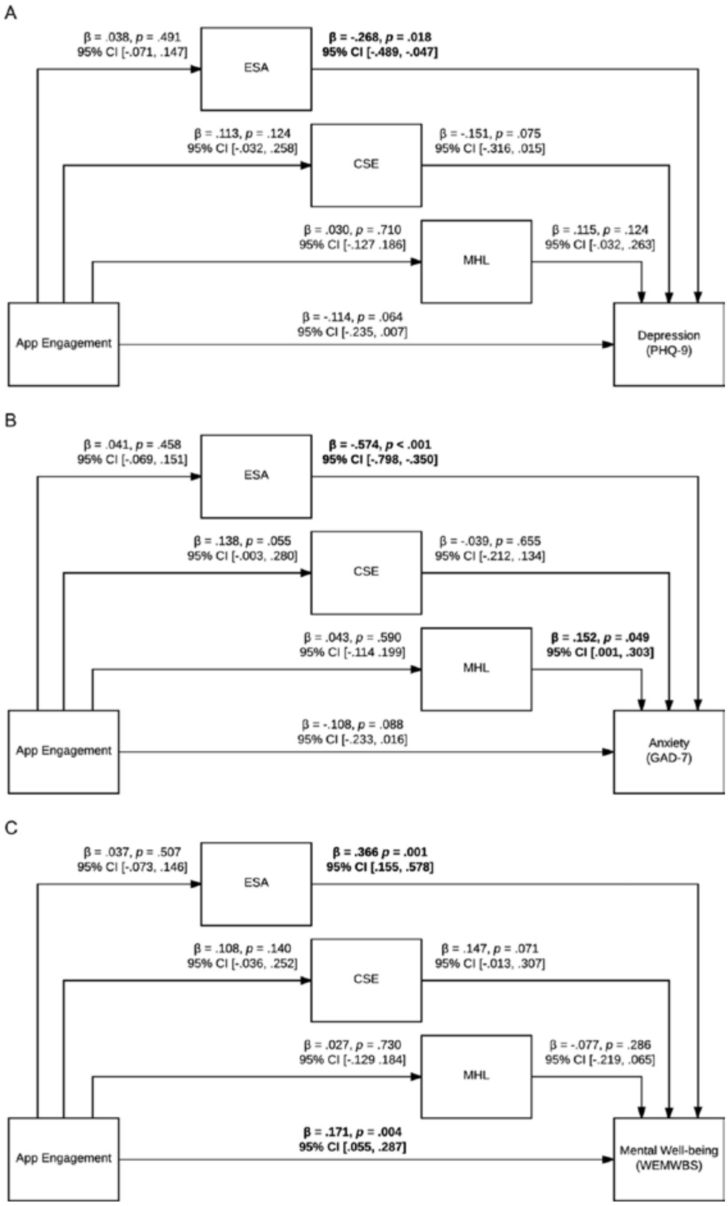


Fig. 1. Whole sample (n = 114) mediated regression model using App Engagement ratings as the predictor and (A) Depression (PHQ-9), (B) Anxiety (GAD-7), and (C) Mental Wellbeing (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p > .05$.

community sample, consisting of participants who scored both under and within the clinical range for depression and anxiety. ESA was a mediator for the mental health and wellbeing improvements experienced by participants who had high baseline levels of depression and anxiety, but did not play a mediation role for other participants. When the samples were combined, mediation effects of ESA were not visible. A possible explanation is that low ESA is a common factor in both anxiety and depression (Suveg et al., 2009). Self-reflection and insight, both elements of ESA, are positive predictors of positive affect and the use of cognitive reappraisal. They are conversely negative predictors of negative affect and the use of expressive suppression (Haga et al., 2009). Therefore, improving ESA in depressed or anxious participants may lead to mental health improvements of a greater magnitude than for nonclinical participants. Another explanation may be due to reduced motivation that nonclinical participants may have experienced to engage with the app as a mental health intervention. Although there were no significant differences between engagement ratings for the clinical and nonclinical subsamples, it is possible that clinical users

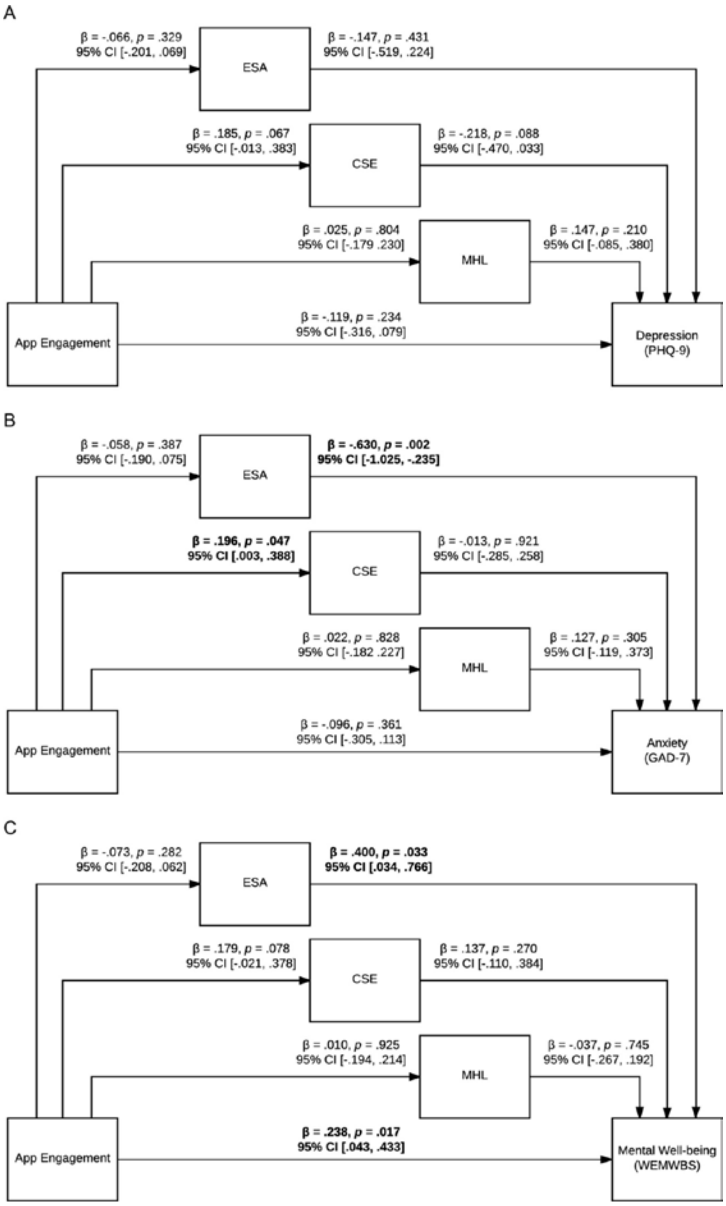


Fig. 2. Nonclinical subsample's (n = 71) mediated regression model using App Engagement ratings as the predictor and (A) Depression (PHQ-9), (B) Anxiety (GAD-7), and (C) Mental Wellbeing (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p > .05$.

were motivated to use the app therapeutically, whereas nonclinical users would have lacked this justification. Regardless of the reasons, the findings reinforce the need to account for participants' initial mental health status in future studies, as mediators may only be relevant for specific groups. Other mediators not included in this study may be involved for participants outside of the clinical range.

Although a direct effect of App Engagement on Depression was not found for the clinical sub-sample, an indirect effect mediated by ESA was found. There could be a number of explanations for this, including the effect of an unmeasured, opposing mediator cancelling out the direct effect (Darlington and Hayes, 2016). For example, an unknown variable that shares a positive relationship with depression, such as change in hopelessness, could be working in opposition to emotional self-awareness. Both mediators working together effectively nullify the overall direct effect (Zhao et al., 2010). Further research is needed to investigate other possible mediators which may have aggravation

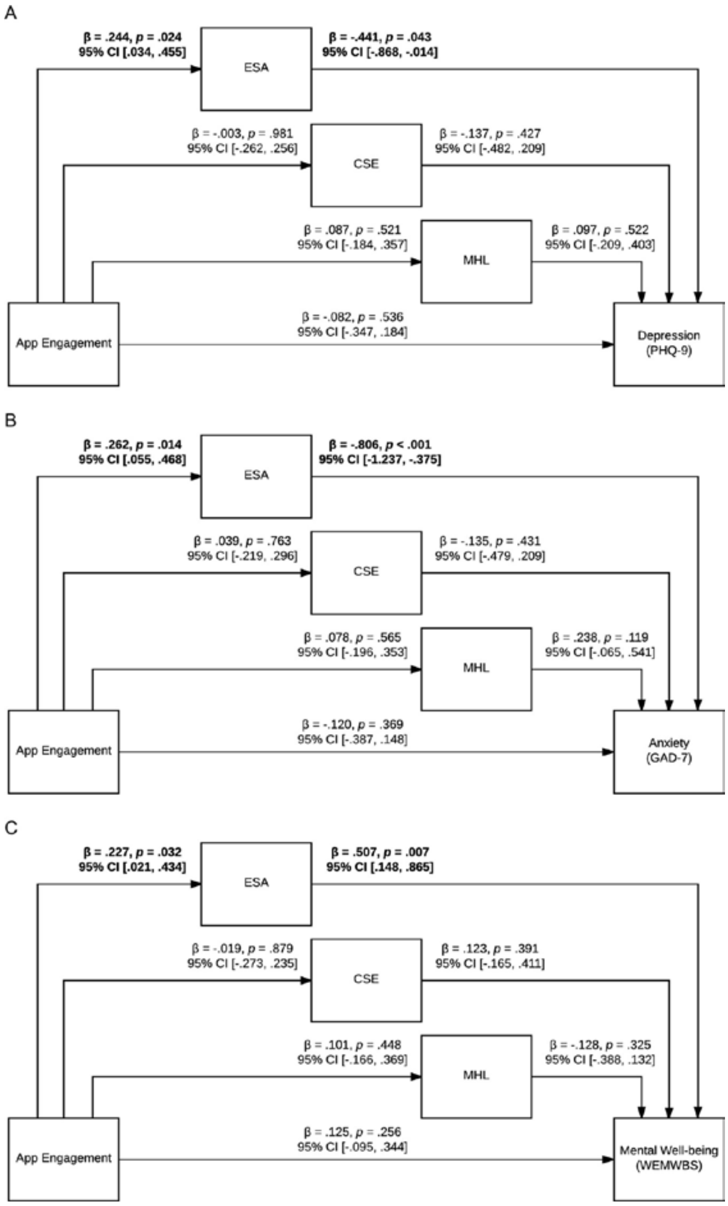


Fig. 3. Clinical subsample's (n = 43) mediated regression model using App Engagement ratings as the predictor and (A) Depression (PHQ-9), (B) Anxiety (GAD-7), and (C) Mental Wellbeing (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p > .05$.

effects on depression, as MHapps should be designed to reduce their impacts.

More research is needed to reveal why ESA did not mediate mental health and wellbeing improvements for nonclinical participants. It is possible that MoodPrism's intervention did not make a meaningful difference on nonclinical participants' ESA because they were either already satisfactorily emotionally self-aware, or they did not learn from the mood patterns reflected to them through the app. Furthermore, nonclinical participants were presumably less emotionally volatile or unstable, so changes in their mood would not be as easily detected and reflected by MoodPrism. In contrast, larger emotional swings that may be experienced by clinical participants, who are more likely to have lower emotion self-regulation (Webb et al., 2012), should be more visible to the measures and feedback displays used by MoodPrism. Regardless of the underlying explanation, the findings show that ESA plays an important role in the benefits experienced by clinically

Table 2
Presence of total, direct and indirect effects of app engagement on each outcome variable for each group.

Outcome variable	Total effect of App Engagement (Unmediated)	Indirect effect via mediator			Direct effect when mediators added
		ESA	CSE	MHL	
Whole sample					
Depression	✓	X	X	X	#
Anxiety	✓	X	X	X	#
Mental Wellbeing	✓	X	X	X	✓
Clinical sub-sample					
Depression	X	✓	X	X	X
Anxiety	✓	✓	X	X	X
Mental Wellbeing	✓	✓	X	X	X
Nonclinical sub-sample					
Depression	X	X	X	X	X
Anxiety	X	X	X	X	X
Mental Wellbeing	✓	X	X	X	✓

Note: X not significant, ✓ significant ($p < .05$), # approaching significance ($p < .10$).

depressed or anxious users of reflection-focussed MHapps.

While other studies have investigated the ESA mediated mental health and wellbeing improvements of reflection-focussed MHapps (Kauer et al., 2012; Morris et al., 2010), none have compared ESA to other mechanisms of change, including CSE and MHL, and none have studied a publicly available MHapp. It is important to assess publicly available interventions, as the participants using the MHapp are more representative of users who download MHapps naturalistically. While RCTs collect data on the raw efficacy of an intervention, public trials like the current study collect data on real-world effectiveness (Arean et al., 2016; Stoll et al., 2017). In the context of MHapps where the aim is to create attractive products that smartphone users can autonomously seek, download, and appreciate, it is exceptionally important to investigate effectiveness.

This study suggests that engagement with MoodPrism, a reflection-focussed MHapp, is related to improvements in mental health and wellbeing. A mechanism underlying this effect, observed particularly in depressed and anxious individuals, is the app's ability to improve ESA. This is an important finding considering to the paucity of research on the effectiveness of MHapps (Donker et al., 2013; Grist et al., 2017), and the clinical potential of reflection-focussed MHapps (van Os et al., 2017). However, more work is required to compare the efficacy of MoodPrism to other MHapps and control conditions, and, more broadly, to investigate the claims of the wide range of MHapps currently available.

Acknowledgements

The authors wish to acknowledge and thank the study participants and MoodPrism users in general for their time and efforts. Two Bulls were the technical developers for the MoodPrism app, and lab members Liz Seabrook and Abdullah Arjmand assisted with the design of the app.

Funding Disclosure

This project was partially funded by a grant from the beyondblue Foundation (TH: 6997).

Appendix A. Feedback Questionnaire and App Engagement Scale Items

Feedback Questionnaire		Included in App Engagement Scale	Cronbach's α if deleted from App Engagement Scale
1	I enjoyed using the app	✓	.795
2	The app was interesting	✓	.775
3	The app suited people of my age		
4	The app was interactive		
5	It was easy to use and understand	✓	.834
6	It drained my battery		
7	It was hard to navigate		
8	It had a nice design and feel		
9	It did what it said it would		
10	It had about the right amount of information	✓	.838
11	I felt I could trust the app		
12	Using it got in the way of my everyday activities		
13	The alerts every day were a hassle		
14	Using it motivated me	✓	.822
15	I would recommend it to people I know	✓	.773
16	Overall I was satisfied with this app	✓	.778

Appendix B. Correlations between variables calculated from the whole sample

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. App Engagement	r	1													
	p														
2. Baseline PHQ-9	r	.007	1												
	p	.942													
3. Final PHQ−9	r	−.133	.701**	1											
	p	.158	< .001												
4. Baseline GAD−7	r	.108	.713**	.511**	1										
	p	.253	< .001	< .001											
5. Final GAD−7	r	−.063	.548**	.746**	.673**	1									
	p	.508	< .001	< .001	< .001										
6. Baseline WEMWBS	r	.008	−.777**	−.662**	−.667**	−.560**	1								
	p	.933	< .001	< .001	< .001	< .001									
7. Final WEMWBS	r	.196*	−.562**	−.789**	−.458**	−.656**	.710**	1							
	p	.036	< .001	< .001	< .001	< .001	< .001								
8. Baseline ESAS-R	r	−.043	−.345**	−.366**	−.357**	−.277**	.510**	.465**	1						
	p	.651	< .001	< .001	< .001	.003	< .001	< .001							
9. Final ESAS-R	r	.006	−.329**	−.477**	−.366**	−.489**	.489**	.597**	.784**	1					
	p	.952	< .001	< .001	< .001	< .001	< .001	< .001	< .001						
10. Baseline MHLQ	r	−.093	−.07	−.038	−.045	−.027	.119	.113	.159	.163	1				
	p	.325	.461	.686	.636	.780	.206	.231	.091	.083					
11. Final MHLQ	r	−.024	−.063	.017	−.129	−.013	.129	.081	.090	.149	.577**	1			
	p	.796	.503	.861	.172	.892	.171	.394	.338	.113	< .001				
12. Baseline CSES	r	−.009	−.277**	−.291**	−.304**	−.220*	.464**	.404**	.330**	.405**	.074	.078	1		
	p	.928	.003	.002	.001	.019	< .001	< .001	< .001	< .001	.432	.409			
13. Final CSES	r	.097	−.349**	−.451**	−.436**	−.413**	.489**	.549**	.408**	.538**	.105	.134	.591**	1	
	p	.305	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	.267	.155	< .001		
14. Age	r	.002	−.228*	−.346**	−.200*	−.279**	.080	.210*	.072	.247**	.178	.080	.014	.093	1
	p	.984	.015	< .001	.033	.003	.396	.025	.450	.008	.059	.398	.886	.327	

* p < .05, ** p < .01.

References

ABS, 2007. National Survey of Mental Health and Wellbeing: Summary of Results. Australian Bureau of Statistics, Canberra.

Arean, P.A., Hallgren, K.A., Jordan, J.T., Gazzaley, A., Atkins, D.C., Heagerty, P.J., Anguera, J.A., 2016. The use and effectiveness of mobile apps for depression: results From a fully remote clinical trial. J. Med. Internet Res. 18 (12), e330. http://dx.doi.org/10.2196/jmir.6482.

Bakker, D., Kazantzis, N., Rickwood, D., Rickard, N., 2016. Mental health smartphone apps: review and evidence-based recommendations. JMIR Ment. Health 3, e7. http://dx.doi.org/10.2196/mental.4984.

Bandura, A., 1993. Perceived self-efficacy in cognitive development and functioning. Educ. Psychol. 28, 117–148. http://dx.doi.org/10.1207/s15326985ep2802_3.

Baron, R.M., Kenny, D.A., 1986. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Personal. Soc. Psychol. 51 (6), 1173–1182.

Barrett, L., Gross, J., Christensen, T., Benvenuto, M., 2001. Knowing what you're feeling and knowing what to do about it: mapping the relation between emotion differentiation and emotion regulation. Cogn. Emot. 15, 713–724. http://dx.doi.org/10.1080/02699930143000239.

Başoğlu, M., Marks, I.M., Sengün, S., 1992. A prospective study of panic and anxiety in agoraphobia with panic disorder. Br. J. Psychiatry 160, 57–64. http://dx.doi.org/10.1192/bjp.160.1.57.

Bidargaddi, N., Musiat, P., Winsall, M., Vogl, G., Blake, V., Quinn, S., Schrader, G., 2017. Efficacy of a web-based guided recommendation service for a curated list of readily available mental health and well-being mobile apps for young people: randomized controlled trial. J. Med. Internet Res. 19 (5), e141. http://dx.doi.org/10.2196/jmir.6775.

Birney, A.J., Gunn, R., Russell, J.K., Ary, D.V., 2016. MoodHacker mobile web app with email for adults to self-manage mild-to-moderate depression: randomized ControlledTrial. JMIR mHealth uHealth 4 (1), e8. http://dx.doi.org/10.2196/mhealth.4231.

Callan, J.A., Wright, J., Siegle, G.J., Howland, R.H., Kepler, B.B., 2017. Use of computer and mobile technologies in the treatment of depression. Arch. Psychiatr. Nurs. 31 (3), 311–318. http://dx.doi.org/10.1016/j.apnu.2016.10.002.

Carpenter, J., Crutchley, P., Zilca, R.D., Schwartz, H.A., Smith, L.K., Cobb, A.M., Parks, A.C., 2016. Seeing the "big" picture: big data methods for exploring relationships between usage, language, and outcome in internet intervention data. J. Med. Internet Res. 18 (8), e241. http://dx.doi.org/10.2196/jmir.5725.

Chesney, M.A., Neilands, T.B., Chambers, D.B., Taylor, J.M., Folkman, S., 2006. A validity and reliability study of the coping self-efficacy scale. Br. J. Health Psychol. 11, 421–437. http://dx.doi.org/10.1348/135910705X53155.

Cohen, J.S., Edmunds, J.M., Brodman, D.M., Benjamin, C.L., Kendall, P.C., 2013. Using self-monitoring: implementation of collaborative empiricism in cognitive-behavioral therapy. Cogn. Behav. Pract. 20, 419–428. http://dx.doi.org/10.1016/j.cbpra.2012.06.002.

Darlington, R.B., Hayes, A.F., 2016. Regression Analysis and Linear Models: Concepts, Applications, and Implementation, 1st ed. The Guilford Press, New York.

Deloitte, 2016. Mobile Consumer Survey 2015 – The Australian Cut. Retrieved from ⟨http://landing.deloitte.com.au/rs/761-IBL-328/images/deloitte-au-tmt-mobile-consumer-survey-2015-291015.pdf⟩.

Donker, T., Griffiths, K.M., Cuijpers, P., Christensen, H., 2009. Psychoeducation for depression, anxiety and psychological distress: a meta-analysis. BMC Med. 7, 79. http://dx.doi.org/10.1186/1741-7015-7-79.

Donker, T., Petrie, K., Proudfoot, J., Clarke, J., Birch, M.-R., Christensen, H., 2013. Smartphones for smarter delivery of mental health programs: a systematic review. J. Med. Internet Res. 15, e247. http://dx.doi.org/10.2196/jmir.2791.

Donker, T., van Straten, A., Marks, I., Cuijpers, P., 2011. Quick and easy self-rating of Generalized Anxiety Disorder: validity of the Dutch web-based GAD-7, GAD-2 and GAD-SI. Psychiatry Res. 188 (1), 58–64. http://dx.doi.org/10.1016/j.psychres.2011.01.016.

Dubad, M., Winsper, C., Meyer, C., Livanou, M., Marwaha, S., 2017. A systematic review of the psychometric properties, usability and clinical impacts of mobile mood-monitoring applications in young people. Psychol. Med. 1–21. http://dx.doi.org/10.1017/S0033291717001659.

Durbin, J., Watson, G.S., 1951. Testing for serial correlation in least squares regression. Biometrika 38 (1/2), 159–177. http://dx.doi.org/10.2307/2332325.

Ehlers, A., Clark, D.M., Hackmann, A., McManus, F., Fennell, M., Herbert, C., Mayou, R., 2003. A randomized controlled trial of cognitive therapy, a self-help booklet, and repeated assessments as early interventions for posttraumatic stress disorder. Archives of General Psychiatry 60. pp. 1024–1032. http://dx.doi.org/10.1001/archpsyc.60.10.1024.

Field, A., 2009. Discovering Statistics Using SPSS, 3rd ed. Sage, London.

Field, A., 2013. 4th ed. Discovering statistics using SPSS Sage, London.

Grist, R., Porter, J., Stallard, P., 2017. Mental health mobile apps for preadolescents and

adolescents: a systematic review. J. Med. Internet Res. 19 (5), e176. http://dx.doi.org/10.2196/jmir.7332.
Haga, S.M., Kraft, P., Corby, E.-K., 2009. Emotion regulation: Antecedents and well-being outcomes of cognitive reappraisal and expressive suppression in cross-cultural samples: J. Happiness Stud.. 10, 271–291. http://dx.doi.org/10.1007/s10902-007-9080-3.
Hayes, A.F., 2013. Introduction to Mediation, Moderation, and Conditional Process Analysis: a Regression-Based Approach, 1st ed. The Guilford Press, New York.
Hayes, A.F., Rockwood, N.J., 2016. Regression-based statistical mediation and moderation analysis in clinical research: observations, recommendations, and implementation. Behav. Res. Ther. http://dx.doi.org/10.1016/j.brat.2016.11.001.
Hill, C.L.M., Updegraff, J.A., 2012. Mindfulness and its relationship to emotional regulation. Emotion 12, 81–90. http://dx.doi.org/10.1037/a0026355.
Holdsworth, E., Bowen, E., Brown, S., Howat, D., 2014. Client engagement in psychotherapeutic treatment and associations with client characteristics, therapist characteristics, and treatment factors. Clin. Psychol. Rev. 34 (5), 428–450. http://dx.doi.org/10.1016/j.cpr.2014.06.004.
Howells, A., Ivtzan, I., Eiroa-Orosa, F.J., 2014. Putting the "app" in happiness: a randomised controlled trial of a smartphone-based mindfulness intervention to enhance wellbeing. J. Happiness Stud. http://dx.doi.org/10.1007/s10902-014-9589-1.
Huguet, A., Rao, S., McGrath, P.J., Wozney, L., Wheaton, M., Conrod, J., Rozario, S., 2016. A systematic review of cognitive behavioral therapy and behavioral activation apps for depression. PLoS One 11 (5). https://doi.org/http://dx.doi.org.ezproxy.lib.monash.edu.au/10.1371/journal.pone.0154248.
Huppert, J.D., Roth Ledley, D., Foa, E.B., 2006. The use of homework in behavior therapy for anxiety disorders. J. Psychother. Integr. 16, 128–139. http://dx.doi.org/10.1037/1053-0479.16.2.128.
Jarrett, R.B., Nelson, R.O., 1987. Mechanisms of change in cognitive therapy of depression. Behav. Ther. 18, 227–241. http://dx.doi.org/10.1016/S0005-7894(87)80017-5.
Joe, G.W., Broome, K.M., Rowan-Szal, G.A., Simpson, D.D., 2002. Measuring patient attributes and engagement in treatment. J. Subst. Abus. Treat. 22 (4), 183–196. http://dx.doi.org/10.1016/S0740-5472(02)00232-5.
Jorm, A.F., Korten, A.E., Jacomb, P.A., Christensen, H., Rodger, B., Pollitt, P., 1997. "Mental health literacy": a survey of the public's ability to recognise mental disorders and their beliefs about the effectiveness of treatment. Med. J. Aust. 166, 5.
Kauer, S.D., Reid, S.C., Crooke, A.H.D., Khor, A., Hearps, S.J.C., Jorm, A.F., Patton, G., 2012. Self-monitoring using mobile phones in the early stages of adolescent depression: randomized controlled trial. J. Med. Internet Res. 14, e67. http://dx.doi.org/10.2196/jmir.1858.
Kazantzis, N., Cronin, T.J., Norton, P.J., Lai, J., Hofmann, S.G., 2015. Reservations about the conclusions of the interdivisional (APA divisions 12 & 29) task force on evidence-based therapy relationships: what do we know, what don't we know? J. Clin. Psychol. 71 (5), 423–427. http://dx.doi.org/10.1002/jclp.22178.
Kazantzis, N., Deane, F.P., Ronan, K.R., Lampropoulos, G.K., 2005. Empirical foundations. In: Kazantzis, N., Deane, F.P., Ronan, K.R., L'Abate, L. (Eds.), Using Homework Assignments in Cognitive Behavior Therapy. Routledge, New York, pp. 29–49.
Kroenke, K., Spitzer, R.L., Williams, J.B.W., 2001. The PHQ-9: validity of a brief depression severity measure. J. General. Intern. Med. 16, 606–613. http://dx.doi.org/10.1046/j.1525-1497.2001.016009606.x.
Kroenke, K., Spitzer, R.L., Williams, J.B.W., Löwe, B., 2010. The patient health questionnaire somatic, anxiety, and depressive symptom scales: a systematic review. General. Hosp. Psychiatry 32, 345–359. http://dx.doi.org/10.1016/j.genhosppsych.2010.03.006.
Lauritsen, L., Andersen, L., Olsson, E., Søndergaard, S.R., Nørregaard, L.B., Løventoft, P.K., Martiny, K., 2017. Usability, acceptability, and adherence to an electronic self-monitoring system in patients with major depression discharged from inpatient wards. J. Med. Internet Res. 19 (4), e123. http://dx.doi.org/10.2196/jmir.6673.
Manea, L., Gilbody, S., McMillan, D., 2012. Optimal cut-off score for diagnosing depression with the patient health questionnaire (PHQ-9): a meta-analysis. Can. Med. Assoc. J. 184 (3), E191–E196. http://dx.doi.org/10.1503/cmaj.110829.
Mental Health First Aid International, 2016. Mental Health First Aid (MHFA) (Version 1. 4) [Mobile application software]. Retrieved July 10, 2017, from ⟨https://itunes.apple.com/au/app/mental-health-first-aid-mhfa/id923191844?Mt = 8⟩.
MoodMission Pty Ltd, 2017. MoodMission (Version 1.1.2) [Mobile application software]. Retrieved May 23, 2017, from ⟨https://itunes.apple.com/au/app/moodmission/id1140332763?Mt = 8⟩.
Morris, M.E., Kathawala, Q., Leen, T.K., Gorenstein, E.E., Guilak, F., Labhard, M., Deleeuw, W., 2010. Mobile therapy: case study evaluations of a cell phone application for emotional self-awareness. J. Med. Internet Res. 12, e10. http://dx.doi.org/10.2196/jmir.1371.
O'Toole, M., Jensen, M., Fentz, H., Zachariae, R., Hougaard, E., 2014. Emotion differentiation and emotion regulation in high and low socially anxious individuals: an experience-sampling study. Cogn. Ther. Res. 38, 428–438. http://dx.doi.org/10.1007/s10608-014-9611-2.
Plummer, F., Manea, L., Trepel, D., McMillan, D., 2016. Screening for anxiety disorders with the GAD-7 and GAD-2: a systematic review and diagnostic metaanalysis. General. Hosp. Psychiatry 39, 24–31. http://dx.doi.org/10.1016/j.genhosppsych.2015.11.005.
Reavley, N.J., Jorm, A.F., 2011. National Survey of Mental Health Literacy and Stigma. Department of Health and Ageing, Canberra.
Reynolds, W.M., 1982. Development of reliable and valid short forms of the marlowe-crowne social desirability scale. J. Clin. Psychol. 38 (1), 119–125. https://doi.org/10.1002/1097-4679(198201)38:13.0.CO;2-I.
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 Ment. Health 3 (4), e49. http://dx.doi.org/10.2196/mental.6202.
Schwartz, S., Schultz, S., Reider, A., Saunders, E.F.H., 2016. Daily mood monitoring of symptoms using smartphones in bipolar disorder: a pilot study assessing the feasibility of ecological momentary assessment. J. Affect. Disord. 191, 88–93. http://dx.doi.org/10.1016/j.jad.2015.11.013.
Spitzer, R.L., Kroenke, K., Williams, J.W., Löwe, B., 2006. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch. Intern. Med. 166, 1092–1097. http://dx.doi.org/10.1001/archinte.166.10.1092.
Statista, 2017. Smartphone users worldwide 2014–2020 | Statistic. Retrieved January 23, 2017, from ⟨https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/⟩.
Stewart-Brown, S., Janmohamed, K., 2008. Warwick-Edinburgh Mental Well-being Scale. *User Guide. Version*, *1*. Retrieved from ⟨http://www.cppconsortium.nhs.uk/admin/files/1343987601WEMWBS%20User%20Guide%20Version%201%20June%202008.pdf⟩.
Stoll, R.D., Pina, A.A., Gary, K., Amresh, A., 2017. Usability of a smartphone application to support the prevention and early intervention of anxiety in youth. Cogn. Behav. Pract. http://dx.doi.org/10.1016/j.cbpra.2016.11.002.
Stoyanov, S.R., Hides, L., Kavanagh, D.J., Wilson, H., 2016. Development and validation of the user version of the mobile application rating scale (uMARS). JMIR mHealth uHealth 4 (2), e72. http://dx.doi.org/10.2196/mhealth.5849.
Sucala, M., Cuijpers, P., Muench, F., Cardoş, R., Soflau, R., Dobrean, A., David, D., 2017. Anxiety: there is an app for that. A systematic review of anxiety apps. Depression Anxiety 34 (6), 518–525. http://dx.doi.org/10.1002/da.22654.
Sucala, M., Schnur, J.B., Constantino, M.J., Miller, S.J., Brackman, E.H., Montgomery, G.H., 2012. The therapeutic relationship in e-therapy for mental health: a systematic review. J. Med. Internet Res. 14 (4), e110. http://dx.doi.org/10.2196/jmir.2084.
Suveg, C., Hoffman, B., Zeman, J.L., Thomassin, K., 2009. Common and specific emotion-related predictors of anxious and depressive symptoms in youth. Child Psychiatry Hum. Dev. 40 (2), 223–239. http://dx.doi.org/10.1007/s10578-008-0121-x.
Tarrier, N., Sommerfield, C., Reynolds, M., Pilgrim, H., 1999. Symptom self-monitoring in the treatment of posttraumatic stress disorder. Behav. Ther. 30, 597–605. http://dx.doi.org/10.1016/S0005-7894(99)80027-6.
Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., Stewart-Brown, S., 2007. The Warwick-Edinburgh mental well-being scale (WEMWBS): development and UK validation. Health Qual. Life Outcomes 5, 63. http://dx.doi.org/10.1186/1477-7525-5-63.
Thorne, K.J., Andrews, J.J.W., Nordstokke, D., 2013. Relations among children's coping strategies and anxiety: the mediating role of coping efficacy. J. General. Psychol. 140, 204–223. http://dx.doi.org/10.1080/00221309.2013.792235.
Torous, J., Firth, J., 2016. The digital placebo effect: mobile mental health meets clinical psychiatry. Lancet Psychiatry 3 (2), 100–102. http://dx.doi.org/10.1016/S2215-0366(15)00565-9.
Van Ameringen, M., Turna, J., Khalesi, Z., Pullia, K., Patterson, B., 2017. There is an app for that! The current state of mobile applications (apps) for DSM-5 obsessive-compulsive disorder, posttraumatic stress disorder, anxiety and mood disorders. Depression Anxiety 34 (6), 526–539. http://dx.doi.org/10.1002/da.22657.
van Os, J., Verhagen, S., Marsman, A., Peeters, F., Bak, M., Marcelis, M., Delespaul, P., 2017. The experience sampling method as an mHealth tool to support self-monitoring, self-insight, and personalized health care in clinical practice. Depression Anxiety 34 (6), 481–493. http://dx.doi.org/10.1002/da.22647.
Van Singer, M., Chatton, A., Khazaal, Y., 2015. Quality of smartphone apps related to panic disorder. Front. Psychiatry 6. http://dx.doi.org/10.3389/fpsyt.2015.00096.
Versluis, A., Verkuil, B., Spinhoven, P., van der Ploeg, M.M., Brosschot, J.F., 2016. Changing mental health and positive psychological well-being using ecological momentary interventions: a systematic review and meta-analysis. J. Med. Internet Res. 18 (6), e152. http://dx.doi.org/10.2196/jmir.5642.
Vickers, A.J., Altman, D.G., 2001. Analysing controlled trials with baseline and follow up measurements. BMJ: Br. Med. J. 323 (7321), 1123–1124.
Vogl, G., Ratnaike, D., Ivancic, L., Rowley, A., Chandy, V., 2016. One click away? Insights into mental health digital self-help by young Australians. EY and ReachOut Australia, Sydney.
Webb, T.L., Miles, E., Sheeran, P., 2012. Dealing with feeling: a meta-analysis of the effectiveness of strategies derived from the process model of emotion regulation. Psychol. Bull. 138 (4), 775–808. http://dx.doi.org/10.1037/a0027600.
Whittaker, R., Stasiak, K., McDowell, H., Doherty, I., Shepherd, M., Chua, S., Merry, S., 2017. MEMO: an mHealth intervention to prevent the onset of depression in adolescents: a double-blind, randomised, placebo-controlled trial. J. Child Psychol. Psychiatry. http://dx.doi.org/10.1111/jcpp.12753.
World Health Organization, 2017. WHO | Depression. Retrieved March 30, 2017, from ⟨http://www.who.int/mediacentre/factsheets/fs369/en/⟩.
Zhao, X., Lynch, J.G., Chen, Q., 2010. Reconsidering Baron and Kenny: myths and truths about mediation analysis. J. Consum. Res. 37, 197–206. http://dx.doi.org/10.1086/651257.

CHAPTER 5: DEVELOPMENT AND PILOT EVALUATION OF SMARTPHONE DELIVERED COGNITIVE BEHAVIOR THERAPY STRATEGIES FOR MOOD AND ANXIETY RELATED PROBLEMS: MOODMISSION

Explanatory Note

The development and planned evaluation of MoodPrism revealed the potential utility of developing a second app that could recommend activities to participants in an attempt to increase coping self-efficacy (CSE). Due to certain limitations, including its design as primarily a research tool, MoodPrism was not able to provide activity recommendations, so was unable to fulfil all sixteen recommendations discussed in Chapter 1. It was therefore decided to create a MHapp that would recommend coping activities for users who were experiencing low moods or anxious feelings. Developing a second app that included different features to MoodPrism was also attractive because it could enable comparisons between different types of MHapp. These comparisons are explored more in Chapter 7 and the Integrated Discussion.

The following chapter presents a manuscript that was submitted to Cognitive and Behavioral Practice for publication in September 2017, and following review was revised and resubmitted in January 2018. While Rickard, Armand, Bakker, and Seabrook (2016; see Appendix B) presented details on the development and usability evaluation of MoodPrism, this chapter's manuscript serves the same purpose for this new app, called MoodMission. For more information about MoodMission, refer to www.moodmission.com, and review the screenshots displayed in Appendix E.

To support the development of MoodMission, 44 participants tested the app in its early, prototype stages and provided data on the usability of the MHapp. The following manuscript presents both quantitative and qualitative data from these participants, which revealed that MoodMission was rated higher than norms for other health apps across a variety of domains. The manuscript serves as the basis for further evaluation of MoodMission, which is presented in Chapter 6.

Abstract

Given the ubiquity and interactive power of smartphones, there are opportunities to develop smartphone applications (apps) that provide novel, highly accessible mental health supports. This paper details the development of a smartphone app, “MoodMission”, that aims to provide evidence-based Cognitive Behavior Therapy (CBT) strategies for mood and anxiety related problems, contributing to the prevention of clinically significant depression and anxiety disorders and serving as an adjunct to therapeutic interventions delivered by trained health professionals. MoodMission was designed to deliver strategies in the form of real-time, momentary responses to user reported low moods and anxiety. The development process involved: 1) construction of a battery of strategies, 2) empirical evaluation, 3) a software and behavioral plan design and testing process, 4) user feedback, and 5) a public launch. A pilot study of 44 participants completed the Mobile Application Rating Scale (MARS; Hides et al., 2014) for usability testing and feedback. MoodMission was rated significantly higher than standardized health app norms on the majority of the domains, including Entertainment, Interest, Customization, Target Group, Graphics, Visual Appeal, Quality of Information, Quantity of Information, Visual Information, Credibility of Source, Recommendation to Use, Estimated Frequency of Use, and Overall Rating (Hedge’s g range 0.57-1.97, $p < .006$). Case examples illustrate the practical uses of the app. In addition to clinical applications, MoodMission holds promise as a research tool either as an augmentation to clinician-delivered therapy, or as a vehicle for standardizing client access to specific CBT strategies (e.g., in studies intending to study different change processes).

Keywords: Mobile, App, Application, Depression, Mood, Anxiety, Cognitive behavior therapy

Development and Pilot Evaluation of Smartphone Delivered Cognitive Behavior Therapy Strategies for Mood and Anxiety Related Problems: MoodMission

Given the exponential growth in smartphone use (Deloitte, 2016b), there is a potential to increase access to and create novel delivery of mental health interventions. Data collection capability for the expressed purpose of evaluating the stated health aims and objectives of smartphone applications (apps) designed for mental health (MHapps) is an important ethical and practice consideration (Luxton, McCann, Bush, Mishkind, & Reger, 2011). Despite this opportunity to significantly transform behavioral health care, recent reviews have found a significant number of MHapps have been developed without an empirical base or evaluation capacity (Bakker, Kazantzis, Rickwood, & Rickard, 2016; Donker et al., 2013; Jones & Moffitt, 2016). For the continued advancement of MHapps, there is a need for careful evaluation that includes user feedback on intended benefits, as well as the overall interface and design of the platform.

Cognitive behavior therapy (CBT) is an effective treatment for depression (Cuijpers et al., 2013) and anxiety (Bolognesi, Baldwin, & Ruini, 2014), and has been translated successfully for delivery via the internet for a range of clinical disorders (Andrews & Williams, 2014; Dèttore, Pozza, & Andersson, 2015; Kuester, Niemeyer, & Knaevelsrud, 2016; Newby, Twomey, Yuan Li, & Andrews, 2016). Many internet CBT (iCBT) programs have been designed to include techniques that can be flexibly applied to a range of disorder groups (Păsărelu, Andersson, Nordgren, & Dobrean, 2017), through their emphasis on core dimensions in psychopathology and treatment processes, including: attention and other processes of cognition (e.g., acceptance, tolerance), cognitive reappraisal (e.g., decentering, defusion), behavior change (e.g., activation, exposure), and emotional dysregulation (Aldao, Nolen-Hoeksema, & Schweizer, 2010; Hayes & Hofmann, 2017, 2018; and see Kazantzis, 2017 for outline of technique-process links). For example, common treatment processes in iCBT for anxiety and depression (Ellard, Fairholme, Boisseau, Farchione, & Barlow, 2010) can be reliably facilitated through psychoeducation, self-monitoring of thoughts and emotions, emotion regulation skills, and relapse prevention (Newby et al., 2016). By enabling individuals to learn broadly relevant skills, such as the ability to identify emotions and evaluate unhelpful thinking patterns, iCBT has the potential to be broadly beneficial, both as an augmentation to therapy, and standalone prevention and therapeutic modality.

In traditional delivery of CBT, a therapist would guide a patient to a shared understanding of their problems using a generic cognitive model illustrating the interactive patterns of cognition, behavior, emotions, and physiology in problematic situations (Layard & Clark, 2014; Westbrook, Kennerley, & Kirk, 2011). The basic CBT components involve the construction of individualized emotion rating scales (e.g., SUDS) for the evaluation of specific interventions focused on behavior change, and interventions focused on cognitive change. Cognitive change is posited as the main change mechanism within standard CBT (Beck, 2011), traditionally facilitated by techniques that involve cognitive re-appraisal or reframing, but can also include techniques that focus on acceptance, building tolerance, decentering, and defusion, among others (Mennin, Ellard, Fresco, & Gross, 2013; Petrik, Kazantzis, & Hofmann, 2013). Interventions focused on behavioral exposure (e.g., in various anxiety disorder treatments) and activation (e.g., in various mood disorder treatments) can also facilitate cognitive change processes. Similarly, there is attention to the process of cognition, such as noticing themes in content of underlying assumptions and core beliefs, as well as the information processes that strengthen maladaptive beliefs and accompanying behavioral strategies. Between sessions, clients practice strategies to consolidate cognitive and behavioral changes, but ensuring engagement can pose unique motivational and practical challenges (Kazantzis, Deane, & Ronan, 2005).

Despite the conceptual clarity of and empirical support for CBT, delivery in community settings can often suffer from low levels of engagement and high treatment dropout (Fernandez, Salem, Swift, & Ramtahal, 2015). These factors may relate to the significant lifestyle and other behavioral changes required by CBT. Thus, maximizing engagement is necessary to reach the full potential of CBT (Ballegooijen et al., 2014). Technology can play a helpful role in enhancing client experience of treatment (Andrews & Williams, 2014), improving engagement and, in turn, accelerating treatment response. For example, the between session practice of therapeutic skills (or homework) can be recorded, tracked and reviewed on an app, and mapped against recordings of symptom severity and improvement (Reger et al., 2013), though the evidence suggests there is currently an untapped potential for apps to support monitoring (Kazantzis, Brownfield, Mosely, Usatoff, & Flighty, 2017). When apps are used, they provide both a memory aid to complete homework and have the potential to improve motivation to experience the benefits of task completion.

A growing literature demonstrates that mobile applications may be useful adjuncts or modes for the delivery of psychological interventions (Firth et al., 2017a, 2017b). For example, Titov et al. (2015) compared four different variants of iCBT for depression, including either self-guided or clinician-guided, and transdiagnostic or disorder-specific. All variants were effective at reducing depressive symptoms and comorbid anxiety, and there were no significant differences in effectiveness between the variants, suggesting that self-guided, transdiagnostic iCBT can be just as effective as clinician-guided diagnosis-specific iCBT. Dear et al. (2016) replicated these findings for participants with social anxiety disorder, noting effects on comorbid depression, generalized anxiety disorder, and panic disorder. Meta-analyses have found strong effect sizes for iCBT programs over both waitlist and active control conditions (i.e., self-monitoring, discussion groups) with an overall superiority in effect size across anxiety and depressive disorders (i.e., $g = .88$, 95% CI = .76-.99 in

Andrews, Cuijpers, Craske, McEvoy, & Titov, 2010), and in transdiagnostic iCBT programs (i.e., g = .84, 95% CI = .67-1.01 for depression, ; g = .78, 95% CI = .57-398 for anxiety, : and g = .48, 95% CI = .35-.61 for quality of life in Newby et al., 2016). A meta-analysis of 13 studies comparing iCBT to face-to-face CBT found equivalence between the two modes of therapy (g = -0.01, 95% CI =-0.13, 0.12). However, iCBT programs are typically designed for use on personal computers and may not be well suited to delivery via smartphones.

Individuals interact with smartphones and with personal computers in different ways. For example, a person's interaction with a therapy intervention delivered by computer in the privacy of their own home is very different from their public use of a smartphone in transit from one location to another. Smartphone use generally involves a greater number of shorter, more momentary interactions than personal computer use, across a greater number of situations and settings (Deloitte, 2016c). Available data suggest Americans may check their phone 46 times a day (Deloitte, 2016a) and engage with their smartphone more than computers (i.e., in (Google, 2016) 170 mins through the day; 12 mins in the evening). Accordingly, there are design and feasibility issues for both the therapeutic intervention being delivered via internet or smartphone, and the way the user interface is designed (Wendel, 2013). Although some evidence suggests that CBT programs can be delivered effectively and equivalently via either computer or smartphone (Watts et al., 2013), further evaluating the extent to which CBT interventions can be effectively delivered via smartphone applications is one of the important ways in which the evidence base for technology-augmented and delivered CBT can be enhanced.

Few available MHapps have been specifically evaluated for their effectiveness as a mode of delivery, even if their techniques and strategies are based on a body of evidence (Bakker et al., 2016; Donker et al., 2013; Van Ameringen, Turna, Khalesi, Pullia, & Patterson, 2017). It is possible, for example, that some CBT strategies are effective when completed under the guidance of a therapist, but when incorporated into a MHapp, unique challenges to smartphone apps may limit their utility. Similarly, smartphone apps may afford some CBT strategies greater flexibility and enhance their effects. For example, behavioral activation strategies and scheduling pleasant activities may be more accurately self-monitored when tracked using a self-guided MHapp, but recording and re-appraising negative automatic thoughts may require initial introduction and skill acquisition in a private learning environment or therapy setting. Thus, as with iCBT, there is a need for research to address the gap that exists regarding CBT delivered via MHapps.

This paper will outline the development and pilot evaluation of a new MHapp, called "MoodMission", for the delivery of CBT strategies for managing mood and anxiety related problems. Details are given to aid practitioners in their understanding and use of the app with clients, and to inform the development of future apps by practitioners.

Current Evidence for Smartphone Delivered CBT

Compared to other modes of delivery, such as group, phone, or internet delivered CBT, there is currently a scarcity of published experimental evidence investigating the outcomes of MHapps using CBT strategies (Donker et al., 2013; Grist, Porter, & Stallard, 2017; Olff, 2015). While several studies have found evidence for the efficacy of MHapp interventions in the acquisition of specific CBT skills (e.g. Franklin et al., 2016; Kauer et al., 2012; Roepke et al., 2015), their limitations suggest the need for more research.

Studies that have investigated MHapps have tended to focus on relatively narrow clinical applications or have used methods that do not represent typical smartphone use. For example, Roepke et al. (2015) found that the use of two different versions of the MHapp "SuperBetter" decreased depression symptoms in participants experiencing depression, compared with a waitlist control condition. However, the exclusion of participants who were not experiencing clinical distress obstructed investigation of preventative utility. Similarly, Kauer et al. (2012) found that the use of an app to track mental health related variables increased emotional self-awareness (ESA) and reduced depressive symptoms in depressed participants when compared to a control group. However, participants did not download the app to their own phones, but instead were given a device with it installed, and they reviewed the self-monitoring data they had collected with their doctor at several time points. While this suggests that MHapps can have impacts on depression and ESA, it does not demonstrate the effectiveness of MHapps in naturalistic self-guided applications.

Franklin et al. (2016) designed a therapeutic evaluative conditioning (TEC) MHapp which was effective at reducing self-cutting episodes, suicidal behaviors, and suicide plans. While this suggests an efficacious intervention, it was for a narrow clinical purpose and 76% of participants reported a history of psychiatric treatment. A publicly available MHapp like this would have significant barriers to access, as the vast majority of smartphone users would not consider downloading it, let alone using it outside of a research study context. There is a need to study MHapps designed for nonclinical populations, as these represent the target of the majority of MHapps available. The present study aimed to fill this gap in the literature by developing a publicly, freely available MHapp that was useful for individuals of all mental health statuses, adhered to latest evidence-based guidelines, and was capable of collecting data for further experimental evaluation.

Many existing MHapps have been designed for adolescent and young adult users (e.g. Ray’s Night Out (Hides et al., 2015), WorryTime (ReachOut, 2016)). This is understandable given the high ownership rates in these demographics, with up to 98% of 18-24 year olds owning a smartphone (Nielsen, 2016). However, high ownership rates are observed in other age demographics, with 97% of 25-34 year olds, 96% of 35-44 year olds, and 89% of 45-54 year olds owning a smartphone. Furthermore, in a survey of 100 psychiatric outpatients, those aged 30-45 were more likely to want to use MHapps (81%) than those under 30 years of age

(78%; (Torous, Friedman, & Keshavan, 2014), and a significant proportion of patients aged 45-60 years also expressed interest in using a MHapp (71%). To meet this demand, future MHapps should be designed for smartphone owners of all ages.

It is important for MHapps to undergo usability testing before public release (Dubad, Winsper, Meyer, Livanou, & Marwaha, 2017). The technical justification for usability testing is to ensure that the intervention works reliably across multiple unique devices and under a variety of usage scenarios (Jaspers, 2009). Furthermore, novel self-guided CBT interventions require pre-release testing to ensure that their therapeutic aims are being achieved through the hypothesized mechanisms (Kinderman et al., 2016). This is to mitigate against the risk that the MHapp is used in an unintended manner and gives the developers the opportunity to adjust the intervention to realign its usage patterns with the therapeutic aims.

The MoodMission Smartphone Application

Reviewing the MHapp marketplace and literature, a gap was noted that could be filled by an app that would meet all 16 of Bakker et al.'s (2016) recommendations. This app would be designed for both clinical and nonclinical users, and help give direction to the question "I'm low/anxious, what can I do right now to help?" The designed app was intended to provide individuals with discrete, "mission"-based coping solutions for mood problems, so was given the name "MoodMission". MoodMission was designed to be an easy-to-use and engaging application to enhance mental health and wellbeing for smartphone users of all ages, adolescents and older, and all mental health statuses. It was a crowd-funded project specifically designed to be a non-commercial product and included comprehensive data collection strategies to facilitate evaluation. Research using this app could investigate the utility of various, discrete strategies for reducing specific types of distress, and, more broadly, the utility of similar MHapps across a range of clinical and nonclinical contexts.

CBT Strategies

MoodMission was designed with three primary aims: (1) to provide self-administered prevention and self-help strategies to reduce the risk of clinically significant mood and anxiety disorders; (2) to support stepped-care interventions (Vogl, Ratnaike, Ivancic, Rowley, & Chandy, 2016; White, 2010) as a platform for access to low-intensity intervention for low-level clinical symptoms or sub-clinical symptoms of depression and anxiety; and (3) as an adjunct to psychotherapy or other face-to-face treatments for mood and anxiety disorders. The strategies, called “Missions”, contained within MoodMission originate from behavioral activation (Dahne, Kustanowitz, & Lejuez, 2017; Mazzucchelli, Kane, & Rees, 2009), relaxation (Manzoni, Pagnini, Castelnuovo, & Molinari, 2008), mindfulness (Hofmann, Sawyer, Witt, & Oh, 2010; Shipherd & Fordiani, 2015), physical exercise (Cooney et al., 2013), cognitive reframing (Butler, Chapman, Forman, & Beck, 2006), and other activities promoted or supported by CBT. Missions are designed specifically to be appropriate for a self-guided smartphone app, and due to the user-friendly interface, do not require introduction by a therapist. Time and environment constraints are also considered, with each Mission achievable within 5-10 minutes and in most public or private spaces. Missions were only included if they were suitable for adolescents as well as older users. Example Missions can be seen in screenshots presented in Figure 2.

Researchers aim to pursue controlled trials for empirical validation of MoodMission, so the app has built-in data collection, which will be collated and analyzed in time. The current paper reports on the development process and usability testing, presenting app functionality and data on user experience.

Interface Design and Engagement

A central consideration to the design of a MHapp is its appeal to the individual using it, which may transfer to how engaged they are in the intervention. Engagement may be defined in different ways; for example, many iCBT studies report retention rates, as a measure of how many participants did not complete all the interventions' stages. Studies in face-to-face CBT have assessed the amount of therapeutic interventions completed by clients, also referred to as "homework" (Kazantzis et al., 2016). However, engagement is a broader concept than adherence or compliance and takes into consideration the degree of difficulty and obstacles experienced by the individual in attempting the intervention (Holdsworth, Bowen, Brown, & Howat, 2014). MHapps may facilitate engagement, not only through ease of access to information, automated recorded and tallying of responses, but through their interface, and the potential for improved assessment of engagement that would not be possible through paper and pencil worksheet completion (Kazantzis et al., 2017).

Game-inspired mechanics, sometimes referred to as gamification, can improve user engagement and understanding in eHealth interventions (Comello et al., 2016). This can be as simple as tracking the number of minutes spent meditating (example apps include Headspace, 2015; Smiling Mind, 2015). Gamification can be understood using self-determination theory (SDT), which emphasizes the roles of perceived autonomy and mastery on intrinsic motivation (Ryan & Deci, 2000). For example, the MHapp SuperBetter (SuperBetter Inc, 2014) awards users "resilience" points for completing short activities, helping users quantify and reflect on achievements (Roepke et al., 2015). SDT principles have previously been considered when improving client engagement and therapeutic outcomes in CBT (Tee & Kazantzis, 2011). Gamification harnesses the same principles to improve engagement with an app, but of the 27 MHapps in the Bakker et al. (2016) review, only 19% included gamification.

Recently published recommendations (Bakker et al., 2016) informed the development of MoodMission. Care was taken to keep MoodMission's design simple, easy to use, and with a distinct purpose so smartphone users, including adolescents and older adults, would be able to understand how to engage with it. Inclusive design cues were taken from broadly accessible apps, such as those that come standard on smartphone operating systems, as these apps are designed to be used by all potential users.

The formation of a behavioral plan for MoodMission was a dynamic process to accommodate as many recommendations as possible without overcomplicating the users' engagement. The Hook model of user-centered design proposed by Eyal (2014) was used to establish triggers for engagement, the actions involved in engagement, variable rewards, and generation of investment. As outlined in Table 1, a pre-intervention engagement plan was formulated to cover the pathway towards engagement with the intervention. Table 2 lists how MoodMission's behavioral plan accommodated Bakker et al.'s (2016) recommendations, and the phases of the behavioral plan are displayed in Table 3. The end goal of the behavioral plan was to encourage repeated use of MoodMission so a positive habit of use forms. This is important for MoodMission to achieve its goal of enhancing an individual's repertoire of useful strategies for overcoming low moods and anxiety in a variety of contexts. It is expected that repeated use will lead to more learning opportunities.

Following formulation of a behavioral plan, the plan was converted into a series of diagrammatic 'wireframes' that set out exactly how the individual would interact with the app through the various screens. Figure 1 shows one of the initial wireframes generated for MoodMission. These were used to approach app development firms and collect proposals and quotes. Spark Digital was the firm chosen to build and launch the app, based on their proposal and experience developing the MHapp Smiling Mind (2015).

Table 1
Pre-intervention Engagement Plan for MoodMission

Stage	**Details**
Promotion - user learns of MoodMission	Potential avenues included: *1. Web search* is likely to be used by individuals looking for self-guided mental health support. A well-designed website, search engine optimization, and options such as Google AdWords (Dirmaier, Liebherz, Sänger, Härter, & Tlach, 2016) may increase the visibility of MoodMission in these searches *2. Healthcare providers* such as general practitioners, psychologists, social workers, or community health organisations, may suggest self-guided support options when they have contact with clients or patients suffering from preclinical or clinical psychological disorders (Bower & Gilbody, 2005). MoodMission can be promoted to healthcare providers, who can then make professional recommendations to suitable clients and patients. *3. Users promoting via their own online social networks* on sites like Facebook and Twitter can provide dissemination of products and ideas, especially ones that are highly viral (Weng, Menczer, & Ahn, 2013). Curation of official Facebook and Twitter pages can enable sharing. *4. Crowdfunding supporters* pledged money in return for rewards to raise the funds for the initial development of MoodMission. Pledgers are invested in the success of the projects they support and are likely to promote them among their own communities (Belleflamme, Lambert, & Schwienbacher, 2014).
Access - user downloads MoodMission	Considerations included: 1. Platform: iPhone development was more efficient to complete, so Android development was postponed until it could be financed. 2. App Store Category: The vast majority of MHapps can be found in *Health & Fitness* rather than *Medical*, *Lifestyle*, or others. 3. Price: Apps that are free to download are more likely to be accessed than ones that require an initial payment, even if it is a very small fee (Garg & Telang, 2012). There are models of revenue that do not rely on payments for downloads, including the subscription models, freemium models, and in-app purchases (Lambrecht et al., 2014). Adopting these free-to-download revenue models at a later date can help cover ongoing development and maintenance costs, while keeping accessibility high.
Onboarding - introducing MoodMission's interface and purpose	The onboarding process can enhance the user's understanding of the app and hence their engagement (Morson, 2015). Five screens of images and text were devised to orient users to the triggers, actions, and rewards associated with MoodMission's use, and emphasize that MoodMission does not replace professional help and users should consult a GP, psychologist, or mental health professional for more support.
Completion of pre-intervention surveys	While compulsory completion of these surveys was predicted to be a potential barrier to further engagement with the app, collection of the survey data was necessary for experimental validation. A rationale was provided to users to encourage persistence through the surveys, emphasizing the short time that each survey would take, and the contribution the user would be making to important research.

Table 2

How MoodMission's Features Adhere to the Recommendations Made by Bakker et al. (2016)

Recommendation from Bakker et al. (2016)			**Use in MoodMission**
1	Cognitive behavior therapy (CBT) based	Start with an evidence-based framework to maximize effectiveness	Uses a CBT-based system for categorization of Missions. Many Missions have origins in CBT
2	Address both anxiety and low mood	Increases accessibility and addresses comorbidity between anxiety and depression. Also compatible with transdiagnostic theories of anxiety and depression	Trigger for access is when users feel low or anxious. Treats anxiety and low mood as two different types of emotional distress
3	Designed for use by nonclinical populations	Avoiding diagnostic labels reduces stigma, increases accessibility, and enables preventative use	No diagnostic labels used. Emphasizes the normality of low moods and anxiety
4	Automated tailoring	Tailored interventions are more efficacious than is rigid self-help	MoodMission learns users' coping styles by noting which categories of Missions reduce distress for each category of problems
5	Reporting of thoughts, feelings, or behaviors	Self-monitoring and self-reflection to promote psychological growth and enable progress evaluation	Users select whether they are experiencing distressing thoughts, feelings, behaviors, or physiological responses. They then rate their distress on a scale 0-10
6	Recommend activities	Behavioral activation to boost self-efficacy and repertoire of coping skills	Five activities are suggested based on the user's report
7	Mental health information	Develop mental health literacy	Missions contain a "Why This Helps" section, providing psychoeducation and a rationale for doing the Mission
8	Real-time engagement	Allows users to use in moments in which they are experiencing distress for optimum benefits of coping behaviors and relaxation techniques	Trigger for engagement is real-time distress. Missions are designed to be real-time coping strategies, achievable in a wide variety of situations

9	Activities explicitly linked to specific reported mood problems	Enhances understanding of cause-and-effect relationship between actions and emotions	Missions are selected for specific mood problems and rationale is explained in "Why This Helps" section
10	Encourage nontechnology-based activities	Helps to avoid potential problems with attention, increase opportunities for mindfulness, and limit time spent on devices	Missions are designed to be nontechnology-based
11	Gamification and intrinsic motivation to engage	Encourage use of the app via rewards and internal triggers, and positive reinforcement and behavioral conditioning. Also links with flourishing	Badge-based rewards structure for completing certain achievements. Rank-based rewards for completing more Missions
12	Log of past app use	Encourage use of the app through personal investment. Internal triggers for repeated engagement	Mission Log documents all past Missions attempted in detail
13	Reminders to engage	External triggers for engagement	Push notifications alert users when they have incomplete Missions or when they have not engaged with MoodMission recently
14	Simple and intuitive interface and interactions	Reduce confusion and disengagement in users	Behavioral plan designed to be linear and intuitive. Clean graphic design reduces confusion
15	Links to crisis support services	Helps users who are in crisis to seek help	Link to Lifeline and other supports available throughout app
16	Experimental trials	It is important to establish the app's own efficacy and effectiveness before recommending it as an intervention	Randomized controlled trial planned to compare MoodMission against waitlist and other MHapps

Table 3
Outline of MoodMission's Behavioral Plan

Phase	**Details**	**MoodMission key information**
Trigger	How the user will be motivated to open MoodMission for mental health purposes	Triggered by distress associated with low mood or anxiety
Action	What the user will do within MoodMission once they open it and start engagement	User inputs information about their distress and is provided with a list of coping activities ("Missions") to choose from
Rewards	What reinforcements will incline the user to maintain their engagement with MoodMission	Gamified rewards are issued based on completion of Missions. User gains a sense of accomplishment and autonomy, and their overall distress is decreased
Generation of investment	How the reinforcements will lead to repeated engagements with MoodMission over time	Only five Missions are presented with every engagement, drawn from a much larger database. This keeps each engagement fresh and the user is constantly discovering new content. MoodMission learns a user's coping style so more engagements will lead to better Mission selections. Users pair MoodMission's use with trigger and will seek to engage with MoodMission under future episodes of distress.

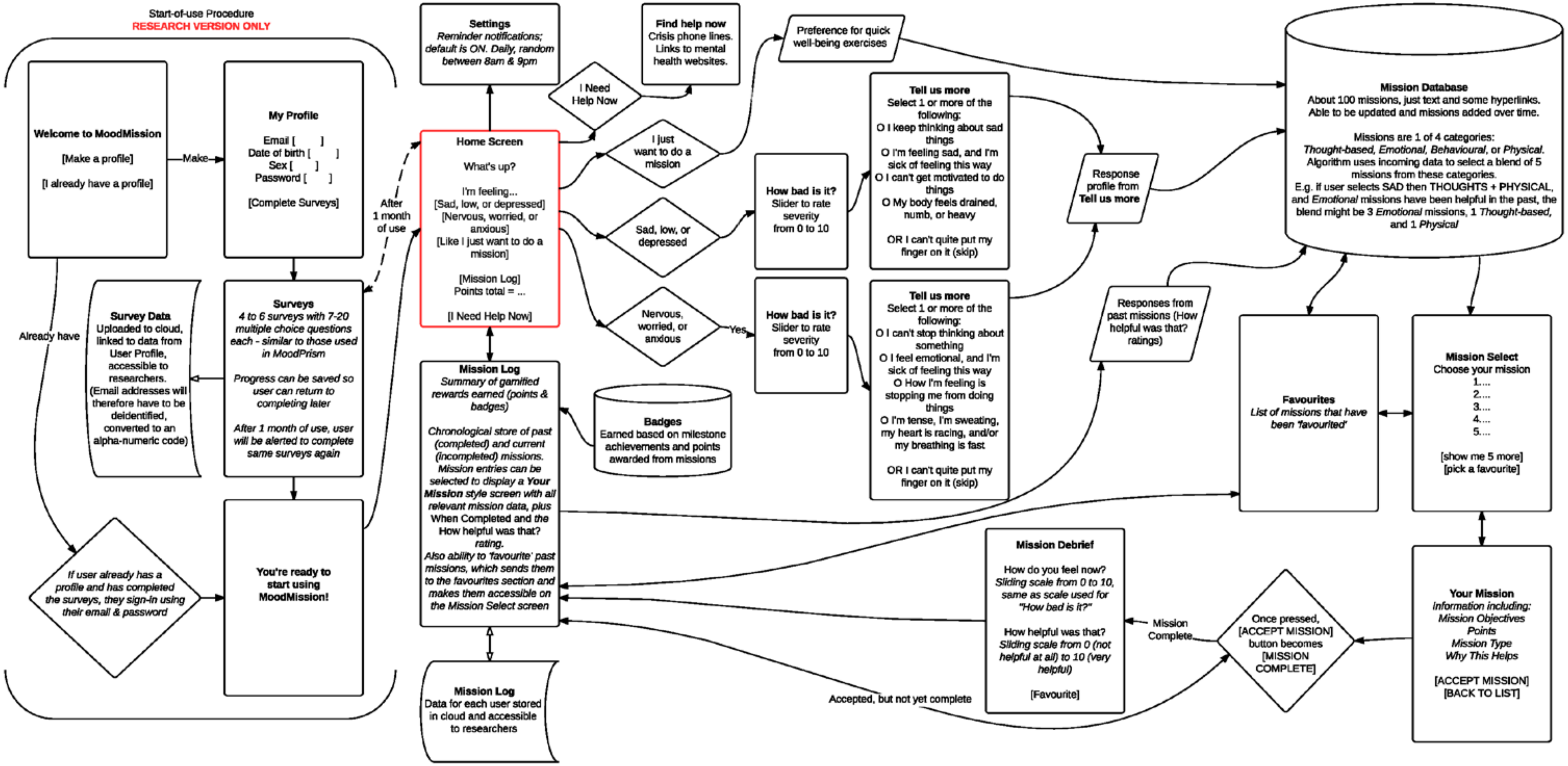


Figure 1. MoodMission early development wireframe

The researchers’ wireframes were clarified and expanded upon by the developers, and once confirmed by all parties, MoodMission’s screens were graphically designed to be attractive and engaging. Design inspiration was taken from several other successful apps, such as the bright color gradients of Vent (2017), and the simple home screen of Pacifica (2016). Several design iterations were made before the researchers and developers confirmed each screen for the prototyping stage. Figure 2 illustrates several screens from MoodMission that demonstrate these designs.

MoodMission was designed to collect data for intervention validation. This accommodates Bakker et al.’s (2016) recommendation for experimental trials and enables ongoing data collection after initial trials have been completed. As such, a battery of pre-intervention surveys was compiled to measure variables of interest. These surveys (summarized in Table 3) are presented to users once again after 30 days to assess the effects of using MoodMission over that period. A demographics survey is also included in the initial surveys.

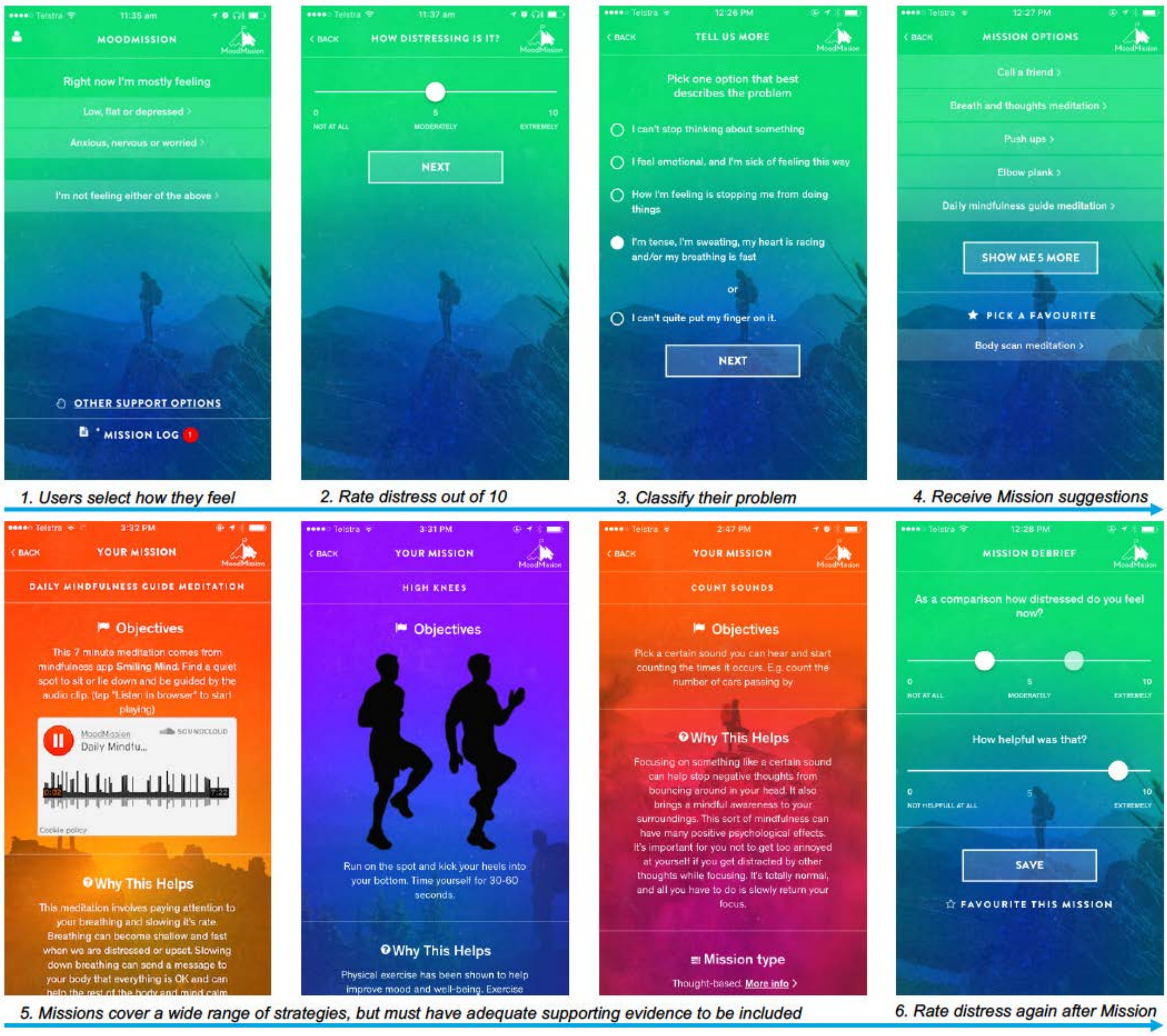


Figure 2. MoodMission sample screens displaying the app's behavioral plan

Table 4
Outcome Surveys Administered in MoodMission

Construct Measured	Name of Measure	Reference	Rationale
Emotional Self-Awareness	Emotional Self-Awareness Scale	(Kauer et al., 2012)	Assess how reflection-focused MoodMission is (see Bakker et al., 2016)
Mental Health Literacy	Mental Health Literacy Questionnaire	No appropriate standardized MHL measure exists, so this questionnaire has been developed by the researchers.	Assess quality of psychoeducation and how education-focused MoodMission is (see Bakker et al., 2016)
Coping Self-Efficacy	Coping Self-Efficacy Scale	(Chesney et al., 2006)	Assess how goal-focused MoodMission is (see Bakker et al., 2016)
Emotional Mental Health	GAD-7 PHQ-9	(Spitzer et al., 2006) (Kroenke et al., 2001)	Assess anxiety and depression symptomatology
Positive Well-being	Warwick-Edinburgh Mental Well-being Scale	(Tennant et al., 2007)	Assess positive psychological functioning and flourishing
Demographics[a]	(self-devised)	(self-devised)	Collect information about users' gender, age, education, and employment status for the benefit of analyses
App Feedback and Engagement[b]	Feedback Questionnaire	Adapted from the Mobile Application Rating Scale (MARS; Hides et al., 2014) by Rickard, Arjmand, Bakker, & Seabrook (2016)	Assess how engaged users are with the app, enabling analyses that correlate engagement with mental health and wellbeing outcomes

[a] Administered only in the initial surveys
[b] Administered only in the 30-day follow-up surveys

MoodMission Usability Evaluation

Once the app's designs were confirmed, a prototype of the app was coded and made available to the developers for initial testing. This process included ensuring that all components from the designs were included, that the interactions proved pleasant and congruent, and that no significant bugs or errors were present. To test the app before it was launched on the App Store, a group of 60 "beta-testers" were recruited to use a pre-release version of MoodMission and provide feedback.

MoodMission was designed to be used in-vivo as participants experienced low moods or anxious feelings throughout their daily lives. This limited the utility of any laboratory-based usability testing methods, in which users engage with the intervention under studied laboratory settings (Jaspers, 2009). Collecting qualitative user reflections and responses on validated self-report usability measures about their experiences using the app was a highly scalable and intervention-appropriate option for informing MoodMission's initial development and ongoing improvements.

The Mobile Application Rating Scale (MARS; Hides et al., 2014; Stoyanov, Hides, Kavanagh, & Wilson, 2016), which was developed to rate mobile health applications, was used as a guide and foundation to determine usability. The guidelines for mobile health (mHealth) evidence reporting and assessment (mERA) checklist (Agarwal et al., 2016) was consulted to ensure that the app's implementation was rigorous and transparently reported.

Method

Participants and recruitment

A total of 44 participants provided feedback about their use of MoodMission. Of these, 13 were beta-testers who were given access to the app before its public release, and 31 were participants in a randomized controlled trial (RCT) who had downloaded MoodMission from the iTunes Store. The beta-testers consisted of individuals who had pledged funds to the crowd-funding campaign that supported the initial development of the iOS app. The RCT participants had voluntarily opted in to a study on MHapps by providing their email address on an online form that had been advertised widely on social media. Like the beta-testers, RCT participants were asked to use MoodMission for the next 30 days before providing feedback as part of an online survey assessment. Participants were not drawn from clinical sources. Ages ranged between 18 and 62 years (M = 36, SD = 13), and 82% were female.

Materials

The User Version of the MARS (uMARS; Stoyanov et al., 2016), is a 26-item measure designed to rate mobile health applications in a standardized, multidimensional way, and is designed for end users rather than experts. Items are rated on a 5-point scale from Inadequate to Excellent, and are classified under six subscales, including Engagement (e.g., is the app interesting to use? Does it present its information in an interesting way compared to other similar apps?), Functionality (e.g., How easy is it to learn how to use the app? How clear are the menu labels, icons and instructions?), Aesthetics (e.g., How good does the app look?), Information (e.g. is the information within the app comprehensive but concise?), Subjective Quality, and App-Specific. Norms for the MARS were developed by analyzing ratings for 50 mental health and wellbeing apps from two expert raters (Hides et al., 2014). Comparing obtained MARS ratings to these scores enables comparison to existing standards for MHapps. The uMARS has high internal consistency, Cronbach's α = .90, and good test-retest reliability, interclass correlation coefficient = .70 after 3 months.

The Homework Rating Scale – Mobile Application Version (HRS-MA; Bakker & Kazantzis, 2017) is a 12 item self-report scale designed to assess engagement and theoretically derived appraisals of CBT strategies used or recommended by MHapps. The HRS-MA contains 12 items (e.g., Quantity: I was able to do the activities, Rationale: The reasons for doing the activities were clear to me), closely modeled on the original HRS

(Kazantzis et al. 2005), rated on a 5-point Likert scale from 0 (*not at all*) to 4 (*completely/extensive/ extremely*). In the present study, the HRS-MA achieved acceptable levels of internal consistency, Cronbach's α = .77, comparable to the original (i.e., Cronbach's α = .85 (Hara, Aviram, Constantino, Westra, & Antony, 2017).

App Design and Content - mERA Checklist

Access of individual participants. The use of nonclinical language in MoodMission is designed to increase the accessibility of the app to individuals who do not identify with having a diagnosed mental illness. However, to be motivated to download the app individuals still have to identify that they have occasional low moods or anxious feelings, and that strategies can help. These are potential barriers to access, so promotional efforts are aimed at reducing them by conveying the normalization message that "everyone has low moods and anxious feelings" and there are interventions that can help. For example, flyers for the app featured the slogan "change the way you feel", and social media posts used inclusive, normalizing language to encourage a "me too" reaction and sharing of posts within individuals' social networks.

Cost assessment. MoodMission is free to download. The costs of maintaining the app, including server fees and developer updates, equate to about AUD$150 per month. Zero equity funding from a start-up accelerator program has been secured to cover these costs for the next 12-24 months. This funding will also support the development of additional features, which will be released as discrete, affordable in-app purchases to secure a self-sustaining revenue stream.

Adoption inputs/program entry. MoodMission is designed to be used by novice, untrained users after downloading directly from the App Store. A series of "onboarding" screens educates the individual on the uses of the app. The app was promoted through social media channels, featured online articles, radio interviews, communications from Monash

University, and blog posts. Care was taken to ensure that MoodMission's website was well designed and made downloading the app very simple, as this was the site linked to from other online promotions. Sending users notifications based on depression-screening measures can enable help-seeking in individuals who would not otherwise seek help (BinDhim et al., 2016), so a notification system was used to suggest mental health contacts and services to individuals who scored above clinical cut-offs on the depression and anxiety measures. These notifications were also delivered when individuals attempted three Missions at high distress and their distress did not significantly decrease following the Mission.

Limitations for delivery at scale. As a completely automated platform, MoodMission is highly accessible at scale. The main limitation to truly global scale is the use of written language and currently only English is supported. As the intervention garners support, the developers and researchers hope that translations can be achieved and multiple languages supported.

Contextual adaptability. The Missions recommended by MoodMission are designed to be achievable across many settings and contexts, and they each take about 5-10 minutes to complete. However, many Missions may not be suitable for contexts where behavior is restricted; for example, when an individual is unable to practice a quick yoga move or go for a walk around the block. Offering a choice of 5-10 Missions overcomes this.

Replicability. Please refer to Figures 1 and 2 for a detailed account of the intervention, which may aid in replicability.

Data security. All data collected by MoodMission are de-identified. Login details, including an email address and password, are stored unlinked to other user data, including survey answers and Mission data. User data are stored using a Firebase backend and hosted on Google's infrastructure. The app WordPress backend is hosted on an Amazon Web Services ec2 server with Linux.

Compliance with national guidelines or regulatory statutes. At the time of writing, there is no regulatory system for MHapps. MoodMission's design has endeavored to follow all current evidence-based recommendations (e.g., Bakker et al., 2016).

Fidelity of the intervention. Dummy accounts were created throughout the testing process to ensure that interactions with the app were being accurately recorded in the backend database. The results presented in this article provide evidence for the utility of MoodMission.

Infrastructure (population level). MoodMission is aimed at engaging typical smartphone users over the age of 12, and 77% of the US population (comScore, 2015), 79% of Australians (Deloitte, 2016b), and 81% of adults in the UK (Deloitte, 2016c) use a smartphone. A survey of Australians revealed that 76% of adult smartphone owners were interested in using MHapps if they are free to download (Proudfoot et al., 2010).

Technology platform. MoodMission was initially developed as an iPhone app for iOS 9 and above. It was coded using hybrid mobile app development and uses a WordPress backend, enabling more streamlined cross-platform development than using native coding. Development of an Android version of the app occurred after the successful launch of the iOS version. MoodMission is now available on both iOS and Android platforms.

Interoperability/ Health information systems (HIS) context. The current version of MoodMission offers no direct integration into existing health systems. However, future proposed developments for the app include a platform for psychologists and mental health practitioners to engage with patients and clients through the app.

Intervention delivery. Individuals access MoodMission when they identify that they are feeling low or anxious. They report how they are feeling and are supplied with 5-10 Mission options. They can review the objectives and rationale for each Mission before accepting it. Following completing the Mission, they again rate how they feel. See Figure 2 for an illustration of this process. While it is possible that individuals may not experience a reduction in distress following a Mission, several design choices were made to help prevent a loss of confidence and subsequent disengagement. Firstly, Missions are not framed as definitive solutions, and are instead suggested as activities that may help out. Secondly, the large diversity of Missions is intended to give individuals hope that there are many options for coping. Thirdly, care was taken to avoid impressions of expected results, so for example, badges and ranks are awarded for completing Missions rather than experiencing decreases in distress. Finally, push notifications are sent to individuals who have stopped using the app after a few days to encourage them to re-engage.

Intervention content. All Missions included in MoodMission have been taken from evidence-based psychotherapies, including but not limited to CBT, acceptance and commitment therapy (ACT; Brown, Glendenning, Hoon, & John, 2016), and dialectical behavior therapy (DBT; Kliem, Kroger, & Kosfelder, 2010). For a Mission to be included, it was required to have at least two good quality sources that established it as an effective strategy for decreasing anxious or depressive symptoms. For example, some Missions are drawn from behavioral activation, which has substantial evidence as an effective treatment for depression from a meta-analysis of 34 studies (Pooled effect size = 0.78, Mazzucchelli et al., 2009). Another meta-analysis of 20 studies found significant effects on improving psychological wellbeing (Pooled effect size = 0.52, Mazzucchelli, Kane, & Rees, 2010). Behavioral activation is made up of many strategies which could be appropriately translated into the MoodMission format, so reliable therapy resources were consulted to extract individual Missions from lists of behavioral activation strategies (e.g. Bakker, 2008; Dobson & Dobson, 2009). Missions in the database were classified as either anxious or depressive, depending on what evidence was available. Classification of Missions determined which were offered when individuals selected their current problem; e.g. only Missions classified as anxious were offered when the individual reported that they were anxious, nervous, or worried.

Procedures

Beta-testing participants downloaded MoodMission to their personal iPhones using app-testing software, before the public release of the app. The other RCT participants downloaded MoodMission from the iTunes Store. Participants were not instructed how to use MoodMission by the researchers, in order to replicate the circumstances by which individuals would naturally access the app throughout their daily routines. They were encouraged to email the researchers if they encountered technical difficulties, such as the app freezing or buttons being unresponsive. Care was taken to be responsive to these emails, and participants were updated about their reported issues and the subsequent software updates that fixed them. Several updates were released for the app throughout both beta-testing and public release phases, but these fixed small technical errors and none altered overall design or functionality. Thirty days after downloading MoodMission participants were emailed with a link to complete a feedback survey, administered by online platform Qualtrics. No identifying information was provided in this survey and because it was administered separately to the app-based surveys, data collected via MoodMission was unable to be paired to online survey responses. The online survey contained the uMARS, the HRS-MA, and several optional text-entry questions relating to the app's specific features. Following completion of the survey, participants were thanked for their time and were encouraged to provide any additional feedback via online form or email.

Results

Quantitative results for usability analysis

Scores obtained on the MARS from 44 users, including 13 beta-testers and 31 study participants, were compared to the established norms (Hides et al., 2014). MoodMission scored higher than the MARS norms across multiple items, as seen in Figure 3 and Table 5.

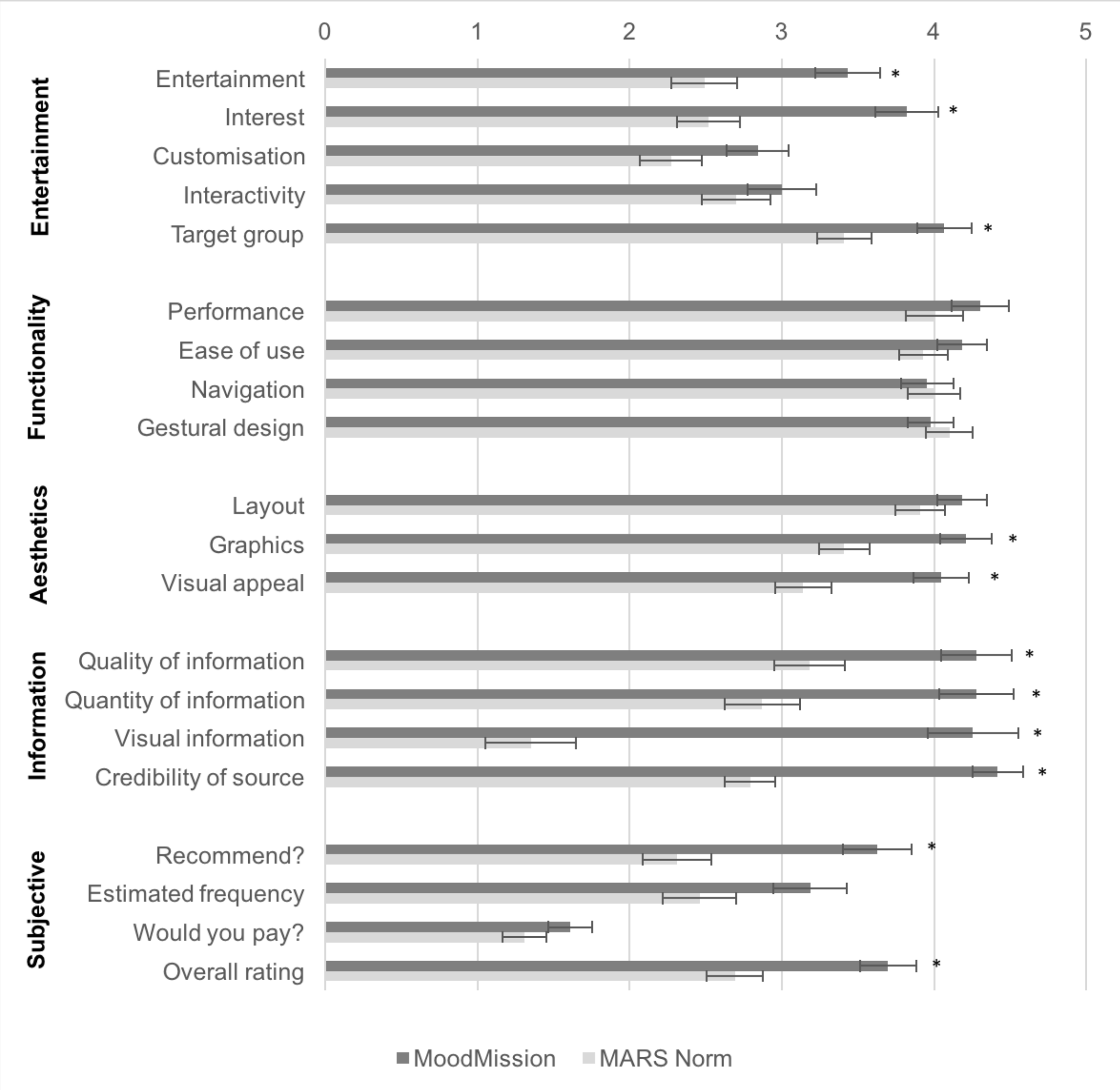


Figure 3. MoodMission MARS scores compared to norms. Error bars represent pooled SD, giving an estimation of 95% confidence intervals with within-subject variance removed. *p<.0025 (Bonferroni corrected p value)

Table 5
Means (SD) of MARS scores for MoodMission and Norms

MARS Item and *Subscale*	**MoodMission (n = 44)**	**MARS Norm (n = 50)**
Entertainment	3.43 (0.81)	2.49 (0.81)
Interest	3.82 (0.78)	2.52 (0.78)
Customization	2.84 (0.80)	2.27 (0.80)
Interactivity	3.00 (0.96)	2.70 (0.96)
Target group	4.06 (0.81)	3.41 (0.81)
Total (Engagement)	3.43 (0.83)	2.67 (0.83)
Performance	4.30 (0.88)	4.00 (0.88)
Ease of use	4.18 (0.69)	3.93 (0.69)
Navigation	3.95 (0.72)	4.00 (0.72)
Gestural design	3.97 (0.67)	4.10 (0.67)
Total (Functionality)	4.10 (0.74)	4.00 (0.74)
Layout	4.18 (0.69)	3.91 (0.69)
Graphics	4.20 (0.70)	3.41 (0.70)
Visual appeal	4.04 (0.87)	3.14 (0.87)
Total (Aesthetics)	4.14 (0.75)	3.48 (0.75)
Quality of information	4.27 (0.70)	3.18 (0.70)
Quantity of information	4.27 (0.76)	2.87 (0.76)
Visual information	4.25 (0.87)	1.35 (0.87)
Credibility of source	4.41 (0.66)	2.79 (0.66)
Total (Information)	4.3 (0.75)	2.54 (0.75)
Recommend?	3.62 (1.02)	2.31 (1.02)
Estimated frequency	3.18 (1.20)	2.46 (1.20)
Would you pay?	1.6 (0.77)	1.31 (0.77)
Overall rating	3.69 (0.70)	2.69 (0.70)

Twenty Bonferroni-corrected two-way independent samples *t*-tests (α = .0025) were performed for each comparison to establish significance, and Table 6 displays the results. Hedges *g* was used as a measure of effect size, given the unequal sample sizes between the normative data and the collected data (Cumming, 2011). MoodMission scored significantly higher than the norms on the following items: Entertainment (*g* = 0.89), Interest (*g* = 1.26), Customization (*g* = 0.57), Target Group (*g* = 0.75), Graphics (*g* = 0.97), Visual Appeal (*g* = 1.02), Quality of Information (*g* = 0.94), Quantity of Information (*g* = 1.14), Visual Information (*g* = 1.93), Credibility of Source (*g* = 1.97), Recommendation to Use (*g* = 1.19), Estimated Frequency of Use (*g* = 0.63), and Overall Rating (*g* = 1.10). No significant differences from the norm ratings were observed in the remaining items.

Table 6
Results of t-Tests Comparing MoodMission MARS Scores to MARS Norms

	t	*p*	Hedge's *g*
Entertainment	4.39	<0.001	0.89
Interest	6.27	<0.001	1.26
Customization	2.81	0.006	0.57
Interactivity	1.33	0.187	0.27
Target group	3.65	<0.001	0.75
Performance	1.61	0.110	0.33
Ease of use	1.58	0.117	0.32
Navigation	-0.27	0.787	-0.06
Gestural design	-0.82	0.416	-0.17
Layout	1.70	0.092	0.35
Graphics	4.75	<0.001	0.97
Visual appeal	4.93	<0.001	1.02
Quality of information	4.74	<0.001	0.94
Quantity of information	5.72	<0.001	1.14
Visual information	9.75	<0.001	1.93
Credibility of source	9.73	<0.001	1.97
Would you recommend the app?	5.82	<0.001	1.19
Estimated frequency of use	3.02	0.003	0.63
Would you pay for the app?	2.08	0.040	0.44
Overall rating	5.48	<0.001	1.10

Note: *df* = 92 for all comparisons.

Twenty-three participants completed the HRS-MA following the MARS: 96% reported that they were able to do some or more of the activities; 91% reported that they were able do the activities moderately well or better; 65% found the activities not at all or somewhat difficult, and 26% rated them as moderately difficult; 70% reported that they had no or little obstacles in doing the activities, and 22% had some obstacles; 96% reported that they understood the activities a lot or completely; 61% understood the rationale for the activities very or completely, with the remaining 39% understanding the rationale moderately; 78% reported that they had some, a lot, or extensive collaboration in planning the activities; 61% reported that the guidelines for carrying out the activities were very or extremely specific, and a further 30% reported that they were moderately specific; 43% agreed a lot or completely that the activities matched their goals for using the app, 30% agreed somewhat, and 22% agreed a little; 43% enjoyed the activities a lot or extremely, 30% enjoyed them somewhat, and 13% enjoyed them a little; 66% reported that the activities helped them somewhat, a lot, or extensively gain a sense of control over their problems, and 22% reported a little gain in control over their problems; and 78% reported that the activities helped somewhat, a lot, or extremely with their progress in using the app.

Qualitative results

Of the 44 participants, 20 (12 beta-testers and 8 RCT participants) provided qualitative feedback via text-entry responses on the online surveys or email. Several themes from these messages were noted, and feedback-informed improvements were made to the app.

Surveys. Participants commented on the length of the surveys and the difficulty they had in feeling motivated to complete them. Some participants also had problems with the interface, as sliders and buttons behaved unpredictably. The interface issues were tuned, and priority was given to removal of the surveys following the research phase of the app's development.

Missions. Participants reported that they enjoyed the Missions, particularly their speed, ease, and emotional relevance. Participants who had experience with mental health services reported that the app helped them discover new mental health strategies or reinforced existing ones. Suggestions were noted to make the Missions more interactive and illustrative (e.g. on screen animations to guide breathing exercises).

Design. Participants reported that they liked the visual and interface design of the app. The Achievements and Stats features were not well understood, so plans were made to make these features more accessible. Some persisting bugs were noted, and plans made to rectify them in future versions.

Overall Impressions. Participants reported that using the app made them more conscious of their mental health, and using nonclinical language was helpful in making the app's messages accessible. However, others suggested that the lack of clinical language avoided addressing the stigma surrounding psychiatric or medication terms, and including psychoeducation about biological and chemical components of mental health problems may help individuals. One participant left the following feedback: "It is really comforting to know that I have MoodMission on my phone as a resource when things get tough. I know it's not connecting me with a real professional/someone to actually talk to in real time, but it serves the equally valuable purpose of just being able to find some helpful strategies to approach challenging times without bothering friends at 1am in the morning; an app doesn't have "bed time" nor is it judgmental. Oddly, in that respect, you can trust an app and feel free to use it anytime. I want to keep using it and finish my goals."

Case Examples

Two constructed case examples are presented below, based on participant reports and the vignettes that informed the app's design process. Each reflects how the app can be used in a different context, but it should be noted that the app can be used in many more contexts than just these listed. For example, the app could be used in group therapy contexts, in hospitals, or in workplaces.

Case 1: Use in Individual Therapy

"Jake" is a 25 year old male undergoing CBT for anxiety. Jake and his therapist decide that it would be useful for Jake to practice progressive muscle relaxation, and Jake's therapist coaches him through the exercise in therapy so Jake can continue practicing at home. However, at the next session, Jake admits that he did not practice the relaxation strategy for a number of different reasons, including his lack of alone time, feeling too anxious to begin the exercise, and ultimately his skepticism that it would work. The therapist could troubleshoot these issues with Jake and develop a new plan for relaxation, or they could coach him through the downloading and use of MoodMission.

Jake uses apps on his phone regularly so is receptive to the idea of using MoodMission. While in the therapy session, he downloads the app and his therapist points out the app's features and uses. Leaving the session, Jake opens MoodMission when he's feeling anxious. He rates his anxiety 7/10, chooses "I can't stop thinking about something" to indicate his anxiety is mainly thought-based, and the app provides a tailored list of suggested strategies. The list gives Jake a choice, so he chooses the one that he feels is most achievable and suits his circumstances. This is the "This situation won't last forever" Mission, which involves him repeating the phrase in his head, applying it to his current situation, and writing it down as a reminder. He feels like this is a little helpful, and when finished rates his distress as slightly lower at 6/10.

The second time Jake uses MoodMission he reports feeling anxious at 8/10, again with anxious thoughts, but this time chooses the "Sit ups" Mission, which involves him doing 20 sit ups. After completing this he rates his distress as 5/10, as performing a short burst of physical exercise was particularly helpful for him to shake his anxious thoughts. The third time Jake uses MoodMission he reports 7/10 thought-based anxiety. The app suggests a few more physical-based Missions than the other categories, as past success indicates that these were helpful for Jake.

When Jake returns to his therapist, he opens MoodMission and shows his therapist his Mission Log. They review each Mission completed and Jake's therapist asks him a few questions about his experiences performing each Mission. Jake has discovered new coping options for him to reduce his anxiety, and his therapist has discovered that physical strategies, such as exercise, will be particularly useful for Jake progressing in therapy.

For Jake, using an app like MoodMission helped him discover a range of alternative coping options that were more achievable than progressive muscle relaxation. Jake's failure in completing the progressive muscle relaxation homework may have increased his sense of hopelessness, reinforcing the belief that relaxing is "too hard". Even if some of the Missions attempted by Jake were not successful at reducing his anxiety, the broad range of strategies on offer increase the likelihood that Jake will be hopeful to find something that works for him. MoodMission provided him psychoeducation about each strategy, giving him a rationale to engage. Reviewing his progress in the Mission Log, alone and with his therapist, enabled him to gain more self-insight and motivation to continue making therapeutic change.

Case 2: Use Outside of Therapy

"Annabel" is a 19-year-old female who has just started an undergraduate university degree. She has no history of mental health issues and does not know when or how she would seek help if she had a mental health related problem. She has moved away from her hometown and is now living in a residential college on campus. As she settles in to her new routine, she realizes that some of the things she used to enjoy doing are no longer available to her. She used to look forward to dinner table discussions with her siblings and parents at the end of the day, and she used to play sport on the weekends. Combined with the new stresses of college social life, starting a degree, and being in an unfamiliar place, she starts to feel quite down on herself. A flyer in her orientation pack mentions MoodMission as something that may help, so she downloads the app and reports feeling low. MoodMission suggests a list of strategies that she tries out and after a few she discovers that doing a short productive chore, like a load of laundry or cleaning her room, helps her feel better about herself. In this example, MoodMission has engaged Annabel in light mastery-based behavioral activation.

As the semester progresses Annabel is doing OK, but she experiences a particularly bad episode of low mood and anxiety in the week following exams. She attempts a few Missions on MoodMission, and due to her persistently high distress scores the app suggests that she visit her doctor about getting support. She sees her doctor who refers her to a therapist for treatment. With this therapist she is able to review her progress with MoodMission, so therapy can be efficiently tailored to her demonstrated strengths. In this example, Annabel is introduced to concepts of mental health self-care, she discovers new context-appropriate strategies for improving her mood, she is prompted to seek clinical support when it would be useful, and the start of her therapy is enhanced by her Mission Log data.

For Annabel, the mere promotional flyer for MoodMission serves as an acknowledgment that mental health is “real”, and self-care is a helpful skill to develop. Using the app, she is able to reframe “boring” chores as important self-care achievements. This improves her understanding of the relationship between mood and activity levels. During her depressive episode, she struggles to experience improvements from the Missions, but is encouraged to seek help early, providing an earlier intervention therapeutic advantage. The app improves her help seeking by reducing barriers of uncertainty (e.g. “Should I see a therapist?” “How do I even arrange therapy?”), and reviewing her Mission Log improves the efficiency of the therapist’s assessment.

Discussion

The purpose of this paper was to outline the development phases of a CBT-based MHapp for managing low moods and anxiety, and recommend future applications of this tool. The app development drew on recently published recommendations (Bakker et al., 2016) to optimize tailoring for individual users, incorporation of data collection capacity, and the use of validated CBT principles. The resulting app, MoodMission, successfully achieved this aim, with the delivery of an engaging CBT-based MHapp based in evidence-based principles. This app was successfully developed, tested, and released on the Apple iTunes Store. Preliminary testing revealed that MoodMission was rated superior to other health apps in terms of entertainment, aesthetics, and information. MoodMission has several anticipated applications across both clinical and research domains.

MoodMission could have many applications in both public and private health sectors as a clinical and preventative tool. MoodMission is an easily accessible, intuitive tool that does not require introduction by a health practitioner. General practitioners, counselors, social workers, and other professionals are able to recommend the use of MoodMission to at-risk populations. The flexibility of MoodMission allows it to cover most kinds of low mood and anxious distress, and built-in alerts recommend accessing professional mental health support if an individuals' responses indicate sufficient severity.

Tang and Kreindler (2017) outline features of MHapps that can be used for the tracking, encouragement, and compliance of homework activities in CBT. MoodMission has features that meet each of the six recommendations: congruency to therapy, fostering learning, guiding therapy, building connections, emphasizing completion, and population specificity. Future work will focus on ways of integrating MoodMission into the practices of CBT clinicians so the app can be used collaboratively to set and review homework.

A firm evidence base establishing the effectiveness and efficacy of MoodMission is required to enable adoption by health professionals. At the time of writing, MoodMission has one RCT in progress investigating its efficacy in improving mental health, positive wellbeing, emotional self-awareness, mental health literacy, and coping self-efficacy. MoodMission also collects effectiveness data from every individual who completes the in-built assessment surveys. Using frequency of use as a variable allows controlled investigation of the app's effects on mental health and wellbeing, as described by Carpenter et al. (2016) for analysis of data from wellbeing app Happify. It is anticipated that future publication of the RCT and the effectiveness data will support MoodMission and other similar MHapps as efficacious and effective self-guided mental health tools.

MoodMission also holds promise as a way of investigating research questions beyond the effects of the app itself. In addition to outcome data collected via surveys, MoodMission collects data that can be used to investigate the effectiveness of specific Missions. Comparing the pre-mission and post-mission distress scores for specific Missions may reveal how effective they are at reducing specific types of distress. This would enable objective comparison between two similar psychological techniques for the same type of distress. Findings could inform therapeutic work done by clinical psychologists and guide them to encourage the most effective evidence-based techniques for their clients' unique distress.

A distinct benefit that MoodMission can afford researchers of different psychological therapies is component analysis. Therapies are made up of collections of techniques and strategies (Mennin, Ellard, Fresco, & Gross, 2013). For example, CBT interventions for panic disorder may include components of exposure, relaxation, and cognitive restructuring (Craske & Barlow, 2014). However, evidence for specific strategies within evidence-based interventions is lacking. This is in part due to methodological limitations, as most studies of CBT treat large groups of participants with different intervention variants, and variation is on the macro level rather than the micro, strategy-based level. MoodMission enables ecologically valid comparisons between each of these components to identify those with the greatest impact on distress and anxiety symptomatology. Furthermore, strategies can be assessed on their preventative power, and their effects on individuals without identifiable clinical disorders. In the case of panic disorder, data from users' anxious thought-based problems could be parceled out and distress score differences could be compared between a mindfulness body scan meditation and a similar simple relaxation exercise. Component analysis research is often confined to strictly controlled situations in which participants receive slightly adjusted versions of the same therapy (e.g. Borkovec, Newman, Pincus, & Lytle, 2002; Jacobson et al., 1996; Linehan et al., 2015). Such research is resource intensive and is only able to compare two or three different techniques at a time. MoodMission allows easier component analysis across a wide range of very different therapeutic techniques to find the most efficient, effective treatments of low mood and anxiety.

The artificial or controlled settings of many laboratory- or clinic-based studies may reduce the ecological validity of findings concerning the effectiveness of certain distress-reduction strategies. For example, recall biases may limit participants' ability to accurately recall levels of distress or the effectiveness of coping strategies hours or days after experiencing the distress (Shiffman, Stone, & Hufford, 2008). MoodMission allows participants to record their distress in the moment that they are experiencing it and rate the effectiveness of strategies immediately after they are used. This reduces recall biases and provides participants with immediate feedback of how helpful strategies are.

Most studies that use therapists to deliver different modes of therapy are inherently influenced by a practitioner's skill level for particular modes of therapy (Lambert, 1989; Westen, Novotny, & Thompson-Brenner, 2004). For example, one therapist may prefer cognitive restructuring over imaginal exposure in their own practice, so when they are involved in a study that compares the two therapeutic modes, they are likely to present cognitive restructuring with more skill than other experimental conditions. MoodMission bypasses these presentation biases by presenting all therapeutic techniques in a consistent fashion.

While MoodMission was designed to be appropriate for all smartphone users over the age of 12, some specific age groups and demographics may derive more benefit than others. For example, the needs of undergraduate university students aged 18-25, like Annabel from Case 2, are particularly compatible with MoodMission's features. These young adults are often exposed to new, stressful situations, and relied upon coping mechanisms may have recently become inconvenient or inappropriate. Teaching flexible, evidence-based coping strategies may have a protective effect for this demographic, potentially preventing the onset of mental health issues at this critical life stage. This age group also has a high rate of smartphone usage, making MoodMission suitable for both clinical and research applications.

Research that investigates models of therapy often uses clinical samples made up of individuals who qualify for some sort of diagnosis or achieve a certain score on a measure of symptoms (Henry & Crawford, 2005). MoodMission allows for inclusion of both clinical and nonclinical samples, as individuals do not need a diagnosis to engage with the intervention. MoodMission is therefore capable of investigating both the clinical and preventative utility of mental health interventions, as well as how different individuals engage with these interventions.

This study was limited by the relatively small sample size and the non-invasive assessment methods used. However, this was a pilot evaluation to prepare MoodMission for public release, and planned future studies aim to collect data from much larger and more representative samples of participants who are using the app in a wider variety of situations. Future studies will also aim to collect in-depth user cases, increasing the resolution and comprehensiveness of the assessments to collect richer data about individuals' experiences using the app.

There is a balance in app development between: (a) releasing a prototype app and making fixes as user feedback is received, and (b) conducting extensive in-house testing before releasing it to the public. The risk with option (a) in the above is that provoking frustration in users who are expecting a fully functional product, while the risk with option (b) is the public may disagree with many of the choices of the in-house team, and the app may need major adjustment. Traditionally, psychologists have designed CBT interventions with patient feedback informing changes after implementation. However, the self-guided nature of MHapps increases the utility of user feedback. This project aimed to achieve a compromise between options (a) and (b), but there is a possibility that more user involvement at the very early stages of design and development may have increased the utility of MoodMission.

In conclusion, MoodMission is a mental health smartphone app, built using evidence-based therapeutic techniques, that aims to build its own evidence base as an effective intervention. It was designed using recommendations from Bakker et al. (2016) informing a behavioral plan using a trigger, action, reward, investment loop (Eyal, 2014). There are many potential therapeutic and research uses for MoodMission, and it is anticipated that these applications will be developed and evaluated over the coming years.

References

Agarwal, S., LeFevre, A. E., Lee, J., L'Engle, K., Mehl, G., Sinha, C., & Labrique, A. (2016). Guidelines for reporting of health interventions using mobile phones: mobile health (mHealth) evidence reporting and assessment (mERA) checklist. *BMJ, 352*, i1174. https://doi.org/10.1136/bmj.i1174

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review*, *30*(2), 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

Andrews, G., Cuijpers, P., Craske, M. G., McEvoy, P., & Titov, N. (2010). Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: A meta-analysis. *PLoS ONE*, *5*, e13196. https://doi.org/10.1371/journal.pone.0013196

Andrews, G., & Williams, A. D. (2014). Internet psychotherapy and the future of personalized treatment. *Depression and Anxiety*, *31*(11), 912–915. https://doi.org/10.1002/da.22302

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2016). Mental health smartphone apps: Review and evidence-based recommendations for future developments. *JMIR Mental Health*, *3*, e7. https://doi.org/10.2196/mental.4984

Bakker, G. (2008). *Practical CBT: Using functional analysis and standardised homework in everyday therapy*. Bowen Hills, Qld.: Australian Academic Press.

Ballegooijen, W. van, Cuijpers, P., Straten, A. van, Karyotaki, E., Andersson, G., Smit, J. H., & Riper, H. (2014). Adherence to internet-based and face-to-face cognitive behavioural therapy for depression: A meta-analysis. *PLoS One*, *9*, e100674. https://doi.org/10.1371/journal.pone.0100674

Beck, J. S. (2011). *Cognitive behavior therapy: Basics and beyond* (2nd ed.). New York: The Guilford Press.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, *29*(5), 585–609. https://doi.org/10.1016/j.jbusvent.2013.07.003

BinDhim, N. F., Alanazi, E. M., Aljadhey, H., Basyouni, M. H., Kowalski, S. R., Pont, L. G., … Alhawassi, T. M. (2016). Does a mobile phone depression-screening app motivate mobile phone users with high depressive symptoms to seek a health care professional's help? *Journal of Medical Internet Research*, *18*(6), e156. https://doi.org/10.2196/jmir.5726

Bolognesi, F., Baldwin, D. S., & Ruini, C. (2014). Psychological interventions in the treatment of generalized anxiety disorder: A structured review. *Journal of Psychopathology*, *20*(2), 111–126.

Borkovec, T. D., Newman, M. G., Pincus, A. L., & Lytle, R. (2002). A component analysis of cognitive-behavioral therapy for generalized anxiety disorder and the role of interpersonal problems. *Journal of Consulting and Clinical Psychology*, *70*(2), 288–298. https://doi.org/10.1037/0022-006X.70.2.288

Bower, P., & Gilbody, S. (2005). Stepped care in psychological therapies: access, effectiveness and efficiency. *The British Journal of Psychiatry*, *186*(1), 11–17. https://doi.org/10.1192/bjp.186.1.11

Brown, M., Glendenning, A., Hoon, A. E., & John, A. (2016). Effectiveness of web-delivered acceptance and commitment therapy in relation to mental health and well-being: A systematic review and meta-analysis. *Journal of Medical Internet Research*, *18*(8). https://doi.org/10.2196/jmir.6200

Butler, A. C., Chapman, J. E., Forman, E. M., & Beck, A. T. (2006). The empirical status of cognitive-behavioral therapy: A review of meta-analyses. *Clinical Psychology Review*, *26*(1), 17–31. https://doi.org/10.1016/j.cpr.2005.07.003

Carpenter, J., Crutchley, P., Zilca, R. D., Schwartz, H. A., Smith, L. K., Cobb, A. M., & Parks, A. C. (2016). Seeing the "big" picture: Big data methods for exploring relationships between usage, language, and outcome in internet intervention data. *Journal of Medical Internet Research*, *18*(8), e241. https://doi.org/10.2196/jmir.5725

Chesney, M. A., Neilands, T. B., Chambers, D. B., Taylor, J. M., & Folkman, S. (2006). A validity and reliability study of the coping self-efficacy scale. *British Journal of Health Psychology*, *11*, 421–437. https://doi.org/10.1348/135910705X53155

Comello, M. L. G., Qian, X., Deal, A. M., Ribisl, K. M., Linnan, L. A., & Tate, D. F. (2016). Impact of game-inspired infographics on user engagement and information processing in an eHealth program. *Journal of Medical Internet Research*, *18*(9), e237. https://doi.org/10.2196/jmir.5976

comScore. (2015). *comScore Reports March 2015 U.S. Smartphone Subscriber Market Share*. Retrieved from http://www.comscore.com/Insights/Market-Rankings/comScore-Reports-March-2015-US-Smartphone-Subscriber-Market-Share

Cooney, G. M., Dwan, K., Greig, C. A., Lawlor, D. A., Rimer, J., Waugh, F. R., … Mead, G. E. (2013). Exercise for depression. *Cochrane Database of Systematic Reviews*, *9*, CD004366. https://doi.org/10.1002/14651858.CD004366.pub6

Craske, M. G., & Barlow, D. H. (2014). Panic disorder and agoraphobia. In D. H. Barlow (Ed.), *Clinical handbook of psychological disorders: A step-by-step treatment manual* (5th ed., pp. 1–61). New York: Guilford Publications.

Cuijpers, P., Berking, M., Andersson, G., Quigley, L., Kleiboer, A., & Dobson, K. S. (2013). A meta-analysis of cognitive-behavioural therapy for adult depression, alone and in comparison with other treatments. *Canadian Journal of Psychiatry, 58*(7), 376–385. https://doi.org/10.1177/070674371305800702

Cumming, G. (2011). *Understanding the new statistics: Effect sizes, confidence intervals, and meta-analysis*. New York: Routledge.

Dahne, J., Kustanowitz, J., & Lejuez, C. W. (2017). Development and preliminary feasibility study of a brief behavioral activation mobile application (Behavioral Apptivation) to be used in conjunction with ongoing therapy. *Cognitive and Behavioral Practice*. https://doi.org/10.1016/j.cbpra.2017.05.004

Dear, B. F., Staples, L. G., Terides, M. D., Fogliati, V. J., Sheehan, J., Johnston, L., … Titov, N. (2016). Transdiagnostic versus disorder-specific and clinician-guided versus self-guided internet-delivered treatment for Social Anxiety Disorder and comorbid disorders: A randomized controlled trial. *Journal of Anxiety Disorders*, *42*, 30–44. https://doi.org/10.1016/j.janxdis.2016.05.004

Deloitte. (2016a). 2016 Global mobile consumer survey: US edition | Deloitte US. Retrieved March 5, 2017, from https://www2.deloitte.com/us/en/pages/technology-media-and-telecommunications/articles/global-mobile-consumer-survey-us-edition.html

Deloitte. (2016b). *Mobile Consumer Survey 2015 – The Australian Cut*. Retrieved from http://landing.deloitte.com.au/rs/761-IBL-328/images/deloitte-au-tmt-mobile-consumer-survey-2015-291015.pdf

Deloitte. (2016c). *There's no place like phone: Consumer usage patterns in the era of peak smartphone*. Retrieved from http://www.deloitte.co.uk/mobileuk/

Dèttore, D., Pozza, A., & Andersson, G. (2015). Efficacy of technology-delivered cognitive behavioural therapy for OCD versus control conditions, and in comparison with therapist-administered CBT: Meta-analysis of randomized controlled trials. *Cognitive Behaviour Therapy*, *44*(3), 190–211. https://doi.org/10.1080/16506073.2015.1005660

Dirmaier, J., Liebherz, S., Sänger, S., Härter, M., & Tlach, L. (2016). Psychenet.de: Development and process evaluation of an e-mental health portal. *Informatics for Health and Social Care*, *41*(3), 267–285. https://doi.org/10.3109/17538157.2015.1008486

Dobson, D., & Dobson, K. S. (2009). *Evidence-based practice of cognitive-behavioral therapy*. New York: The Guilford Press.

Donker, T., Petrie, K., Proudfoot, J., Clarke, J., Birch, M.-R., & Christensen, H. (2013). Smartphones for smarter delivery of mental health programs: A systematic review. *Journal of Medical Internet Research*, *15*, e247. https://doi.org/10.2196/jmir.2791

Dubad, M., Winsper, C., Meyer, C., Livanou, M., & Marwaha, S. (2017). A systematic review of the psychometric properties, usability and clinical impacts of mobile mood-monitoring applications in young people. *Psychological Medicine*, 1–21. https://doi.org/10.1017/S0033291717001659

Ellard, K. K., Fairholme, C. P., Boisseau, C. L., Farchione, T. J., & Barlow, D. H. (2010). Unified protocol for the transdiagnostic treatment of emotional disorders: Protocol development and initial outcome data. *Cognitive and Behavioral Practice*, *17*(1), 88–101. https://doi.org/10.1016/j.cbpra.2009.06.002

Eyal, N. (2014). *Hooked: How to build habit-forming products*. Penguin Group US.

Fernandez, E., Salem, D., Swift, J. K., & Ramtahal, N. (2015). Meta-analysis of dropout from cognitive behavioral therapy: Magnitude, timing, and moderators. *Journal of Consulting and Clinical Psychology*, *83*(6), 1108–1122. https://doi.org/10.1037/ccp0000044

Firth, J., Torous, J., Nicholas, J., Carney, R., Pratap, A., Rosenbaum, S., & Sarris, J. (2017a). The efficacy of smartphone-based mental health interventions for depressive symptoms: A meta-analysis of randomized controlled trials. *World Psychiatry*, *16*(3), 287–298. https://doi.org/10.1002/wps.20472

Firth, J., Torous, J., Nicholas, J., Carney, R., Rosenbaum, S., & Sarris, J. (2017b). Can smartphone mental health interventions reduce symptoms of anxiety? A meta-analysis of randomized controlled trials. *Journal of Affective Disorders*, *218*(Supplement C), 15–22. https://doi.org/10.1016/j.jad.2017.04.046

Franklin, J. C., Fox, K. R., Franklin, C. R., Kleiman, E. M., Ribeiro, J. D., Jaroszewski, A. C., … Nock, M. K. (2016). A brief mobile app reduces nonsuicidal and suicidal self-injury: Evidence from three randomized controlled trials. *Journal of Consulting and Clinical Psychology*, *84*(6), 544–557. https://doi.org/10.1037/ccp0000093

Garg, R., & Telang, R. (2012). Inferring app demand from publicly available data. *MIS Quarterly, Forthcoming*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1924044

Google. (2016). *How people use their devices: What marketers need to know*. Retrieved from https://www.thinkwithgoogle.com/advertising-channels/mobile/device-use-marketer-tips/

Grist, R., Porter, J., & Stallard, P. (2017). Mental health mobile apps for preadolescents and adolescents: A systematic review. *Journal of Medical Internet Research*, *19*(5), e176. https://doi.org/10.2196/jmir.7332

Hara, K. M., Aviram, A., Constantino, M. J., Westra, H. A., & Antony, M. M. (2017). Therapist empathy, homework compliance, and outcome in cognitive behavioral therapy for generalized anxiety disorder: partitioning within- and between-therapist effects. *Cognitive Behaviour Therapy*, *46*(5), 375–390. https://doi.org/10.1080/16506073.2016.1253605

Hayes, S. C., & Hofmann, S. G. (2017). The third wave of cognitive behavioral therapy and the rise of process-based care. *World Psychiatry*, *16*(3), 245–246. https://doi.org/10.1002/wps.20442

Hayes, S. C., & Hofmann, S. G. (Eds.). (2018). *Process-based CBT: The science and core clinical competencies of Cognitive Behavioral Therapy* (1 edition). Oakland CA: New Harbinger.

Headspace. (2015). Headspace: Meditation techniques for mindfulness, stress relief & peace of mind (Version 2.4) [Mobile application software]. Retrieved from https://itunes.apple.com/au/app/headspace-meditation-techniques/id493145008?mt=8

Henry, J. D., & Crawford, J. R. (2005). The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample. *British Journal of Clinical Psychology*, *44*(2), 227–239. https://doi.org/10.1348/014466505X29657

Hides, L., Kavanagh, D. J., Zelenko, O., Tjondronegoro, D., Stoyanov, S. R., & Cockshaw, W. (2015). *Ray's Night Out: A new iPhone app targeting alcohol use in young people*. Retrieved from https://www.youngandwellcrc.org.au/knowledge-hub/publications/raysnightout/

Hides, L., Kavanagh, D., Stoyanov, S., Zelenko, O., Tjondronegoro, D., & Mani, M. (2014). *Mobile application rating scale (MARS)*. Abbotsford, Victoria, AUS: Young and Well Cooperative Research Centre.

Hofmann, S. G., Sawyer, A. T., Witt, A. A., & Oh, D. (2010). The effect of mindfulness-based therapy on anxiety and depression: A meta-analytic review. *Journal of Consulting*, *78*, 169–183. https://doi.org/10.1037/a0018555

Holdsworth, E., Bowen, E., Brown, S., & Howat, D. (2014). Client engagement in psychotherapeutic treatment and associations with client characteristics, therapist characteristics, and treatment factors. *Clinical Psychology Review*, *34*(5), 428–450. https://doi.org/10.1016/j.cpr.2014.06.004

Jacobson, N. S., Dobson, K. S., Truax, P. A., Addis, M. E., Koerner, K., Gollan, J. K., … Prince, S. E. (1996). A component analysis of cognitive-behavioral treatment for depression. *Journal of Consulting and Clinical Psychology*, *64*(2), 295–304. https://doi.org/10.1037/0022-006X.64.2.295

Jaspers, M. W. M. (2009). A comparison of usability methods for testing interactive health technologies: Methodological aspects and empirical evidence. *International Journal of Medical Informatics*, *78*(5), 340–353. https://doi.org/10.1016/j.ijmedinf.2008.10.002

Jones, N., & Moffitt, M. (2016). Ethical guidelines for mobile app development within health and mental health fields. *Professional Psychology: Research and Practice*, *47*(2), 155–162. https://doi.org/10.1037/pro0000069

Kauer, S. D., Reid, S. C., Crooke, A. H. D., Khor, A., Hearps, S. J. C., Jorm, A. F., … Patton, G. (2012). Self-monitoring using mobile phones in the early stages of adolescent depression: Randomized controlled trial. *Journal of Medical Internet Research*, *14*, e67. https://doi.org/10.2196/jmir.1858

Kazantzis, N. (2017). Introduction to the special issue on processes of cognitive behavioral therapy: Does "necessary, but not sufficient" still capture it? *Cognitive Therapy and Research*.

Kazantzis, N., Brownfield, N. R., Mosely, L., Usatoff, A. S., & Flighty, A. J. (2017). Homework in Cognitive Behavioral Therapy: A Systematic Review of Adherence Assessment in Anxiety and Depression (2011–2016). *Psychiatric Clinics of North America*, *40*(4), 625–639. https://doi.org/10.1016/j.psc.2017.08.001

Kazantzis, N., Deane, F. P., & Ronan, K. R. (2005). Assessment of homework completion. In N. Kazantzis, F. P. Deane, K. R. Ronan, & L. L'Abate (Eds.), *Using homework assignments in cognitive behavior therapy* (pp. 103–122). New York: Routledge.

Kazantzis, N., Whittington, C., Zelencich, L., Kyrios, M., Norton, P. J., & Hofmann, S. G. (2016). Quantity and quality of homework compliance: A meta-analysis of relations with outcome in cognitive behavior therapy. *Behavior Therapy*, *47*(5), 755–772. https://doi.org/10.1016/j.beth.2016.05.002

Kinderman, P., Hagan, P., King, S., Bowman, J., Chahal, J., Gan, L., … Tai, S. (2016). The feasibility and effectiveness of Catch It, an innovative CBT smartphone app. *British Journal of Psychiatry Open*, *2*(3), 204–209. https://doi.org/10.1192/bjpo.bp.115.002436

Kliem, S., Kroger, C., & Kosfelder, J. (2010). Dialectical behavior therapy for borderline personality disorder: A meta-analysis using mixed-effects modeling. *Journal of Consulting and Clinical Psychology*, *78*(6), 936–951. https://doi.org/10.1037/a0021015

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*, 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kuester, A., Niemeyer, H., & Knaevelsrud, C. (2016). Internet-based interventions for posttraumatic stress: A meta-analysis of randomized controlled trials. *Clinical Psychology Review*, *43*, 1–16. https://doi.org/10.1016/j.cpr.2015.11.004

Lambert, M. J. (1989). The individual therapist's contribution to psychotherapy process and outcome. *Clinical Psychology Review, 9*(4), 469–485. https://doi.org/10.1016/0272-7358(89)90004-4

Lambrecht, A., Goldfarb, A., Bonatti, A., Ghose, A., Goldstein, D. G., Lewis, R., … Yao, S. (2014). How do firms make money selling digital goods online? *Marketing Letters*, *25*(3), 331–341.

Layard, R., & Clark, D. (2014). *Thrive: The power of evidence-based psychological therapies*. London: Penguin UK.

Linehan, M. M., Korslund, K. E., Harned, M. S., Gallop, R. J., Lungu, A., Neacsiu, A. D., … Murray-Gregory, A. M. (2015). Dialectical behavior therapy for high suicide risk in individuals with borderline personality disorder: A randomized clinical trial and component analysis. *JAMA Psychiatry, 72*(5), 475–482. https://doi.org/10.1001/jamapsychiatry.2014.3039

Luxton, D. D., McCann, R. A., Bush, N. E., Mishkind, M. C., & Reger, G. M. (2011). mHealth for mental health: Integrating smartphone technology in behavioral healthcare. *Professional Psychology: Research and Practice, 42*(6), 505–512. https://doi.org/10.1037/a0024485

Manzoni, G., Pagnini, F., Castelnuovo, G., & Molinari, E. (2008). Relaxation training for anxiety: a ten-years systematic review with meta-analysis. *BMC Psychiatry, 8*(1), 41. https://doi.org/10.1186/1471-244X-8-41

Mazzucchelli, T., Kane, R., & Rees, C. (2009). Behavioral activation treatments for depression in adults: A meta-analysis and review. *Clinical Psychology: Science and Practice*, *16*(4), 383–411. https://doi.org/10.1111/j.1468-2850.2009.01178.x

Mazzucchelli, T., Kane, R. T., & Rees, C. S. (2010). Behavioral activation interventions for well-being: A meta-analysis. *The Journal of Positive Psychology*, *5*(2), 105–121. https://doi.org/10.1080/17439760903569154

Mennin, D. S., Ellard, K. K., Fresco, D. M., & Gross, J. J. (2013). United we stand: Emphasizing commonalities across cognitive-behavioral therapies. *Behavior Therapy*, *44*, 234–248. https://doi.org/10.1016/j.beth.2013.02.004

Newby, J. M., Twomey, C., Yuan Li, S. S., & Andrews, G. (2016). Transdiagnostic computerised cognitive behavioural therapy for depression and anxiety: A systematic review and meta-analysis. *Journal of Affective Disorders*, *199*, 30–41. https://doi.org/10.1016/j.jad.2016.03.018

Nielsen. (2016). Millennials Are Top Smartphone Users. Retrieved January 23, 2018, from http://www.nielsen.com/us/en/insights/news/2016/millennials-are-top-smartphone-users

Olff, M. (2015). Mobile mental health: A challenging research agenda. *European Journal of Psychotraumatology*, *6*, 27882. https://doi.org/10.3402/ejpt.v6.27882

Pacifica Labs Inc. (2016). Pacifica - Anxiety, Stress, & Depression relief based on CBT & Mindfulness on the App Store. Retrieved March 6, 2016, from https://itunes.apple.com/au/app/pacifica-anxiety-stress-depression/id922968861?mt=8

Păsărelu, C. R., Andersson, G., Nordgren, L. B., & Dobrean, A. (2017). Internet-delivered transdiagnostic and tailored cognitive behavioral therapy for anxiety and depression: a systematic review and meta-analysis of randomized controlled trials. *Cognitive Behaviour Therapy*, *46*(1), 1–28. https://doi.org/10.1080/16506073.2016.1231219

Proudfoot, J., Parker, G., Hadzi Pavlovic, D., Manicavasagar, V., Adler, E., & Whitton, A. (2010). Community attitudes to the appropriation of mobile phones for monitoring and managing depression, anxiety, and stress. *Journal of Medical Internet Research*, *12*, e64.

ReachOut. (2016). ReachOut WorryTime. Retrieved March 7, 2016, from http://au.professionals.reachout.com/reachout-worrytime

Reger, G., Hoffman, J., Riggs, D., Rothbaum, B., Ruzek, J., Holloway, K., & Kuhn, E. (2013). The “PE coach” smartphone application: An innovative approach to improving implementation, fidelity, and homework adherence during prolonged exposure. [References]. *Psychological Services*, *10*(3), 342–349. http://dx.doi.org/10.1037/a0032774

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. https://doi.org/10.2196/mental.6202

Roepke, A. M., Jaffee, S. R., Riffle, O. M., McGonigal, J., Broome, R., & Maxwell, B. (2015). Randomized controlled trial of SuperBetter, a smartphone-based/internet-based self-help tool to reduce depressive symptoms. *Games for Health Journal*, *4*(3), 235–246. https://doi.org/10.1089/g4h.2014.0046

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*, 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, *4*, 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Shipherd, J. C., & Fordiani, J. M. (2015). The application of mindfulness in coping with intrusive thoughts. *Cognitive and Behavioral Practice*, *22*(4), 439–446. https://doi.org/10.1016/j.cbpra.2014.06.001

Morson., S. (2015). *Designing for iOS with Sketch*. Berkeley, CA: Apress; New York, NY.

Smiling Mind. (2015). Smiling Mind (Version 2.1.6) [Mobile application software]. Retrieved January 16, 2015, from https://itunes.apple.com/au/app/smiling-mind/id560442518?mt=8

Spitzer, R. L., Kroenke, K., Williams, J. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, *166*, 1092–1097. https://doi.org/10.1001/archinte.166.10.1092

Stoyanov, S. R., Hides, L., Kavanagh, D. J., & Wilson, H. (2016). Development and validation of the user version of the Mobile Application Rating Scale (uMARS). *JMIR MHealth and UHealth*, *4*(2), e72. https://doi.org/10.2196/mhealth.5849

SuperBetter Inc. (2014). SuperBetter (Version 1.1) [Mobile application software]. Retrieved January 13, 2015, from https://itunes.apple.com/au/app/superbetter/id536634968?mt=8

Tang, W., & Kreindler, D. (2017). Supporting homework compliance in cognitive behavioural therapy: Essential features of mobile apps. *JMIR Mental Health*, *4*(2), e20. https://doi.org/10.2196/mental.5283

Tee, J., & Kazantzis, N. (2011). Collaborative empiricism in cognitive therapy: A definition and theory for the relationship construct. *Clinical Psychology: Science and Practice*, *18*, 47–61. https://doi.org/10.1111/j.1468-2850.2010.01234.x

Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., … Stewart-Brown, S. (2007). The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Development and UK validation. *Health and Quality of Life Outcomes*, *5*, 63. https://doi.org/10.1186/1477-7525-5-63

Titov, N., Dear, B. F., Staples, L. G., Terides, M. D., Karin, E., Sheehan, J., … McEvoy, P. M. (2015). Disorder-specific versus transdiagnostic and clinician-guided versus self-guided treatment for major depressive disorder and comorbid anxiety disorders: A randomized controlled trial. *Journal of Anxiety Disorders*, *35*, 88–102. https://doi.org/10.1016/j.janxdis.2015.08.002

Torous, J., Friedman, R., & Keshavan, M. (2014). Smartphone ownership and interest in mobile applications to monitor symptoms of mental health conditions. *JMIR MHealth and UHealth*, *2*(1), e2. https://doi.org/10.2196/mhealth.2994

Van Ameringen, M., Turna, J., Khalesi, Z., Pullia, K., & Patterson, B. (2017). There is an app for that! The current state of mobile applications (apps) for DSM-5 obsessive-compulsive disorder, posttraumatic stress disorder, anxiety and mood disorders. *Depression and Anxiety*, *34*(6), 526–539. https://doi.org/10.1002/da.22657

Vent. (2017). Vent (Version 5.7) [Mobile application software]. Retrieved from https://itunes.apple.com/WebObjects/MZStore.woa/wa/viewSoftware?id=780298346&mt=8

Vogl, G., Ratnaike, D., Ivancic, L., Rowley, A., & Chandy, V. (2016). *One click away? Insights into mental health digital self-help by young Australians*. Sydney: EY and ReachOut Australia.

Watts, S., Mackenzie, A., Thomas, C., Griskaitis, A., Mewton, L., Williams, A., & Andrews, G. (2013). CBT for depression: A pilot RCT comparing mobile phone vs. computer. *BMC Psychiatry*, *13*, 49. https://doi.org/10.1186/1471-244X-13-49

Wendel, S. (2013). *Designing for behavior change: Applying psychology and behavioral economics*. Sebastopol, California: O'Reilly Media.

Weng, L., Menczer, F., & Ahn, Y.-Y. (2013). Virality Prediction and Community Structure in Social Networks. *Scientific Reports*, *3*. https://doi.org/10.1038/srep02522

Westbrook, D., Kennerley, H., & Kirk, J. (2011). *An introduction to cognitive behaviour therapy: Skills and applications* (2nd ed.). Los Angeles: SAGE Publications Ltd.

Westen, D., Novotny, C. M., & Thompson-Brenner, H. (2004). The empirical status of empirically supported psychotherapies: Assumptions, findings, and reporting in controlled clinical trials. *Psychological Bulletin*, *130*(4), 631–663. https://doi.org/10.1037/0033-2909.130.4.631

White, J. (2010). The STEPS model: A high volume, multi-level, multi-purpose approach to address common mental health problems. In J. Bennett-Levy, D. Richards, P. Farrand, H. Christensen, K. Griffiths, D. Kavanagh, … J. Proudfoot (Eds.), *Oxford Guide to Low Intensity CBT Interventions* (1st ed., pp. 35–52). Oxford: Oxford University Press.

CHAPTER 6: ENGAGEMENT WITH A COGNITIVE BEHAVIORAL THERAPY MOBILE PHONE APP PREDICTS CHANGES IN MENTAL HEALTH AND WELL-BEING: MOODMISSION

Explanatory Note

Following the development, usability testing, and pilot evaluation of MoodMission, the same evaluation applied to MoodPrism in Chapter 4 was also pursued for MoodMission. The following chapter presents a manuscript detailing this evaluation, which was submitted for publication in November 2017 and is currently under review. It reports data from 617 participants and, similar to MoodPrism, relationships were found between app engagement and mental health benefits. Mediation analyses were also conducted, however CSE rather than ESA was revealed to be a significant source of mental health effects. This supported the suggestions of Chapter 1 that reflection-focused apps work via increasing ESA and problem-focused apps, like MoodPrism, work via increasing CSE.

Abstract

Objective: There is an abundance of evidence supporting the efficacy of computerised cognitive behavioral therapy (CBT), but few studies have evaluated mobile applications (apps) that provide CBT strategies. This study investigating the relationships between mental health outcomes and engagement with a mobile app that recommended short CBT strategies. Method: Participants downloaded the MoodMission app from the iOS and Android app stores, completed in-app baseline assessments, and final assessments 30 days later. Participants reported their mood to MoodMission when they were feeling low or anxious and received a list of short CBT strategies to choose from and engage in. Data from 617 assessment completers (71% female; M age = 27 years) were analysed via hierarchical and mediated regressions. Results: App engagement ratings predicted increases in mental well-being. Mediation analyses revealed that there were indirect effects of app engagement on depression, anxiety, and mental wellbeing via the mediator of coping self-efficacy. Subsample analyses found this only for participants who were experiencing a moderate level of depression or anxiety at the time of the baseline assessment. Mental health literacy and coping self-efficacy did not play mediating roles. Conclusions: Engaging with an app that provides CBT strategies can increase mental well-being. Increases in coping self-efficacy may mediate mental health and well-being effects of the app in individuals experiencing moderate depression or anxiety.

Keywords: Computer/Internet technology; Anxiety; Depression; Mobile; Cognitive Behavioral Therapy

Public Health Significance Statement: There are hundreds of unevaluated mental health apps used by millions of smartphone users worldwide, but it is unclear whether these apps can produce mental health and well-being benefits. This study presents evidence supporting the effectiveness of an app that provides users with short cognitive behavioral therapy strategies.

Engagement with a cognitive behavioral therapy mobile phone app predicts changes in mental health and well-being: MoodMission

The ubiquity, portability, and ease of data entry of smartphones makes them ideal tools for health and behaviour change interventions (Aung, Matthews, & Choudhury, 2017; Dogan, Sander, Wagner, Hegerl, & Kohls, 2017; Wendel, 2013). Simultaneously, the need for accessible mental health interventions continues to be dire. Depression has become the top cause of disability worldwide (World Health Organization, 2017), and while effective psychotherapies for affective disorders are available (Andrews, Cuijpers, Craske, McEvoy, & Titov, 2010), the proportion of people who access them is disappointingly low, with 65% of Australians who experience a mental health issue not accessing treatment (ABS, 2007).

Mental health apps (MHapps) aim to provide highly accessible mental health supports with a wide range of smartphone-based tools, including guided meditations, thought and mood tracking, psychoeducation, and coping skills training (Bakker, Kazantzis, Rickwood, & Rickard, 2016). While many MHapps have been developed and released on app stores, very few have been empirically validated (Donker et al., 2013; Grist, Porter, & Stallard, 2017; Huguet et al., 2016; Sucala et al., 2017). The mechanisms underlying the purported benefits of their use remain unstudied.

Cognitive behavioural therapy (CBT) is an evidence-based psychotherapy that has been successfully translated to self-guided computer-based programs (Andrews & Williams, 2014), known as computerised CBT (cCBT) or internet CBT (iCBT). Meta-analyses have found cCBT effective in treating a range of issues (e.g. Heber et al., 2017; Twomey & O'Reilly, 2017) and can serve as an effective transdiagnostic treatment for both anxiety and depression (Cuijpers, Cristea, Weitz, Gentili, & Berking, 2016; Newby, Twomey, Yuan Li, & Andrews, 2016; Păsărelu, Andersson, Nordgren, & Dobrean, 2017). While the successes of cCBT suggest that programs can be effectively translated to delivery via mobile devices

(Proudfoot et al., 2013; Watts et al., 2013), the interaction style used with a mobile device is fundamentally different to that used with a personal computer (Wendel, 2013). MHapps that teach CBT strategies may be effective at improving mental health outcomes, but more studies are required to confirm these effects (Callan, Wright, Siegle, Howland, & Kepler, 2017; Sucala et al., 2017).

Among the other relevant CBT-based apps reported in the literature thus far, Kinderman et al. (2016) presented data on the effectiveness of Catch It, a CBT-based MHapp that coached users in a short cognitive reframing and reflection strategy. Significant increases in positive mood and decreases in negative mood were noted when comparing the first and second times the app had been used. However, the long term use of the app was not studied, so it was unclear whether these effects maintained over, for example, a 30 day period. Comparative measurements of depression, anxiety, and mental well-being were also absent. Similarly, Meinlschmidt et al. (2016) found that a MHapp that coached 27 male participants through CBT-based “micro-interventions” resulted in short term mood improvements, but the long term effects of the app were unclear.

Mohr et al. (2017) reported the efficacy of a suite of “IntelliCare” apps in significantly reducing depression and anxiety. Fourteen different apps were developed and 95% of the participants downloaded five or more of the IntelliCare apps. Participants also received phone calls and text messages to coach their use of the apps. While this study demonstrates the theoretical efficacy of using MHapps, the influence of coaching calls should be considered before concluding that consumers who independently download MHapps can receive benefits. Furthermore, using a suite of 14 individual MHapps rather than a single multipurpose MHapp is inconsistent with principles of intuitive app design. It may be overly complex for users to navigate between apps, and the prevention of intercommunication between the apps is a major shortcoming.

Roepke et al. (2015) found that two different versions of the MHapp “SuperBetter”, including a version using CBT strategies and one using more general self-esteem and acceptance focused strategies, successfully reduced depression symptoms when compared to a waitlist group. There was no significant difference between the SuperBetter versions, but no measures of app use or app engagement were made, so conclusions were not informed by how engaging the participants found the different app versions.

Participants in all the studies summarized above (Kinderman et al., 2016; Meinlschmidt et al., 2016; Mohr et al., 2017; Roepke et al., 2015) were experiencing significant depression and/or anxiety symptoms, so it is unclear whether the MHapps would be effective for users experiencing subclinical symptoms. This has important implications for the recommendation of MHapps to different users. For example, if a MHapp is effective for users experiencing mild to moderate symptoms of depression or anxiety, but not as effective for those experiencing severe distress, alternative supports should be recommended.

Practicing coping skills is a central part of CBT (Mennin, Ellard, Fresco, & Gross, 2013). Coping self-efficacy (CSE) is a measure of an individual’s confidence in their ability to engage in coping strategies (Thorne, Andrews, & Nordstokke, 2013) and cope with adversity (Chesney, Neilands, Chambers, Taylor, & Folkman, 2006). CSE is positively associated with psychological thriving (Sirois & Hirsch, 2013) and negatively associated with depression (Philip, Merluzzi, Zhang, & Heitzmann, 2013) and overall psychological distress (Benka et al., 2014; Pritchard & Gow, 2012; Smith, Benight, & Cieslak, 2013). While the outcomes of using some CBT-based MHapps have been studied (e.g. Dahne, Kustanowitz, & Lejuez, 2017; Huguet et al., 2016), the role of improving CSE to elicit mental health benefits remains unclear. Kuhn et al. (2017) conducted a Randomised Controlled Trial (RCT) comparing the “PTSD Coach” app, for Post Traumatic Stress Disorder, to a waitlist condition over 3 months of treatment. Compared to waitlist participants, PTSD Coach users experienced greater reductions in PTSD and depression symptoms, and greater increases in psychosocial functioning. CSE specifically related to PTSD symptoms was also assessed, but no effect of the app was found. The authors recommended more research to be done to clarify the potential mediating role that CSE plays in the effects of MHapps.

In addition to CSE, Bakker et al. (2016) detail two other potential mechanisms for MHapps to exert positive effects on mental health and well-being, including emotional self-awareness (ESA) and mental health literacy (MHL). It is theorised that CSE, ESA, and MHL may mediate the relationship between engagement in different MHapps and mental health outcomes. ESA refers to the ability for an individual to understand and differentiate their own emotions, which can result in emotional self-regulation improvements (Barrett, Gross, Christensen, & Benvenuto, 2001; Hill & Updegraff, 2012), and positive mental health outcomes (O'Toole, Jensen, Fentz, Zachariae, & Hougaard, 2014). MHapps have been developed with mood-tracking functionality, and a handful have been studied regarding their impact on ESA (Bakker & Rickard, 2017; Kauer et al., 2012; Morris et al., 2010; Rickard, Arjmand, Bakker, & Seabrook, 2016). MHL is the "knowledge and beliefs about mental disorders which aid their recognition, management or prevention" (p. 182, Jorm et al., 1997), which can be gained through psychoeducation interventions (Macrodimitris, Hamilton, Backs-Dermott, & Mothersill, 2010). Internet delivered psychoeducation is effective at reducing depressive symptoms and distress (Brijnath, Protheroe, Mahtani, & Antoniades, 2016; Donker, Griffiths, Cuijpers, & Christensen, 2009), and can be embedded into MHapps.

To measure the effect of using MHapps, some have suggested studying the relationship between frequency of app usage and mental health outcomes (Carpenter et al., 2016). This can help avoid digital placebo effects (Torous & Firth, 2016) and other confounding effects present in real-world deployment studies. Bakker and Rickard (2017) detail how app engagement may be more useful than raw usage to consider for this relationship. Items on a short feedback questionnaire can be used to measure a user's engagement with the MHapp, and if app engagement ratings are positively associated with mental health and well-being outcomes, it suggests the MHapp has efficacy.

The current study aimed to investigate the mental health and well-being impacts of using a CBT strategy app ("MoodMission") over a period of 30 days in a community sample, including the underlying mechanisms that make it effective, and whether users' mental health status influenced the effects. MoodMission provides users with CBT strategies that they can use to cope with low moods and anxiety. Practising such strategies may improve CSE. The strategies also have small amounts of integrated psychoeducation, which may increase MHL. While the app does have a rudimentary log of past use, this is not optimised in a mood diary format, so it was not designed to increase ESA. Considering these features of MoodMission, an additional aim of this study was to investigate whether CSE and MHL mediated the MHapp's mental health and well-being effects. The mediation role of ESA was also explored as an alternative to CSE and MHL.

It was hypothesised that after using MoodMission for 30 days, participant app engagement would be associated with an increase in mental well-being and a decrease in depression and anxiety symptomatology. Furthermore, these predicted relationships were hypothesised to be mediated by increases in CSE and MHL that users experienced while using the app, rather than an increase in ESA. It was hypothesised that participants who scored in the clinical range on the baseline depression and anxiety measures would experience stronger mediated effects than those who scored in the nonclinical range.

Method

Participants

The sample was drawn from data 617 users who had downloaded the app between August 2016 and June 2017, and had complete baseline and final assessment data. These users had downloaded MoodMission naturally off the iOS and Android app stores, so were not recruited as part of a study and were not necessarily seeking a clinical mental health treatment. Age ranged from 13 to 70 (*M* = 26.9, *SD* = 10.9), with 151 males, 439 females, and 27 participants who did not specify their gender. The majority of this sample had completed tertiary education (65%) and were currently employed (29% full-time, 34% part-time).

Materials - App Description

MoodMission (2017) is an app that was developed to provide users with CBT strategies for managing low moods and anxiety. Bakker, Kazantzis, Rickwood and Rickard (2017) detailed the development of MoodMission and how it was designed for three primary uses: “(1) to provide self-administered prevention and self-help strategies to reduce the risk of clinically significant mood and anxiety disorders; (2) to support stepped-care interventions (Vogl, Ratnaike, Ivancic, Rowley, & Chandy, 2016; White, 2010) as a platform for access to low-intensity intervention for low-level clinical symptoms or sub-clinical symptoms of depression and anxiety; and (3) as an adjunct to psychotherapy or other face-to-face treatments for mood and anxiety disorders” (p. 7). When users report their low moods or anxious feelings to MoodMission, the app provides them with a choice of five CBT strategies called “Missions”. Missions are short, easily achievable activities and strategies, taken from evidence-based psychotherapies, that aim to soothe users’ distress. Missions are tailored to the problem that a user reports, so for example, if a user reports low mood, MoodMission may suggest physical exercises (Cooney et al., 2013), behavioural activation activities (Dimidjian, Martell, Herman-Dunn, & Hubley, 2014), or gratitude thought experiments (Lambert, Fincham, & Stillman, 2012; Sin & Lyubomirsky, 2009). Missions are “intelligently” selected based on an adaptive learning algorithm determined by successful past missions the user has completed. MoodMission’s intervention therefore supports the user preference for short, tailored modules in internet mental health interventions (Batterham & Calear, 2017).

MoodMission collected responses from users on several self-report measures at the start of use and 30 days later. The surveys deployed by the app are listed in Table 1.

Table 1

Measures Included in MoodMission Assessments

Measure	No of Items	Scale	Psychometrics
Patient Health Questionnaire (PHQ-9)	9	5 point; Not At All (0) to Nearly Every Day (4)	Scores over 10 have good sensitivity (88%) and specificity (88%) for diagnosis of major depression by interview. High internal reliability, Cronbach's α = .89 (Kroenke et al., 2001).
Generalized Anxiety Disorder scale (GAD-7)	7	5 point; Not At All (0) to Nearly Every Day (4)	Scores over 10 have good sensitivity (89%) and specificity (82%) for diagnosis of Generalised Anxiety Disorder (GAD) by interview. High internal reliability, Cronbach's α = .92 (Spitzer et al., 2006).
Warwick-Edinburgh Mental Well-being Scale (WEMWBS)	14	5 point; None Of The Time (1) to All Of The Time (5)	Shares high correlations with measures of life satisfaction and other measures of well-being. Has high internal reliability, Cronbach's α = .91 (Tennant et al., 2007).
Emotional Self-Awareness Scale – Revised (ESAS-R)	30	5 point; Strongly Disagree (0) to Strongly Agree (4)	Internal reliability of this revised scale is high, Cronbach's α = .90 (Bakker & Rickard, 2017).
Coping Self-Efficacy Scale (CSES)	26	11 point; Cannot Do At All (0) to Certain Can Do (10)	Good validity, indicated by significant positive relationships with well-being and negative relationships with psychological distress. High internal reliability, Cronbach's α = .95, (Chesney et al., 2006).
Mental Health Literacy Questionnaire (MHLQ)	25	Mixed	No standardised measure of MHL exists, so for MHapp MoodPrism Bakker and Rickard (2017) developed a questionnaire using elements from measures used in the literature.
App Engagement Scale	7	5 point; Strongly Disagree (1) to Strongly Agree (5)	Based on items from the well-validated tool for rating health apps, the Mobile Application Rating Scale (MARS; Hides et al., 2014). Good reliability was found in previous use, Cronbach's α = .84 (Bakker & Rickard, 2017).

Procedure

As detailed in Bakker et al. (2017), MoodMission was developed and made freely available on the iTunes and Google Play app stores. To encourage downloads of the app, a multiformat promotional effort was made, including social media pages, news articles, blog posts, conference and trade show presentations, school and university presentations, and printed flyers.

Participants downloaded the app and completed a series of "onboarding" introductory steps. This included completing the baseline assessment, containing the survey measures used in this study. After the assessment was completed, MoodMission's mission suggestion features were unlocked and the app encouraged users to access the app when they were feeling low or anxious. A series of push notifications on the days following the assessment completion were used to remind users to engage with the app. After 30 days of use, MoodMission prompted users to complete the final assessment, which included the same measures from the baseline assessment, with the addition of the App Engagement Scale.

Design and Analyses

A power analysis using G*Power 3 software and based on the smallest effect sizes reported by Kuhn et al. (2017) revealed that 90 participants would be required to detect effects at α=.05. Some data were missing for some participants due to partial assessment completions. Missing data were not replaced, and analyses were conducted excluding participants with missing data in a listwise fashion. IBM SPSS software was used for all analyses, each with bootstrapping using 5000 samples. Preliminary analyses investigated the potential confounding influences of Age and Gender on the analyses. For Age, a series of partial correlations with the three outcome variables (final scores) were performed, with the baselines scores partialled out. Gender, as a categorical variable, instead was included as a covariate in a within-subjects ANCOVA. The results determined whether Age or Gender would be included in the main analyses as covariates. Three hierarchical regressions were used to determine total (unmediated) effects between App Engagement and each outcome measure, with final depression, anxiety and mental well-being scores as the respective outcome variable. The first step in the hierarchical regression included entry of potential confounds identified from preparatory analyses and baseline depression, anxiety or mental well-being scores. App Engagement was entered in the second step.

To investigate the role of mediators, three mediated regression models were used, each using one of the three outcome variables; Depression (PHQ-9), Anxiety (GAD-7), and Mental Well-being (WEMWBS). Three mediating variables were used in each model; CSE measured by the CSES, ESA measured by the ESAS-R, and MHL measured by the MHLQ. As per recommendations from Darlington and Hayes' (2016) and Zhao, Lynch, and Chen's (2010), a significant total (unmediated) effect was not a prerequisite for investigation of mediation effects. This allows the investigation of mediators, even if omitted or opposing mediators are masking total or direct effects (Darlington & Hayes, 2016).

All mediated regression analyses were conducted with the PROCESS plug-in for SPSS (Hayes, 2013) using procedures detailed in Field (2013) and Hayes and Rockwood (2016). To quantify change over time for each mediator or outcome variable, each analysis followed Hayes and Rockwood's (2016) recommendations to use baseline scores as covariates and final (post-30 days of app use) scores as outcome variables. This avoids "self-selection", regression to the mean, and other biases found in other techniques, such as the use of difference scores. Regardless, when baseline and final scores are highly correlated (as was the case for this sample; see Appendix A), this approach often yields a similar output to using difference scores (Vickers & Altman, 2001). For ease of interpretation, reported regressions refer to 'Depression', 'Anxiety' or 'Mental Well-being' scores, but all take baseline scores into account and therefore operationalize change over the 30 day app use period. All Beta (β) statistics reported in the regressions are standardised effect sizes.

Three subsamples based on baseline measures of clinical symptomatology were identified. The Nonclinical subsample scored 9 or under on both the baseline PHQ-9 and the GAD-7. Guidelines for the PHQ-9 (Kroenke, Spitzer, & Williams, 2001) and the GAD-7 (Spitzer, Kroenke, Williams, & Löwe, 2006) both list 10 to 14 as in the "moderate" range, so the Moderate-clinical subsample scored between 10 and 14 on either the baseline PHQ-9 or GAD-7, but not both. The Severe-clinical subsample scored 15 or over on the PHQ-9 or GAD-7, or scored 10 or over on both PHQ-9 and GAD-7 to account for those participants experiencing comorbid depression and anxiety.

Results

The data were inspected and cleaned to ensure that assumptions for linear regression were met. Participants with missing data and outlying cases ±3SDs from the mean were excluded, leaving 617 participants for the subsequent analyses. Durbin-Watson statistics were found to be above specified limits for all regressions, suggesting independence of errors (Durbin & Watson, 1951). All variance inflation factors (VIFs) were between 1.0 and 1.1, and tolerance statistics > .9, suggesting an absence of multicollinearity (Field, 2013). Each outcome variable's residuals were inspected to confirm homoscedasticity and normally distributed errors.

Descriptive Results

Means, standard deviations (SD), and 95% confidence intervals (CI) for each subsample and the whole sample are displayed in Table 2.

Table 2

Descriptive Statistics for Each Analysis Group and Results from Paired Samples t-tests Comparing Baseline and Final Scores

	Nonclinical (n=144)			Moderate-clinical (n=123)			Severe-clinical (n=350)			Whole Sample (n=617)		
	Mean (SD)	95% CI	*t*	Mean (SD)	95% CI	*t*	Mean (SD)	95% CI	*t*	Mean (SD)	95% CI	*t*
PHQ-9												
Baseline	5.75 (2.21)	[5.38, 6.10]	5.75**	10.76 (2.35)	[10.33, 11.18]	1.13	16.90 (4.23)	[16.46, 17.34]	4.49**	13.07 (5.86)	[12.60, 13.53]	1.49
Final	7.72 (4.44)	[6.99, 8.45]		10.28 (4.65)	[9.46, 11.11]		15.75 (5.58)	[15.16, 16.32]		12.79 (6.23)	[12.30, 13.28]	
GAD-7												
Baseline	4.90 (2.44)	[4.49, 5.29]	4.21**	7.92 (2.81)	[7.42, 8.40]	1.37	12.99 (4.18)	[12.55, 13.42]	2.45*	10.09 (4.99)	[9.69, 10.49]	0.40
Final	6.22 (4.09)	[5.57, 6.90]		8.45 (4.42)	[7.66, 9.25]		12.39 (4.77)	[11.88, 12.88]		10.16 (5.26)	[9.76, 10.57]	
WEMWBS												
Baseline	45.52 (6.82)	[44.44, 46.66]	3.82**	39.79 (6.03)	[38.70, 40.84]	1.17	33.64 (6.71)	[32.94, 34.34]	5.27**	37.64 (8.25)	[36.99, 38.30]	2.60**
Final	43.17 (8.31)	[41.79, 44.51]		40.54 (8.45)	[39.07, 42.01]		35.74 (8.45)	[34.86, 36.60]		38.43 (8.99)	[37.72, 39.15]	
CSES												
Baseline	162.25 (36.57)	[156.38, 168.17]	0.75	149.51 (28.99)	[144.42, 154.68]	0.02	129.07 (34.26)	[125.54, 132.58]	0.01	140.89 (36.64)	[138.02, 143.82]	0.36
Final	160.53 (35.24)	[154.69, 166.22]		149.45 (34.35)	[143.36, 155.54]		129.06 (37.97)	[125.14, 132.97]		140.47 (39.02)	[137.45, 143.60]	
ESAS												
Baseline	43.44 (10.64)	[41.68, 45.15]	5.49**	46.07 (10.29)	[44.26, 47.82]	1.55	51.40 (10.39)	[50.31, 52.46]	6.74**	48.48 (10.97)	[47.58, 49.32]	1.55
Final	50.64 (7.77)	[49.37, 51.92]		48.19 (7.55)	[46.85, 49.51]		45.90 (37.17)	[45.09, 46.74]		47.47 (8.16)	[46.83, 48.11]	
MHLQ												
Baseline	15.57 (2.44)	[15.19, 15.96]	0.41	15.26 (2.47)	[14.83, 15.69]	0.35	14.77 (2.69)	[14.48, 15.04]	1.65	15.05 (2.61)	[14.85, 15.25]	1.30
Final	15.64 (2.62)	[15.22, 16.05]		15.20 (2.66)	[14.72, 15.65]		14.95 (2.57)	[14.68, 15.22]		15.16 (2.61)	[14.94, 15.37]	
App Engagement												
Final	26.67 (4.44)	[25.91, 27.39]		27.11 (4.02)	[26.40, 27.82]		27.06 (3.94)	[26.66, 27.47]		26.98 (4.08)	[26.66, 27.30]	

*p = .05, **p = .01

Potential Confounds

Age and gender were considered as potentially confounding variables for each of the regression analyses. Partial correlations (with baseline Depression, Anxiety or Mental Well-being scores partialled out respectively) revealed that Age yielded significant relationships with Depression (PHQ-9), r (614) = -.160, p < .001, and Anxiety (GAD-7), r (614) = -.123, p = .002, but not Mental Well-being (WEMWBS), r (614) = .045, p = .260. No significant effects were observed for Gender, as it was a non-significant covariate for Depression (PHQ-9), F (1, 413) = .34, p = .563, η_p^2 = .001, Anxiety (GAD-7), F (1, 413) = 1.64, p = .201, η_p^2 = .004, and Mental Well-being (WEMWBS), F (1, 413) = 1.92, p = .167, η_p^2 = .005. Significance did not change with the exclusion of participants who selected "Other" for gender. Based on these results, Age was controlled in the first step of each regression analysis. To ensure suitability for further investigation and adequate relatedness between baseline and final measures, correlations between each of the variables were calculated and inspected (see Appendix A). A univariate ANOVA revealed no significant differences in App Engagement between the Nonclinical, Moderate-clinical, and Severe-clinical subsamples, F (2, 614) = .54, p = .586, η_p^2 = .002.

Total (unmediated) Effects

Hierarchical regressions (controlling for the age confound, and baseline scores) on the whole sample demonstrated that App Engagement significantly predicted an increase in Mental Well-being scores, ΔF(1, 613) = 16.92, p < .001, ΔR^2=.017. However, App Engagement did not significantly predict changes in Depression, ΔF (1, 613) = .62, p = .430, ΔR^2 = .001, or Anxiety, ΔF (1, 613) = .11, p = .742, ΔR^2 < .001. When split into Nonclinical, Moderate-clinical, and Severe-clinical subsamples, the same was found, with App Engagement significantly predicting Well-being (Nonclinical: ΔF(1, 140) = 4.49, p = .036, ΔR^2 = .021 ΔF(1, 140) = 4.49, p = .036, ΔR^2 = .021; Moderate: ΔF(1, 119) = 4.75, p = .031,

$\Delta R^2 = .026$; Severe: $\Delta F(1, 613) = 7.013$, $p = .008$, $\Delta R^2 = .014$), but not Depression (Nonclinical: ΔF (1, 140) = .08, $p = .782$, $\Delta R^2 < .001$; Moderate: ΔF (1, 119) = .55, $p = .458$, $\Delta R^2 = .004$; Severe: ΔF (1, 346) = .54, $p = .464$, $\Delta R^2 = .001$), or Anxiety (Nonclinical: ΔF (1, 140) = .51, $p = .477$, $\Delta R^2 = .003$; Moderate: ΔF (1, 119) = .80, $p = .374$, $\Delta R^2 = .006$; Severe: ΔF (1, 346) = .27, $p = .602$, $\Delta R^2 = .001$).

Mediation Analyses

Mediation analyses were first performed for the whole sample (N=617), even in the absence of significant total effects for Depression and Anxiety (as per Zhao et al, 2010). There were significant standardised indirect effects of App Engagement through CSE for Depression, β = -.063, 95% CI [-.100, -.031] (Figure 1A), Anxiety, β = -.058, 95% CI [-.094, -.027] (Figure 1B), and Mental Well-being, β = .085, 95% CI [.041, .133] (Figure 1C). A significant positive relationship between App Engagement and MHL was also observed in each regression. All other direct and indirect effects were not significant.

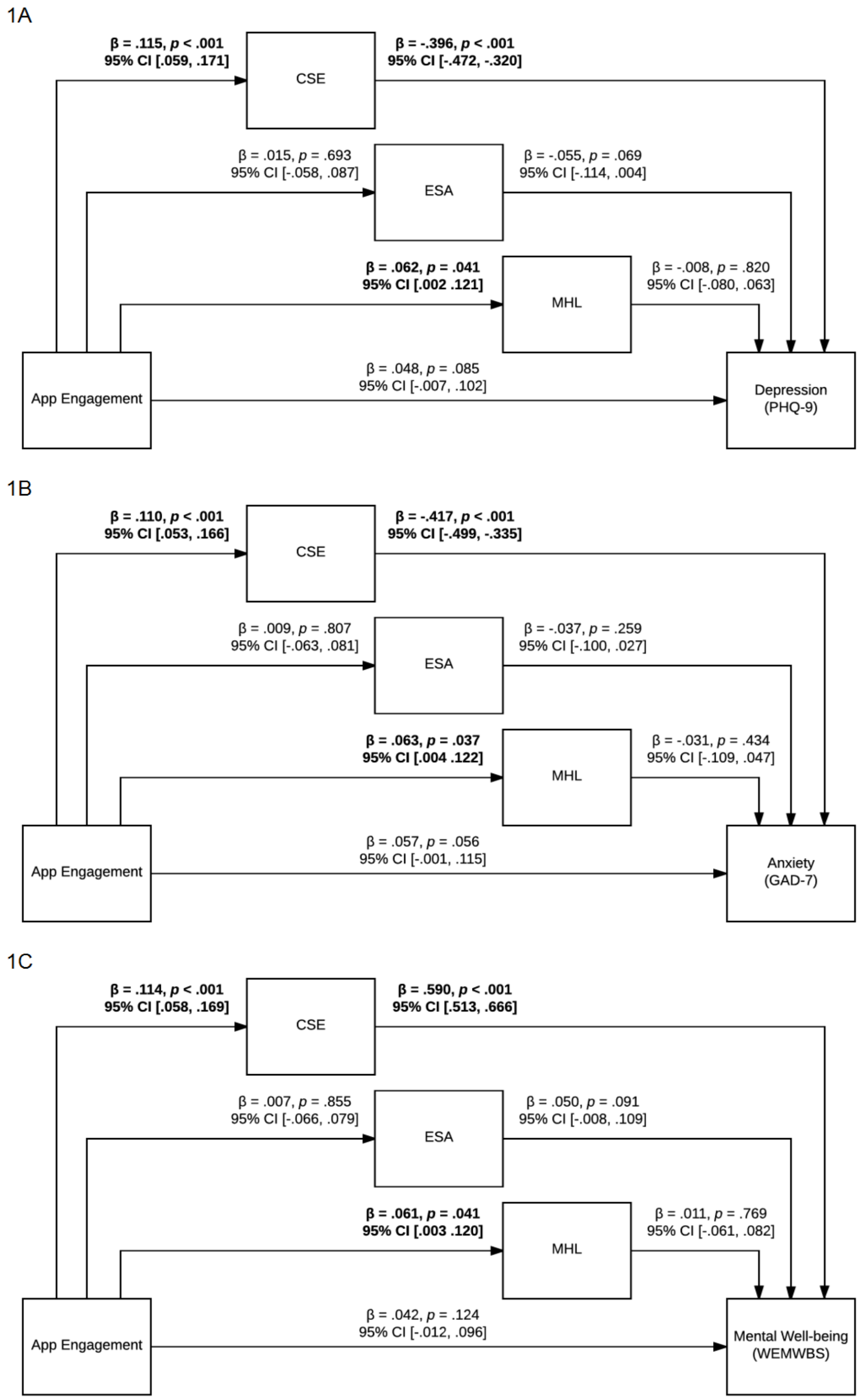


Figure 1. Whole sample mediated regression model using App Engagement ratings as the predictor and (A) Depression (PHQ-9), (B) Anxiety (GAD-7), and (C) Mental Well-being (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < .05$

Following the analyses of the whole sample, mediated regressions were pursued independently for the Nonclinical (n=144), Moderate-clinical (n=123), and Severe-clinical (n=350) subsamples. In the Nonclinical subsample, no direct or indirect effects were found to be significant in the regressions for Depression (Figure 2A) or Anxiety (Figure 2B). However, a significant mediation effect for Mental Well-being (Figure 2C) was found for CSE, with a standardised indirect effect of $\beta = .103$, 95% CI [.002, .221]. No other direct or indirect effects were significant for Mental Well-being.

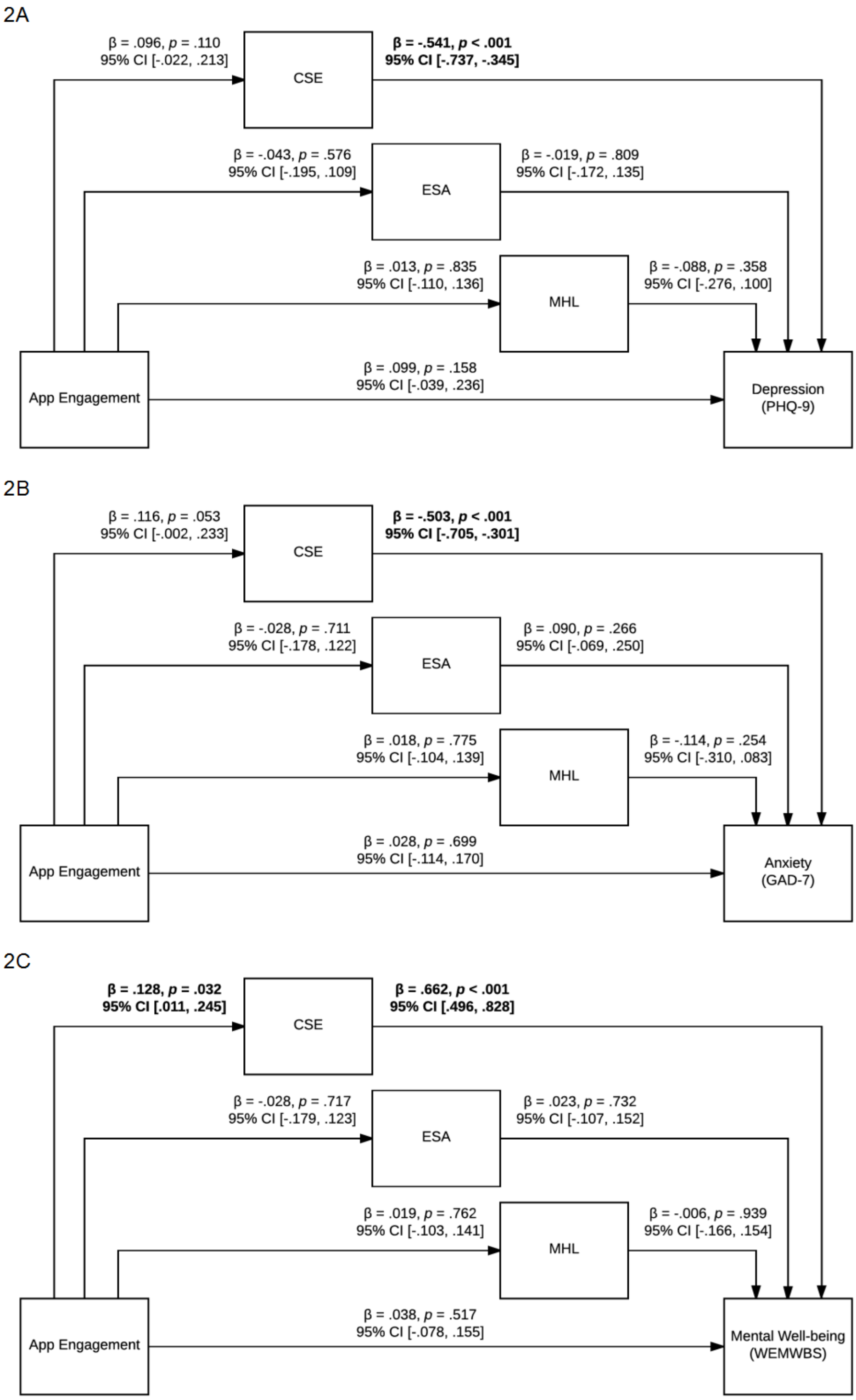


Figure 2. Nonclinical subsample mediated regression model using App Engagement ratings as the predictor and (A) Depression (PHQ-9), (B) Anxiety (GAD-7), and (C) Mental Well-being (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < .05$

In the Moderate-clinical subsample, there were significant mediation effects for CSE in all three regressions, with standardised indirect effects of β = -.173, 95% CI [-.291, -.080] for Depression (Figure 3A), β = -.195, 95% CI [-.326, -.094] for Anxiety (Figure 3B), and β = .221, 95% CI [.114, .345] for Mental Well-being (Figure 3C). No other direct or indirect effects were found significant.

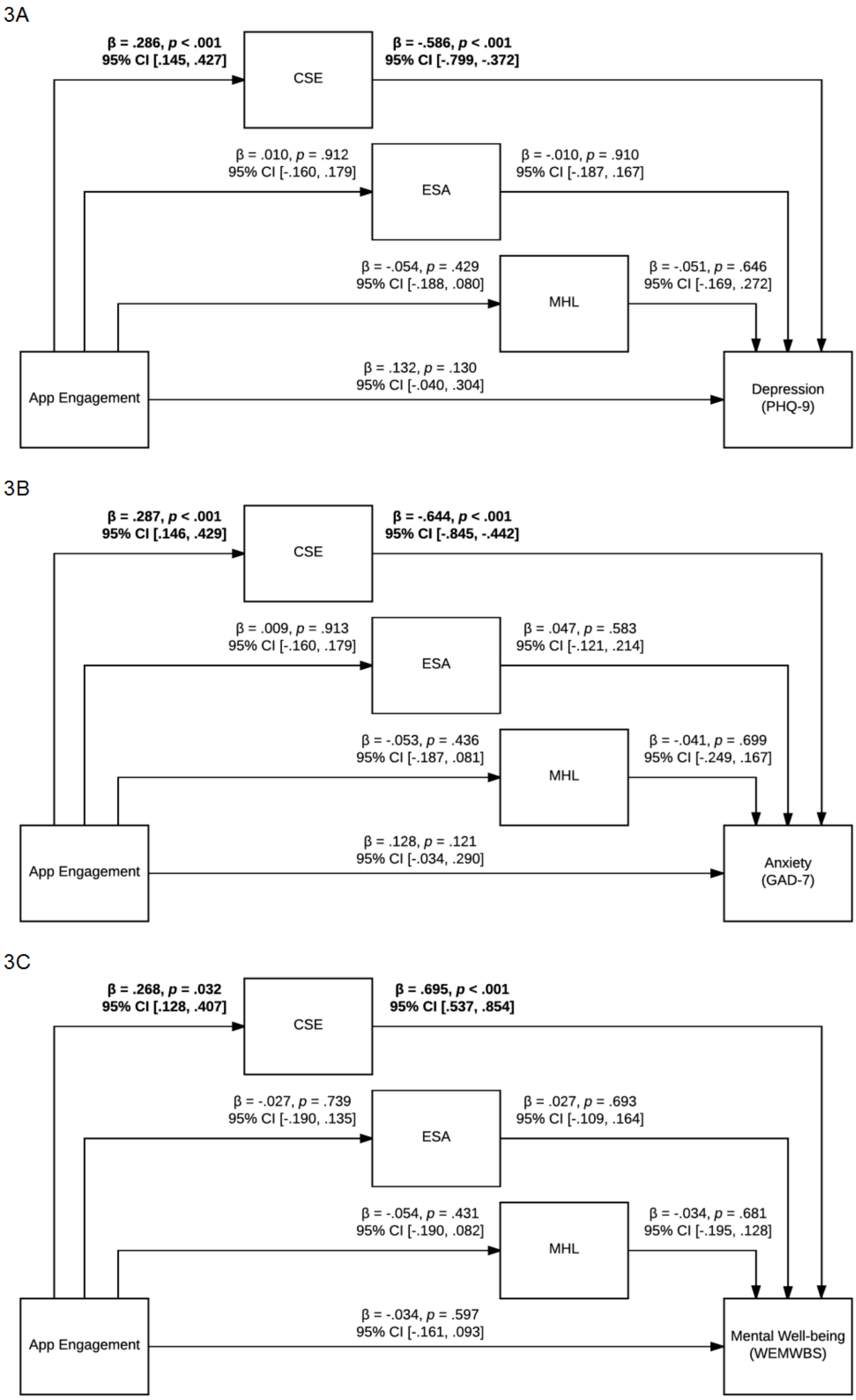


Figure 3. Moderate-clinical subsample mediated regression model using App Engagement ratings as the predictor and (A) Depression (PHQ-9), (B) Anxiety (GAD-7), and (C) Mental Well-being (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < .05$

In the Severe-clinical subsample, there were no significant direct or indirect effects in any of the three regressions. However, there were significant positive relationships observed between App Engagement and MHL in all three regressions. There were also significant negative relationships between CSE and Depression, and CSE and Anxiety, and a significant positive relationship between CSE and Mental Well-being. A summary of the presence of direct and indirect effects from all regressions is presented in Table 3.

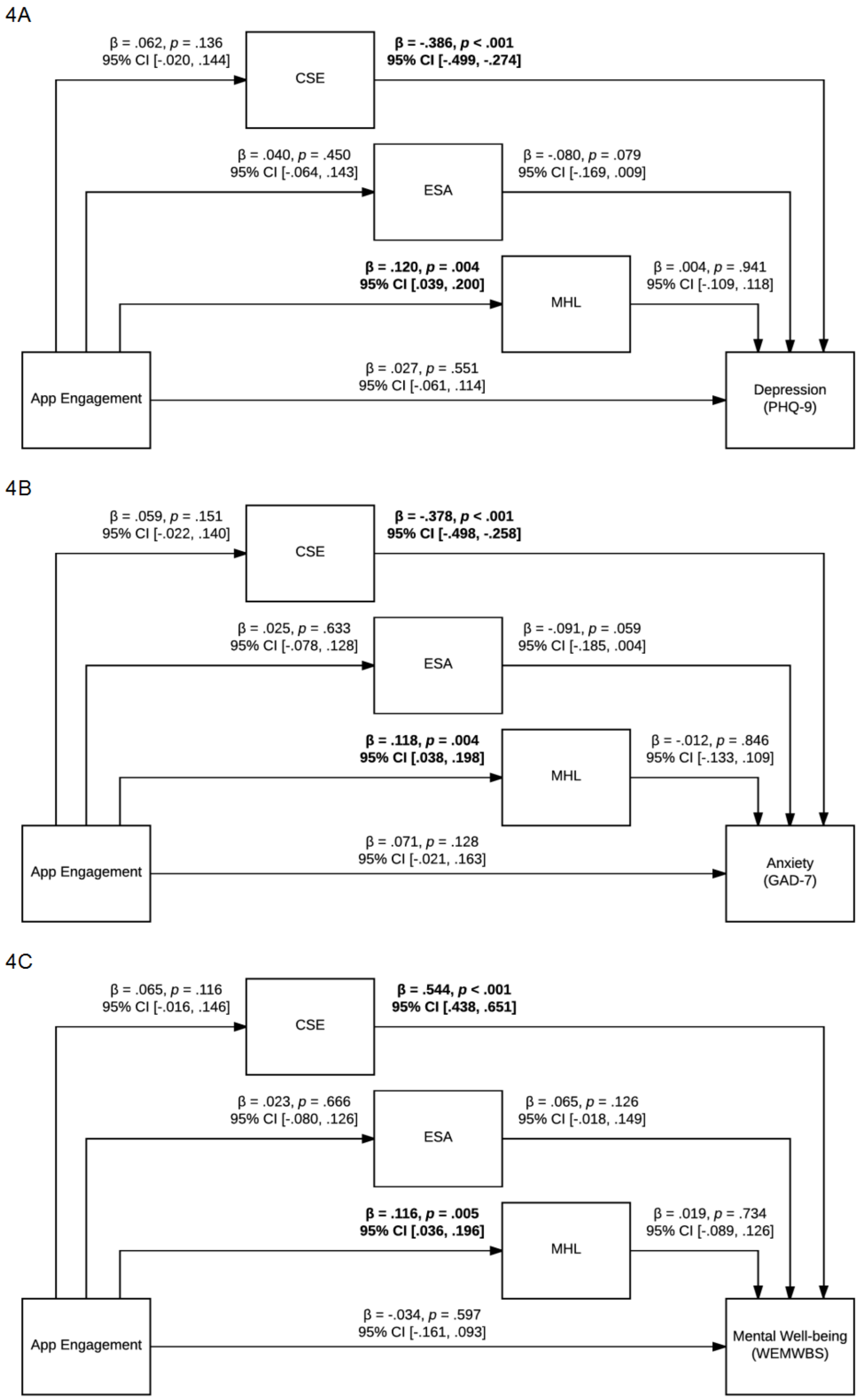


Figure 4. Severe-clinical subsample mediated regression model using App Engagement ratings as the predictor and (A) Depression (PHQ-9), (B) Anxiety (GAD-7), and (C) Mental Well-being (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < .05$

Table 3

Presence of Total, Direct and Indirect Effects of App Engagement on Each Outcome Variable for Each Group

Outcome variable	Total effect of App Engagement (Unmediated)	Indirect effect via mediator ESA	CSE	MHL	Direct effect when mediators added
Whole sample					
Depression	X	X	✓	X	#
Anxiety	X	X	✓	X	#
Mental Well-being	✓	X	✓	X	X
Nonclinical subsample					
Depression	X	X	X	X	X
Anxiety	X	X	X	X	X
Mental Well-being	✓	X	✓	X	X
Moderate-clinical subsample					
Depression	X	X	✓	X	X
Anxiety	X	X	✓	X	X
Mental Well-being	✓	X	✓	X	X
Severe-clinical subsample					
Depression	X	X	X	X	X
Anxiety	X	X	X	X	X
Mental Well-being	✓	X	X	X	X

X not significant, ✓ significant ($p<.05$), # approaching significance ($p<.10$).

Discussion

This study aimed to assess whether engaging with MoodMission, a MHapp that intelligently suggested CBT strategies, predicted improvements in mental health (depression and anxiety) and well-being. The primary finding was that app engagement predicted improvements in mental well-being, and this relationship was mediated by CSE for all but the severely clinical subsample.

It was also found that while app engagement did not directly predict reductions in depression and anxiety, a mediated pathway was identified via CSE for the whole community sample and the moderately clinical subsample. ESA and MHL did not act as mediators for any of the app engagement relationships. This suggests that, for users experiencing moderate levels of depression and anxiety, engaging with MoodMission improved CSE, which subsequently decreased depression and anxiety. However, the lack of a direct effect suggests that there may be other interpretations, such as the presence of an unmeasured, conflicting mediator nullifying the direct effect (Darlington & Hayes, 2016). More research is needed to explore other possible mediators and clarify why there was no direct effect observed.

It was noted that the depression and anxiety scores increased between baseline and final assessments in the nonclinical group. There was no relationship between app engagement and increasing depression or anxiety in the nonclinical group, so this difference between baseline and final assessments should be interpreted a result of measurement effects like regression to the mean, rather than an effect of the app intervention. The nonclinical group was comprised of participants who initially scored low on the depression and anxiety measures and due to floor effects in those measures, there was a much higher chance of their score increasing rather than decreasing on a subsequent assessment. This highlights the importance of investigating the relationship between app engagement and change in depression or anxiety, or including some sort of control group. Many studies of MHapp interventions recruit participants who are experiencing clinical symptoms at baseline (e.g. Kinderman et al., 2016; Meinlschmidt et al., 2016; Mohr et al., 2017; Roepke et al., 2015), and due to measurement effects and regression to the mean, there is an above average likelihood of scores decreasing rather than increasing.

These findings support the use of MoodMission to improve mental well-being, regardless of the users' clinical status. When accounting for clinical status, mediated effects on depression and anxiety levels were only observed for moderately clinical users. A possible explanation for this is that nonclinical users already had low levels of depression and anxiety, and increasing CSE did not detectably lowered them further, and severely clinical users required a more intensive intervention to improve their CSE and reduce their depression and anxiety. This lack of effect on depression and anxiety for users experiencing severe levels of these disorders suggests that MoodMission should not be recommended as a standalone treatment, and demonstrably effective therapies such as CBT with a psychologist should still be sought first. There may also be other advantages of using MoodMission for this subsample that were not detected in this study. For example, MoodMission may change the attitude towards help-seeking for severely clinical users, as they receive notifications about seeking professional support, or it may have relapse prevention effects. In addition, the app may have preventative effects for users who are not currently experiencing depression or anxiety, but the 30-day window of assessment used in this study was too short to detect these.

Previously developed iCBT interventions, such as MoodGYM, were designed as clinical interventions for diagnosed disorders. As such MoodGYM had significant treatment effects for depression, g = 0.36, 95% CI = 0.17-0.56, and anxiety, g = 0.57, 95% CI = 0.20-0.94 (Twomey & O'Reilly, 2017). The adherence rates for the thousands of MoodGYM users that used the intervention outside of an experimental context was extremely low, and less than 7% of users progressed past the first two sessions (Christensen et al., 2006), compared to within experimental contexts when adherence ranged between 10-100%. All data collected in the current study was outside of an experimental context, with participants naturally discovering and downloading the app from the public app store. MoodMission, and apps like it, are designed to be low-intensity and preventative supports for a range of problem severities, including routine, everyday low moods and anxious feelings. As such the expected treatment effects are much smaller, and expected adherence rates much lower.

Bakker and Rickard (2017) conducted a study using the self-monitoring MHapp MoodPrism with the same measures and methodologies reported in the current study. MoodPrism enabled users to track their moods over time by completing daily surveys and creating an interactive, colourful mood diary. Findings suggested that engaging with MoodPrism significantly decreased depression and anxiety, and increased mental well-being. Additionally, it was hypothesised that engaging with MoodPrism's reflection-focussed features would promote gains in ESA, and so ESA would serve as a mediator between app engagement and mental health and well-being outcomes. However, it was found that this was only the case for individuals who scored 15 or over on the PHQ-9 or GAD-7 measures, the same as the current study's Severe-clinical subsample. ESA was not a significant mediator for individuals who scored under this on the depression and anxiety measures.

Bakker et al. (2016) suggests three different types of MHapps; goal-focussed MHapps are designed to improve CSE by recommending activities and active coping skills, reflection-focussed MHapps are designed to improve ESA by using self-monitoring features, and education-focussed MHapps are designed to improve MHL by supplying users with mental health information. MoodMission's main function is the recommendation of CBT strategies, so it best fits into the goal-focussed category. While MoodPrism was a reflection-focussed MHapp, MoodMission contains features that lends to a goal-focussed MHapp design, so the role of CSE as a mediator was expected. However, while the mediation effects of ESA were observed for MoodPrism participants in the Severe-clinical range, MoodMission participants in this range did not experience any measured effects of engaging with the app. This suggests that reflection-focussed features, such as those used in MoodPrism, may be better suited to users who are severely depressed or anxious, whereas goal-focussed features, such as those used in MoodMission, may be more useful for users who are experiencing moderate levels of depression or anxiety. More research is needed to directly compare these features across different groups and different circumstances. A RCT contrasting the effects of MoodPrism and MoodMission, along with other experimental conditions, is currently underway. A systematic comparison between these different MHapps will further illuminate the mechanisms underlying MHapp effects.

MoodMission is designed to be accessed when the user is experiencing low moods or anxious feelings. This may explain why there was no effect of app engagement on depression or anxiety for participants who were not already experiencing significant depression or anxiety symptoms. These users may not have been able to use the Missions to meaningfully decrease their emotional distress, as they were experiencing fewer episodes of less severe distress. There may have also been a floor effects of the PHQ-9 and GAD-7 measures to detect further reductions in depression and anxiety. The finding that these users experienced significant, measurable effects of app engagement on mental well-being support this theory, as there would be less of a ceiling effect on this measure.

There is a perception among some health and mental health practitioners that smartphone use has detrimental mental health outcomes. However, research has linked only non-social use of smartphones to depression and anxiety (Elhai, Levine, Dvorak, & Hall, 2017), highlighting that it is not the devices themselves that cause issues, but the way they are used. Further support for this comes from the results from this study, which suggest that using the features of a MHapp can result in reductions in depression and anxiety, and improvements in mental well-being.

This study suggests that engagement with MoodMission, a goal-focussed MHapp that intelligently suggests CBT strategies to users, is related to improvements in coping self-efficacy, which in turn is related to improvements in mental health and well-being. This is particularly relevant for moderately depressed or anxious users. These findings contrast with those from reflection-focussed apps like MoodPrism (Bakker & Rickard, 2017), which work through the mediator of emotional self-awareness. Considering the clinical potential of MHapps (van Os et al., 2017) and the paucity of research in the area (Donker et al., 2013; Grist et al., 2017), these findings are important for the development, promotion, and refinement of effective MHapps. More work is required to compare the efficacy of MoodMission to other MHapps and control conditions, and to investigate different contexts of its potential use.

References

ABS. (2007). *National survey of mental health and wellbeing: Summary of results* (No. 4326.0). Canberra: Australian Bureau of Statistics.

Andrews, G., Cuijpers, P., Craske, M. G., McEvoy, P., & Titov, N. (2010). Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: A meta-analysis. *PLoS ONE*, *5*, e13196. https://doi.org/10.1371/journal.pone.0013196

Andrews, G., & Williams, A. D. (2014). Internet psychotherapy and the future of personalized treatment. *Depression and Anxiety*, *31*(11), 912–915. https://doi.org/10.1002/da.22302

Aung, M. H., Matthews, M., & Choudhury, T. (2017). Sensing behavioral symptoms of mental health and delivering personalized interventions using mobile technologies. *Depression and Anxiety*, *34*(7), 603–609. https://doi.org/10.1002/da.22646

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2016). Mental health smartphone apps: Review and evidence-based recommendations. *JMIR Mental Health*, *3*, e7. https://doi.org/10.2196/mental.4984

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2017). *Development and pilot evaluation of smartphone delivered cognitive behavior therapy strategies for mood and anxiety related problems: MoodMission*. Manuscript submitted for publication.

Bakker, D., & Rickard, N. (2017). Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism. *Journal of Affective Disorders*. https://doi.org/10.1016/j.jad.2017.11.016

Barrett, L., Gross, J., Christensen, T., & Benvenuto, M. (2001). Knowing what you're feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. *Cognition and Emotion*, *15*, 713–724. https://doi.org/10.1080/02699930143000239

Batterham, P. J., & Calear, A. L. (2017). Preferences for internet-based mental health interventions in an adult online sample: Findings from an online community survey. *JMIR Mental Health*, *4*(2), e26. https://doi.org/10.2196/mental.7722

Benka, J., Nagyova, I., Rosenberger, J., Macejova, Z., Lazurova, I., Klink, J. V. der, … Dijk, J. V. (2014). Is coping self-efficacy related to psychological distress in early and established rheumatoid arthritis patients? *Journal of Developmental and Physical Disabilities*, *26*, 285–297. https://doi.org/10.1007/s10882-013-9364-y

Brijnath, B., Protheroe, J., Mahtani, K. R., & Antoniades, J. (2016). Do web-based mental health literacy interventions improve the mental health literacy of adult consumers? Results from a systematic review. *Journal of Medical Internet Research*, *18*(6), e165. https://doi.org/10.2196/jmir.5463

Callan, J. A., Wright, J., Siegle, G. J., Howland, R. H., & Kepler, B. B. (2017). Use of computer and mobile technologies in the treatment of depression. *Archives of Psychiatric Nursing*, *31*(3), 311–318. https://doi.org/10.1016/j.apnu.2016.10.002

Carpenter, J., Crutchley, P., Zilca, R. D., Schwartz, H. A., Smith, L. K., Cobb, A. M., & Parks, A. C. (2016). Seeing the "big" picture: Big data methods for exploring relationships between usage, language, and outcome in internet intervention data. *Journal of Medical Internet Research*, *18*(8), e241. https://doi.org/10.2196/jmir.5725

Chesney, M. A., Neilands, T. B., Chambers, D. B., Taylor, J. M., & Folkman, S. (2006). A validity and reliability study of the coping self-efficacy scale. *British Journal of Health Psychology*, *11*, 421–437. https://doi.org/10.1348/135910705X53155

Cooney, G. M., Dwan, K., Greig, C. A., Lawlor, D. A., Rimer, J., Waugh, F. R., … Mead, G. E. (2013). Exercise for depression. *Cochrane Database of Systematic Reviews, 9,* CD004366. https://doi.org/10.1002/14651858.CD004366.pub6

Cuijpers, P., Cristea, I. A., Weitz, E., Gentili, C., & Berking, M. (2016). The effects of cognitive and behavioural therapies for anxiety disorders on depression: a meta-analysis. *Psychological Medicine; Cambridge*, *46*(16), 3451–3462. https://doi.org/http://dx.doi.org.ezproxy.lib.monash.edu.au/10.1017/S0033291716002348

Dahne, J., Kustanowitz, J., & Lejuez, C. W. (2017). Development and preliminary feasibility study of a brief behavioral activation mobile application (Behavioral Apptivation) to be used in conjunction with ongoing therapy. *Cognitive and Behavioral Practice*. https://doi.org/10.1016/j.cbpra.2017.05.004

Darlington, R. B., & Hayes, A. F. (2016). *Regression Analysis and Linear Models: Concepts, Applications, and Implementation* (1 edition). New York: The Guilford Press.

Dimidjian, S., Martell, C. R., Herman-Dunn, R., & Hubley, C. P. (2014). Behavioral activation for depression. In D. H. Barlow (Ed.), *Clinical handbook of psychological disorders: A step-by-step treatment manual* (5th ed., pp. 353–393). New York: Guilford Publications.

Dogan, E., Sander, C., Wagner, X., Hegerl, U., & Kohls, E. (2017). Smartphone-based monitoring of objective and subjective data in affective disorders: Where are we and where are we going? Systematic review. *Journal of Medical Internet Research*, *19*(7), e262. https://doi.org/10.2196/jmir.7006

Donker, T., Griffiths, K. M., Cuijpers, P., & Christensen, H. (2009). Psychoeducation for depression, anxiety and psychological distress: A meta-analysis. *BMC Medicine*, *7*, 79. https://doi.org/10.1186/1741-7015-7-79

Donker, T., Petrie, K., Proudfoot, J., Clarke, J., Birch, M.-R., & Christensen, H. (2013). Smartphones for smarter delivery of mental health programs: A systematic review. *Journal of Medical Internet Research*, *15*, e247. https://doi.org/10.2196/jmir.2791

Durbin, J., & Watson, G. S. (1951). Testing for serial correlation in least squares regression. *Biometrika*, *38*(1/2), 159–177. https://doi.org/10.2307/2332325

Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2017). Non-social features of smartphone use are most related to depression, anxiety and problematic smartphone use. *Computers in Human Behavior*, *69*, 75–82. https://doi.org/10.1016/j.chb.2016.12.023

Field, A. (2013). *Discovering statistics using SPSS* (4th ed.). London: Sage.

Grist, R., Porter, J., & Stallard, P. (2017). Mental health mobile apps for preadolescents and adolescents: A systematic review. *Journal of Medical Internet Research*, *19*(5), e176. https://doi.org/10.2196/jmir.7332

Hayes, A. F. (2013). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (1 edition). New York: The Guilford Press.

Hayes, A. F., & Rockwood, N. J. (2016). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy*. https://doi.org/10.1016/j.brat.2016.11.001

Heber, E., Ebert, D. D., Lehr, D., Cuijpers, P., Berking, M., Nobis, S., & Riper, H. (2017). The benefit of web- and computer-based interventions for stress: A systematic review and meta-analysis. *Journal of Medical Internet Research*, *19*(2), e32. https://doi.org/10.2196/jmir.5774

Hill, C. L. M., & Updegraff, J. A. (2012). Mindfulness and its relationship to emotional regulation. *Emotion*, *12*, 81–90. https://doi.org/10.1037/a0026355

Huguet, A., Rao, S., McGrath, P. J., Wozney, L., Wheaton, M., Conrod, J., & Rozario, S. (2016). A systematic review of cognitive behavioral therapy and behavioral activation apps for depression. *PLoS One; San Francisco*, *11*(5). https://doi.org/http://dx.doi.org.ezproxy.lib.monash.edu.au/10.1371/journal.pone.0154248

Jorm, A. F., Korten, A. E., Jacomb, P. A., Christensen, H., Rodger, B., & Pollitt, P. (1997). “Mental health literacy”: A survey of the public’s ability to recognise mental disorders and their beliefs about the effectiveness of treatment. *Medical Journal of Australia*, *166*, 5.

Kauer, S. D., Reid, S. C., Crooke, A. H. D., Khor, A., Hearps, S. J. C., Jorm, A. F., … Patton, G. (2012). Self-monitoring using mobile phones in the early stages of adolescent depression: Randomized controlled trial. *Journal of Medical Internet Research*, *14*, e67. https://doi.org/10.2196/jmir.1858

Kinderman, P., Hagan, P., King, S., Bowman, J., Chahal, J., Gan, L., … Tai, S. (2016). The feasibility and effectiveness of Catch It, an innovative CBT smartphone app. *British Journal of Psychiatry Open*, *2*(3), 204–209. https://doi.org/10.1192/bjpo.bp.115.002436

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*, 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kuhn, E., Kanuri, N., Hoffman, J. E., Garvert, D. W., Ruzek, J. I., & Taylor, C. B. (2017). A randomized controlled trial of a smartphone app for posttraumatic stress disorder symptoms. *Journal of Consulting and Clinical Psychology*, *85*(3), 267–273. https://doi.org/10.1037/ccp0000163

Lambert, N. M., Fincham, F. D., & Stillman, T. F. (2012). Gratitude and depressive symptoms: The role of positive reframing and positive emotion. *Cognition and Emotion*, *26*(4), 615–633. https://doi.org/10.1080/02699931.2011.595393

Macrodimitris, S. D., Hamilton, K. E., Backs-Dermott, B. J., & Mothersill, K. J. (2010). CBT basics: A group approach to teaching fundamental cognitive-behavioral skills. *Journal of Cognitive Psychotherapy*, *24*, 132–146. https://doi.org/10.1891/0889-8391.24.2.132

Meinlschmidt, G., Lee, J.-H., Stalujanis, E., Belardi, A., Oh, M., Jung, E. K., … Tegethoff, M. (2016). Smartphone-based psychotherapeutic micro-interventions to improve mood in a real-world setting. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01112

Mennin, D. S., Ellard, K. K., Fresco, D. M., & Gross, J. J. (2013). United we stand: Emphasizing commonalities across cognitive-behavioral therapies. *Behavior Therapy*, *44*, 234–248. https://doi.org/10.1016/j.beth.2013.02.004

Mohr, D. C., Tomasino, K. N., Lattie, E. G., Palac, H. L., Kwasny, M. J., Weingardt, K., … Schueller, S. M. (2017). IntelliCare: An eclectic, skills-based app suite for the treatment of depression and anxiety. *Journal of Medical Internet Research*, *19*(1), e10. https://doi.org/10.2196/jmir.6645

MoodMission Pty Ltd. (2017). MoodMission (Version 1.1.2) [Mobile application software]. Retrieved May 23, 2017, from https://itunes.apple.com/au/app/moodmission/id1140332763?mt=8

Morris, M. E., Kathawala, Q., Leen, T. K., Gorenstein, E. E., Guilak, F., Labhard, M., & Deleeuw, W. (2010). Mobile therapy: Case study evaluations of a cell phone application for emotional self-awareness. *Journal of Medical Internet Research*, *12*, e10. https://doi.org/10.2196/jmir.1371

Newby, J. M., Twomey, C., Yuan Li, S. S., & Andrews, G. (2016). Transdiagnostic computerised cognitive behavioural therapy for depression and anxiety: A systematic review and meta-analysis. *Journal of Affective Disorders*, *199*, 30–41. https://doi.org/10.1016/j.jad.2016.03.018

Păsărelu, C. R., Andersson, G., Nordgren, L. B., & Dobrean, A. (2017). Internet-delivered transdiagnostic and tailored cognitive behavioral therapy for anxiety and depression: a systematic review and meta-analysis of randomized controlled trials. *Cognitive Behaviour Therapy*, *46*(1), 1–28. https://doi.org/10.1080/16506073.2016.1231219

Philip, E. J., Merluzzi, T. V., Zhang, Z., & Heitzmann, C. A. (2013). Depression and cancer survivorship: Importance of coping self-efficacy in post-treatment survivors. *Psycho-Oncology*, *22,* 987–994. https://doi.org/10.1002/pon.3088

Pritchard, C., & Gow, K. (2012). Coping self-efficacy and psychological distress in flood victims. In K. Gow & M. J. Celinski (Eds.), *Individual trauma: Recovering from deep wounds and exploring the potential for renewal* (pp. 207–219). Hauppauge, NY, US: Nova Science.

Proudfoot, J., Clarke, J., Birch, M.-R., Whitton, A. E., Parker, G., Manicavasagar, V., … Hadzi-Pavlovic, D. (2013). Impact of a mobile phone and web program on symptom and functional outcomes for people with mild-to-moderate depression, anxiety and stress: a randomised controlled trial. *BMC Psychiatry*, *13,* 312. https://doi.org/10.1186/1471-244X-13-312

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. https://doi.org/10.2196/mental.6202

Roepke, A. M., Jaffee, S. R., Riffle, O. M., McGonigal, J., Broome, R., & Maxwell, B. (2015). Randomized controlled trial of SuperBetter, a smartphone-based/internet-based self-help tool to reduce depressive symptoms. *Games for Health Journal*, *4*(3), 235–246. https://doi.org/10.1089/g4h.2014.0046

Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: a practice-friendly meta-analysis. *Journal of Clinical Psychology*, *65*(5), 467–487. https://doi.org/10.1002/jclp.20593

Sirois, F. M., & Hirsch, J. K. (2013). Associations of psychological thriving with coping efficacy, expectations for future growth, and depressive symptoms over time in people with arthritis. *Journal of Psychosomatic Research*, *75*, 279–286. https://doi.org/10.1016/j.jpsychores.2013.06.004

Smith, A., Benight, C., & Cieslak, R. (2013). Social support and postdeployment coping self-efficacy as predictors of distress among combat veterans. *Military Psychology*, *25*, 452–461. https://doi.org/10.1037/mil0000013

Spitzer, R. L., Kroenke, K., Williams, J. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, *166*, 1092–1097. https://doi.org/10.1001/archinte.166.10.1092

Sucala, M., Cuijpers, P., Muench, F., Cardoș, R., Soflau, R., Dobrean, A., … David, D. (2017). Anxiety: There is an app for that. A systematic review of anxiety apps. *Depression and Anxiety*, *34*(6), 518–525. https://doi.org/10.1002/da.22654

Thorne, K. J., Andrews, J. J. W., & Nordstokke, D. (2013). Relations among children’s coping strategies and anxiety: The mediating role of coping efficacy. *The Journal of General Psychology*, *140*, 204–223. https://doi.org/10.1080/00221309.2013.792235

Torous, J., & Firth, J. (2016). The digital placebo effect: mobile mental health meets clinical psychiatry. *The Lancet Psychiatry*, *3*(2), 100–102. https://doi.org/10.1016/S2215-0366(15)00565-9

Twomey, C., & O’Reilly, G. (2017). Effectiveness of a freely available computerised cognitive behavioural therapy programme (MoodGYM) for depression: Meta-analysis. *Australian & New Zealand Journal of Psychiatry*, *51*(3), 260–269. https://doi.org/10.1177/0004867416656258

van Os, J., Verhagen, S., Marsman, A., Peeters, F., Bak, M., Marcelis, M., … Delespaul, P. (2017). The experience sampling method as an mHealth tool to support self-monitoring, self-insight, and personalized health care in clinical practice. *Depression and Anxiety*, *34*(6), 481–493. https://doi.org/10.1002/da.22647

Vickers, A. J., & Altman, D. G. (2001). Analysing controlled trials with baseline and follow up measurements. *BMJ : British Medical Journal*, *323*(7321), 1123–1124.

Vogl, G., Ratnaike, D., Ivancic, L., Rowley, A., & Chandy, V. (2016). *One click away? Insights into mental health digital self-help by young Australians*. Sydney: EY and ReachOut Australia.

Watts, S., Mackenzie, A., Thomas, C., Griskaitis, A., Mewton, L., Williams, A., & Andrews, G. (2013). CBT for depression: A pilot RCT comparing mobile phone vs. computer. *BMC Psychiatry*, *13*, 49. https://doi.org/10.1186/1471-244X-13-49

Wendel, S. (2013). *Designing for behavior change: Applying psychology and behavioral economics*. Sebastopol, California: O’Reilly Media.

White, J. (2010). The STEPS model: A high volume, multi-level, multi-purpose approach to address common mental health problems. In J. Bennett-Levy, D. Richards, P. Farrand, H. Christensen, K. Griffiths, D. Kavanagh, … J. Proudfoot (Eds.), *Oxford Guide to Low Intensity CBT Interventions* (1st ed., pp. 35–52). Oxford: Oxford University Press.

World Health Organization. (2017). WHO | Depression. Retrieved March 30, 2017, from http://www.who.int/mediacentre/factsheets/fs369/en/

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*, 197–206. https://doi.org/http://dx.doi.org/10.1086/651257

Appendix A

Correlations Between Measures Calculated from the Whole Sample

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. App Engagement	*r*	1													
	p														
2. Baseline PHQ-9	*r*	.010	1												
	p	.811													
3. Final PHQ-9	*r*	-.009	.688**	1											
	p	.817	<.001												
4. Baseline GAD-7	*r*	.027	.626**	.468**	1										
	p	.495	<.001	<.001											
5. Final GAD-7	*r*	.012	.493**	.665**	.628**	1									
	p	.761	<.001	<.001	<.001										
6. Baseline WEMWBS	*r*	.059	-.720**	-.575**	-.494**	-.421**	1								
	p	.144	<.001	<.001	<.001	<.001									
7. Final WEMWBS	*r*	.162**	-.441**	-.675**	-.275**	-.516**	.618**	1							
	p	<.001	<.001	<.001	<.001	<.001	<.001								
8. Baseline CSES	*r*	.184**	-.520**	-.455**	-.343**	-.314**	.650**	.494**	1						
	p	<.001	<.001	<.001	<.001	<.001	<.001	<.001							
9. Final CSES	*r*	.229**	-.434**	-.556**	-.277**	-.448**	.552**	.691**	.708**	1					
	p	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001						
10. Baseline ESAS-R	*r*	-.078	.369**	.337**	.199**	.232**	-.481**	-.374**	-.534**	-.460**	1				
	p	.052	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001					
11. Final ESAS-R	*r*	.032	-.292**	-.313**	-.216**	-.248**	.311**	.303**	.273**	.306**	-.430**	1			
	p	.432	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001				
12. Baseline MHLQ	*r*	.018	-.102*	-.074	-.105**	-.039	.102*	.042	.104*	.066	-.155**	.095*	1		
	p	.648	.011	.067	.009	.337	.011	.293	.010	.102	<.001	0.018			
13. Final MHLQ	*r*	.067	-.088*	-.070	-.100*	-.062	.095*	.049	.089*	.049	-.173**	.095*	.682**	1	
	p	.098	.028	.082	.013	.125	.018	.221	.027	.229	<.001	0.018	<.001		
14. Age	*r*	-.060	-.167**	-.229**	-.189**	-.213**	.183**	.148**	.146**	.114**	-.261**	.230**	.234**	.242**	1
	p	.140	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.005	<.001	<.001	<.001	<.001	

Note: * *p* <.05; ** *p* <.01

CHAPTER 7: A RANDOMIZED CONTROLLED TRIAL OF THREE SMARTPHONE APPS FOR ENHANCING PUBLIC MENTAL HEALTH

Explanatory Note

As detailed in Chapter 1, MHapps require thorough evaluation through experimental trials. The papers presented in Chapters 4 and 6 investigated the relationships between app engagement and mental health outcomes in participants who naturally found and downloaded the apps off the public app store. The findings supported the real-world effectiveness of MoodPrism and MoodMission. To further investigate the apps' efficacy, a randomised controlled trial (RCT) was designed and pursued.

The following chapter presents a manuscript submitted for publication in February 2018, and resubmitted to respond to reviewer feedback in May 2018. It details a RCT that was conducted following the release of both MoodPrism and MoodMission. An additional MHapp was sought to be included in the RCT to enable comparison to an existing intervention. MoodKit was the MHapp that was chosen, based on its quality and its structure as a "toolbox style" intervention, offering a number of tools to users in an unguided format. MoodKit's tools are similar to those contained within MoodPrism and MoodMission, but they are deployed in a less directive behavioural plan, enabling comparisons to MoodPrism's and MoodMission's behavioural plans. In line with journal requirements, the study adhered to CONSORT guidelines (see Figure 1 in the manuscript).

Data from 226 participants was analysed to draw conclusions that using any of the three MHapps provided mental health benefits, in comparison to the waitlist control condition. Mediation analyses were also performed and resulted in different conclusions to those of Chapter 4. CSE rather than ESA was a significant mediator for all apps, including MoodPrism.

Abstract

Many smartphone applications (apps) for mental health (MHapps) are available to the public. However, few have been the subject of a randomized controlled trial (RCT), and the change processes that are hypothesized to mediate claimed effects have not been previously studied. This RCT compared the efficacy of three publicly available MHapps to a waitlist control condition in a community sample, in which no MHapp was provided. The three MHapps included cognitive behavioural therapy (CBT) toolkit app MoodKit, mood tracking app MoodPrism, and CBT strategy app MoodMission. Participants were randomly allocated to each condition, completed a baseline assessment, downloaded their allocated MHapp, and completed a second assessment 30 days later, with n = 226 included in final analyses (81% female; M age = 34 years). Compared to the control condition, all MHapp groups experienced increases in mental wellbeing, MoodKit and MoodMission groups experienced decreases in depression, and no groups experienced effects on anxiety. Mediated regressions revealed that increasing coping self-efficacy, rather than emotional self-awareness or mental health literacy, was the underlying process contributing to effects on mental health for all three MHapps. MHapps appear to be an effective solution for improving public mental health, notably by improving users' confidence in their ability to cope.

Keywords: Technology; Anxiety; Depression; Cognitive Behavioral Therapy; Randomized Controlled Trial; Mobile

A Randomised Controlled Trial of Three Smartphone Apps for Enhancing Public Mental Health

Depression and anxiety disorders are highly prevalent, with depression being the leading cause of global disease burden and disability (World Health Organization, 2017). However, treatment access is generally poor; while 18.1% of adults in the United States experience an anxiety disorder every year, only 36.9% received treatment (Kessler, Chiu, Demler, Merikangas, & Walters, 2005), and 4.3% are diagnosed with a Major Depressive Episode, with 65.3% receiving treatment (Ahrnsbrak, Bose, Hedden, Lipari, & Park-Lee, 2017).

Self-guided preventative interventions, classified under the broad term “low-intensity interventions”, use fewer economic and clinical resources which are predominantly self-guided and can be used for preventative purposes (Bennett-Levy, Richards, & Farrand, 2010). Examples include workbooks, websites, and digital therapies, which can be efficient and effective when core dimensions in psychopathology common to both anxiety and depression are targeted (Barlow et al., 2017). Self-guided interventions are part of a stepped-care approach, which prioritizes “high intensity” psychological interventions (e.g. psychotherapy and psychoactive medications) for those with the greatest distress and clinical need, and “low intensity interventions” for those who may not require one-on-one clinician support (van Straten, Hill, Richards, & Cuijpers, 2015). However, emotional disorders continue to have high prevalence and represent significant public health and global economic burden (Whiteford et al., 2013). Low-intensity interventions show promise (Williams & Martinez, 2008), but new modes of delivery including those that do not require clinician support are required to increase their accessibility. Thus, smartphone applications (apps) for mental health (MHapps) represent a compelling new delivery mode for self-guided psychological interventions in prevention and stepped-care.

MHapps have a number of advantages over traditional intervention paradigms, including financial affordability, anonymity, context and geographic flexibility, and ease of feedback data collection for the intervention developers (Vogl, Ratnaike, Ivancic, Rowley, & Chandy, 2016). However, as more MHapps become available to the public, so does the need to rigorously evaluate them as therapeutic tools (Donker et al., 2013). Firth et al. (2017a) conducted a meta-analysis on 18 randomized controlled trials (RCTs) assessing 22 different smartphone-delivered interventions for depression, and found significant reductions in depressive symptoms for apps compared to controls across the 3414 participants (g = 0.38, 95% CI = 0.24-0.52). Similar support for anxiety MHapps was found in Firth et al.'s (2017b) meta-analysis of nine RCTs on smartphone-delivered interventions for anxiety, with significantly greater reductions in anxiety symptoms compared to controls across the 1837 participants (g = 0.33, 95% CI = 0.17-0.48). Sixteen of the 27 RCTs included in both meta-analyses used waitlist control conditions, in which no alternative intervention was provided. However, a number of limitations were noted across the existing RCTs, particularly limiting ecological validity. These include an overreliance on clinical samples, involve clinician-delivered feedback, or use of MHapps that are not available to the public, and a lack of investigation into the mechanisms underlying mental health benefits. Each of these limitations is discussed in turn to inform the design of the current study.

Clinical and Community Samples

The majority of MHapp RCTs have examined clinical samples, with elevated levels of anxiety or depression (Donker et al., 2013). However, the main implementation strengths and population-level utility of MHapps lie in preventative or stepped-care use (Bakker, Kazantzis, Rickwood, & Rickard, 2016; Grist, Porter, & Stallard, 2017; Nicholas, Larsen, Proudfoot, & Christensen, 2015), and the significant effects observed for clinical samples may not be generalized to the broader population. Few MHapp RCTs have used community samples, and these have limited findings. For example, Howells, Ivtzan, and Eiroa-Orosa (2014) found only a small effect of a mindfulness app on depression after 10 days in a community sample (87 % female; age M = 40, SD = 11), g = 0.38[i], 95% CI = 0.02-0.74, and no significant effects were found on satisfaction with life, flourishing (social-psychological prosperity and subjective positive wellbeing) or negative affect. Larger effect sizes have been found in RCTs using depressed clinical samples and MHapp interventions that target psychological dysfunction (e.g., g = 1.12[ii], 95% CI = 0.81-1.42, Roepke et al., 2015). More investigation is needed into the effects of similar interventions on depression and anxiety in community samples.

Clinician Contact

Meta-analysis has revealed that MHapp interventions involving contact with a clinician to receive in-person feedback about their use of the app have had significantly smaller effects, g = 0.14, 95% CI = -0.08-0.35, than MHapps used as stand-alone interventions without in-person feedback, g = 0.47, 95% CI = 0.30-0.63 (Firth et al., 2017a). It was speculated that this is partially due to the more integrated, comprehensive nature of apps that do not require in-person sessions. Automated stand-alone interventions, which do not involve clinician contact, also require fewer resources to maintain, provide greater privacy, and may encourage a greater sense of autonomy for the individual (Anton & Jones, 2017). However, the intervention paradigms used may be more experimental and novel, warranting deeper investigation.

Accessibility of MHapps

The population-level utility and accessibility of stand-alone MHapps is maximized when they are available to the public. While some apps are available for immediate download and use from the iOS and Android app stores, others are only accessible through referral from a researcher or clinical service. Of the 22 MHapps that Firth et al. (2017a, 2017b) reviewed, only six were available for public download on the iOS or Android app stores. There is an ethical responsibility for app developers to demonstrate that their mental health claims are supported by scientific and meaningful evidence, but the number of publically available MHapps that make claims of mental health improvements far outweighs the number of MHapps that have supporting evidence and robust experimental research studies. MHapps are capable of automatically collecting outcome data from users, which can be used in research and to guide improvements to interventions (Bakker et al., 2016; Nicholas et al., 2015).

Mechanisms Underlying the Mental Health Benefits of MHapps

Most MHapp studies have focused on proximal measures of mental ill health, such as depression and anxiety symptomatology. Fewer have incorporated measures of positive mental health wellbeing, which is an important factor in comprehensive assessment of mental health and functioning (World Health Organization, 2004; Slade, 2010; Hofmann, 2015). Fewer still have investigated secondary factors that reflect common therapeutic processes in cognitive behavioural therapy (CBT), and are malleable, such as emotional self-awareness (ESA; Kauer et al., 2012), coping self-efficacy (CSE; Chesney, Neilands, Chambers, Taylor, & Folkman, 2006), or mental health literacy (MHL; Jorm, 2012). ESA is an individual's ability to comprehend their own emotions, leading to positive mental health outcomes (O'Toole, Jensen, Fentz, Zachariae, & Hougaard, 2014) via emotion self-regulation improvements (Barrett, Gross, Christensen, & Benvenuto, 2001; Hill & Updegraff, 2012). CBT commonly incorporates objective tracking of emotional states, and MHapps with mood-tracking functionality can improve ESA (Bakker & Rickard, 2017a; Kauer et al., 2012; Morris et al., 2010; Rickard, Arjmand, Bakker, & Seabrook, 2016). CSE is a measure of an individual's confidence in their coping ability (Thorne, Andrews, & Nordstokke, 2013). Increasing CSE through practicing coping skills is fundamental in CBT (Mennin, Ellard, Fresco, & Gross, 2013), and has beneficial effects on psychological thriving (Sirois & Hirsch, 2013), depression (Philip, Merluzzi, Zhang, & Heitzmann, 2013) and psychological distress (Benka et al., 2014; Pritchard & Gow, 2012; Smith, Benight, & Cieslak, 2013). MHL is an individual's understanding of mental disorders, which can lead to mental health improvements via recognition, prevention, or management of dysfunction (Jorm, 2012). Psychoeducation is the part of CBT that aims to increase MHL, and psychoeducation is effective at reducing depressive symptoms and distress when delivered via technology (Brijnath, Protheroe, Mahtani, & Antoniades, 2016; Donker, Griffiths, Cuijpers, & Christensen, 2009). Investigating secondary measures, such as ESA, CSE, and MHL, may reveal the treatment processes that underpin change in the more proximal primary measures (Hayes & Hofmann, 2017, 2018; Kazantzis et al., in press), as they more closely represent the skills that MHapps teach individuals (Kazantzis, 2018). While there are numerous positive mental health factors that could mediate the effect of MHapps, ESA, CSE and MHL were selected for investigation in the current study given their close relationships with CBT change mechanisms (Mennin et al., 2013) and based on recommendations outlined in Bakker et al. (2016).

MoodPrism (2016), MoodMission (2017), and MoodKit (2016) are three MHapps that are: a) CBT-based and include features that may increase ESA, CSE, and MHL; b) designed for transdiagnostic use, by individuals who meet partial or full diagnostic criteria for a range of emotional disorders; c) capable of preventative and stepped-care support; d) completely self-guided; and e) currently available in public app stores. The three apps include different therapeutic techniques and tools that target different mechanisms for promoting mental health.

MoodPrism is a self-monitoring mood-tracking app that prompts users to report their emotional state daily via a short survey. Users can review their mood diary, which displays their mood and emotional health over time, and the app provides relevant links to mental health resources. Bakker and Rickard (2017a) found that users who were more engaged with MoodPrism experienced greater decreases in depression and anxiety, and greater increases in mental wellbeing. The observed mental health improvements were found to be partially mediated by ESA, suggesting that one means by which MoodPrism's mood-tracking features were beneficial to users was by increasing emotional self-reflection.

MoodMission is an app that recommends CBT strategies in response to user-reported low moods and anxious feelings. Users input their current emotional distress and MoodMission provides a tailored list of five CBT-based activities, called "Missions", from which to choose. Practicing the strategies in these Missions can improve an individual's confidence in their ability to cope with stressors and increase CSE (Chesney et al., 2006). Data from 617 MoodMission users demonstrated that the mental health improvements associated with engaging with MoodMission were mediated by gains in CSE (Bakker & Rickard, 2017b).

MoodKit is a CBT-based app that contains four main tools: a collection of activities, a thought checker, a mood tracker, and a journal. MoodKit's activities are hypothesized to engage CSE, while the other reflective features may engage ESA as a mediator for mental health improvements. Unlike MoodPrism (Bakker & Rickard, 2017a) and MoodMission (Bakker & Rickard, 2017b), which were recently developed and released, MoodKit was released in 2012, and remains untested. Additionally, MoodKit uniquely deploys its features in an unstructured, unprompted way, and was therefore included in the study as a toolbox-style intervention, used by participants to access tools at their unguided discretion.

MoodPrism, MoodMission, and MoodKit each contain psychoeducational features and information about mental health, so may additionally increase MHL (Brijnath et al., 2016). Research to date has not yet identified the features or mechanisms of MHapps which may contribute most to mental health outcomes (Firth et al., 2017a, 2017b). Comparing the mediating effects of ESA, MHL, and CSE across three different MHapps may clarify the transdiagnostic mechanisms engaged by various MHapp features.

Evidence is accumulating to support the efficacy of MHapps (Firth et al., 2017a, 2017b), but studies of their utility in nonclinical, community populations suffer from shortcomings such as lack of control conditions, small sample sizes, and no investigation of underlying therapeutic mechanisms. There is also a need to investigate the efficacy of existing, publicly available MHapps (i.e., MoodKit, MoodMission, and MoodPrism), given their widespread public use. As such, the current RCT aimed to evaluate the superiority of the three available, stand-alone MHapps to a waitlist control condition, in which no MHapp would be provided. It was hypothesized that participants randomly allocated to each of the three app conditions would experience significantly greater decreases in depression and anxiety and increases in mental wellbeing (primary outcome measures), and significantly greater increases in ESA, CSE, and MHL (secondary measures and potential mediators), than those in the waitlist condition. Comparing the three app conditions, it was hypothesized that participants using apps that included coping strategies (i.e., MoodMission and MoodKit) would experience a greater increase in CSE, and that CSE would mediate changes in primary outcome measures. In contrast, it was expected that the magnitude of increase and mediating role of ESA would be greater for apps that focused on mood-tracking functionality (i.e., MoodPrism).

Method

Participants

This research was reviewed and approved by the Monash University Human Research Ethics Committee (MUHREC; Project Number: CF14/968 - 2014000398). Recruitment occurred between August 2016 and June 2017. Participants volunteered to take part by providing their email address on an online form. Links to the form were advertised on Twitter and Facebook, via accounts of various Australian mental health organizations. Participants were randomized to one of the four conditions and sent relevant instructions. Demographic data for the participants included in the analyses are displayed in Table 1. Chi-squared tests and ANOVAs suggested no significant differences in age or gender between the groups. Providing responses for both baseline and final assessments earned participants entry into a prize draw to win an iPad.

Table 1

Participant Demographics and Data Status

Characteristic	Waitlist	MoodKit	MoodPrism	MoodMission	Total
Gender					
Male (%)	14 (22)	12 (21)	4 (7)	9 (18)	39 (17)
Female (%)	49 (77)	42 (75)	50 (89)	41 (82)	182 (81)
Don't know/want to answer (%)	1 (1)	2 (4)	2 (4)	0 (0)	5 (2)
Age					
Mean (SD)	33.6 (10.7)	33.8 (13.6)	36.1 (11.5)	33.3 (12.8)	34.2 (12.1)
Min - Max	18 - 64	18 - 76	20 - 67	18 - 62	18 - 76
Data Status					
Complete Data	53	39	26	27	145
Imputed 30-day	11	17	30	23	81
Group Total	64	56	56	50	226

A range of effect sizes have been found in the literature, depending on the clinical status of the sample and the type of MHapp intervention used. Power analysis using G*Power v.3 software was based on effect sizes found by Kauer et al. ($\kappa 2$ = .54, 95% CI = .43–.64; 2012), as this study used similar measures in mediation analyses. This power analysis suggested a minimum of 45 participants per group was required to find between and within group effects at α = .05 in the planned analyses. Smaller effect sizes have been found in community samples (e.g. g = 0.38, 95% CI = 0.02-0.74; Howells et al., 2014), and power analyses suggested n = 105 per group, but n = 45 per group was decided upon to conservatively control both Type I and II error rates.

Primary Outcome Measures

The Patient Health Questionnaire 9-item PHQ-9 (PHQ-9; Kroenke, Spitzer, & Williams, 2001) and Generalized Anxiety Disorder Scale 7-item (GAD-7; Spitzer, Kroenke, Williams, & Löwe, 2006) are extensively used assessments of depression and anxiety, respectively. Symptoms (e.g. "*Poor appetite or overeating*", "*Trouble relaxing*") are rated on frequency over the past two weeks on a five-point scale from 0 (*not at all*) to 4 (*nearly every day*). The PHQ-9 has high internal reliability, Cronbach's α =.89 (Kroenke et al., 2001), and scores over 10 have good sensitivity (88%) and specificity (88%) for diagnosis of major depression by interview. In this study, Cronbach's α = .90. The GAD-7 has high internal reliability, Cronbach's α =.92 (Spitzer et al., 2006), and scores over 10 have good sensitivity (89%) and specificity (82%) for diagnosis of Generalized Anxiety Disorder (GAD) by interview. In this study, Cronbach's α = .92.

The Warwick-Edinburgh Mental Well-being Scale (WEMWBS; Stewart-Brown & Janmohamed, 2008) is a 14-item assessment of mental wellbeing. The frequency of positive psychological experiences over the past two weeks (e.g. "*been feeling close to other people*") are rated on a five-point scale from 1 (*none of the time*) to 5 (*all of the time*). The WEMWBS shares high correlations with measures of life satisfaction and other measures of well-being, and has high internal reliability, Cronbach's α = .91 (Tennant et al., 2007). In this study, Cronbach's α = .92.

Secondary Measures - Potential Mediators

The Emotional Self-Awareness Scale – Revised (ESAS-R; Bakker & Rickard, 2017a), is a revised version of the ESAS used by Kauer et al. (2012), and was used to assess ESA. It uses 30 items (e.g. "*I usually know why I feel the way I do*") rated from 0 (*strongly disagree*) to 4 (*strongly agree*), and in this study, Cronbach's α = .92.

The Coping Self-Efficacy Scale (CSES; Chesney et al., 2006) was used to assess CSE, and in this study, Cronbach's α = .96. To complete, participants rate their confidence in their ability to do 26 different coping actions (e.g. "*Take your mind off unpleasant thoughts*") from 0 (*cannot do at* all) to 10 (*certain can do*).

The Mental Health Literacy Questionnaire developed for use in MoodPrism (Bakker & Rickard, 2017a) and MoodMission (Bakker & Rickard, 2017b) was used to assess MHL. This 25 item measure requires respondents to rate the appropriateness of different forms of help-seeking for individuals described in two vignettes. It also includes multiple choice questions to assess general mental health knowledge, such as "*What is the most common mental condition in Australia?*" Items were scored 1 (correct), 0.5 (partly correct), or 0 (incorrect) and summed, so Cronbach's α = .53.

Procedure

Flow of the participants through the study is illustrated in Figure 1. After participant emails were collected, allocation to condition was performed at random using a repeating sequence on a spreadsheet. Participants were not informed of the other possible condition assignments. Participants were emailed a link to an online Qualtrics survey which administered the initial assessment. The assessment contained their allocated condition's relevant measures and instructions; for example, how to download and set up the allocated app. As MoodKit was a paid app, participants were provided a free download code to redeem on the iTunes Store. Once participants completed all the steps outlined, they provided their email address via a separate online form to indicate completion and maintain participants' anonymity. Participants were emailed a link to the final Qualtrics assessment 30 days later. This assessment contained the final measures. Waitlist participants were emailed with links to the MoodMission and MoodPrism apps following the completion of the study.

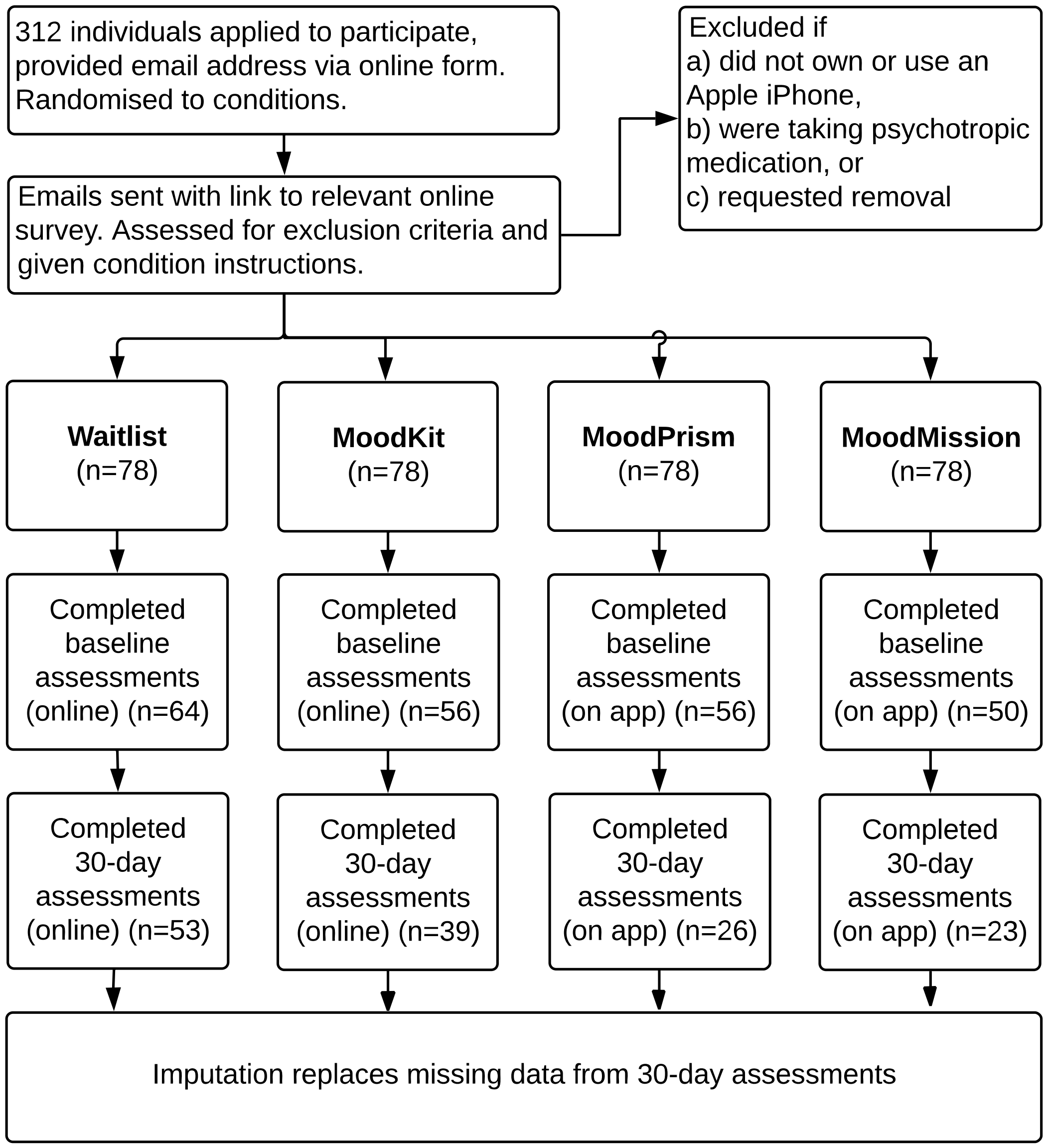


Figure 1. CONSORT flow diagram.

Analysis

Analyses were completed using IBM SPSS v.23. Participants were excluded if they: (a) were missing data from their baseline assessments; (b) reported that they had used MHapps other than the one allocated since the baseline assessment; or (c) had not used the MHapp at all. As is the case with eHealth research, attrition rates of up to 50-60% were expected (Hochheimer et al., 2016). Missing data from 30-day assessments were replaced via multiple imputation as recommended in guidelines for eHealth research (Blankers, Koeter, & Schippers, 2010). This method was chosen because data were considered missing at random (MAR), as attrition rates were relatively equal across groups that used the same assessment platforms and the likelihood of a participant completing the 30-day assessment was moderated by many random and situational factors, such as overall phone use, conscientiousness, interpretation of the importance of completing the assessment, and environmental distractions. The Markov Chain Monte Carlo algorithm was used with five imputations, and all baseline measures were included as predictors to replace missing data from 30-day assessments.

Prior to further analysis, each group was compared to the control on baseline PHQ-9 and GAD-7 scores to detect any significant differences. It was found that the MoodKit group scored significantly higher than the Control group on PHQ-9, $t(118) = -2.24$, $p = .027$, and GAD-7, $t(118) = -2.14$, $p = .035$, but the differences between the Control, MoodPrism, and MoodMission groups were non-significant.

Each app group was analysed against the control group in separate mixed design analyses of variance (ANOVAs), independent of the other app groups. Significant Group by Time interactions were investigated further through examination of the effects of Time for each group. Analyses were also replicated using just the non-imputed data and no substantial differences in point estimates were found.

To investigate the potential mediating effects of the secondary measures on the primary outcome measures, a series of mediated regression models were used. These analyses were conducted with the PROCESS plug-in for SPSS (A. F. Hayes, 2013) using procedures detailed in Field (2013) and Hayes and Rockwood (2016), which included bootstrapping using 5000 samples. To quantify change over time for each mediator or outcome variable, baseline scores were used as covariates and final scores as outcome variables. This follows Hayes and Rockwood's (2016) recommendations and avoids "self-selection", regression to the mean, and other biases found in other techniques, such as the use of difference scores. All Beta (β) statistics reported in the regressions are standardized effect sizes, and confidence intervals were inspected to determine statistical significance.

Results

Preliminary Analyses

An univariate ANOVA revealed no significant differences between groups on Age, and a Chi-squared test revealed no significant differences for Gender (all $p > .05$). At baseline, 54.7% of participants had a PHQ-9 score of 10 or over, indicating a likely diagnosis of a depressive disorder, and 35.8% had a GAD-7 score of 10 or over, indicating a likely diagnosis of an anxiety disorder. The WEMWBS has a normative median of 51 and inter-quartile range of 45 to 56, and the current study found a median of 42 with an inter-quartile range of 37 to 50, indicating lower levels of wellbeing.

Comparison of Group Effects

Means for all groups on the primary outcome measures are displayed in Figure 2. Descriptive statistics and significant Group by Time interactions for each app group against the Control group are reported in Table 2. MoodKit yielded significant Group by Time interactions for PHQ-9, WEMWBS and CSES scores. For MoodPrism, significant Group by Time interactions were observed for WEMWBS and ESAS-R scores. For MoodMission, significant Group by Time interactions were observed for PHQ-9, WEMWBS, and CSES scores. All other Group by Time interactions for each of the app analyses were non-significant. The within group effects of Time listed in Table 2 support each significant Group by Time interaction, with significant decreases in PHQ-9 scores for MoodKit and MoodMission, increases in WEMWBS for all app groups, increases in ESAS-R for MoodPrism, and increases in CSES for MoodKit and MoodMission. All analyses were replicated using just the non-imputed data and findings were congruent with those reported.

Mediation Analyses

To further investigate the significant effects of Time for each app group compared to the waitlist group, three sets of mediation analyses were pursued, with bivariate group as the predictor (waitlist = 0, MoodKit/MoodPrism/MoodMission = 1), the three primary outcome measures as the outcome and the secondary measures as mediators (see Table 3). These revealed that CSE, rather than ESA or MHL, played a significant mediation role for each app's effects. Additionally, there was a significant indirect effect of App on WEMWBS scores via ESA for MoodPrism. The confidence intervals for all indirect effects suggested that comparative significant differences could not be drawn between them.

Table 2

Primary and Secondary Measure Means, SDs, Confidence Intervals, and Effect Sizes and F-values for Within Group Comparisons and Group by Time Interactions

Measure	Group	Baseline		Follow-up		Group by Time interactions (against Control)		Within group effect of Time	
		M (SD)	95% CI	M (SD)	95% CI	η_p^2	*F*	η_p^2	*F*
PHQ-9	Control	8.55 (6.62)	[7.04, 10.06]	7.42 (5.84)	[6.12, 8.71]	-	-	.069	4.68*
	MoodKit	11.25 (6.54)	[9.64, 12.86]	8.63 (5.47)	[7.24, 10.02]	.035	4.24*	.341	28.46***
	MoodPrism	8.04 (4.9)	[6.42, 9.65]	6.30 (3.86)	[4.91, 7.69]	.007	.78	.237	17.12***
	MoodMission	10.94 (6.22)	[9.23, 12.65]	8.17 (5.62)	[6.70, 9.64]	.038	4.39*	.318	22.81***
GAD-7	Control	6.84 (5.55)	[5.48, 8.2]	6.25 (4.55)	[5.15, 7.35]	-	-	.020	1.28
	MoodKit	9.00 (5.47)	[7.55, 10.45]	7.32 (4.56)	[6.15, 8.49]	.017	2.10	.153	9.96**
	MoodPrism	6.80 (5.33)	[5.35, 8.26]	5.47 (4.13)	[4.30, 6.64]	.009	1.11	.136	8.69**
	MoodMission	8.58 (5.74)	[7.04, 10.12]	6.89 (4.55)	[5.65, 8.13]	.017	1.95	.146	8.39**
WEMWBS	Control	44.50 (9.44)	[42.38, 46.62]	46.33 (9.82)	[44.24, 48.42]	-	-	.066	4.45*
	MoodKit	40.63 (7.27)	[38.36, 42.89]	46.22 (7.41)	[43.99, 48.45]	.074	9.47**	.438	42.80***
	MoodPrism	45.09 (8.21)	[42.82, 47.35]	49.37 (7.93)	[47.14, 51.6]	.037	4.59*	.392	35.46***
	MoodMission	41.24 (9.24)	[38.84, 43.64]	46.96 (8.31)	[44.59, 49.32]	.089	11.00***	.558	61.91***
ESAS-R	Control	58.54 (13.54)	[55.21, 61.87]	59.36 (13.16)	[56.28, 62.45]	-	-	.014	.88
	MoodKit	57.94 (13.28)	[54.38, 61.5]	61.21 (12.48)	[57.92, 64.51]	.029	3.55	.171	11.36**
	MoodPrism	61.38 (12.40)	[57.82, 64.94]	64.64 (11.96)	[61.34, 67.94]	.033	4.00*	.217	15.25***
	MoodMission	52.41 (14.90)	[48.64, 56.17]	55.66 (12.34)	[52.17, 59.15]	.025	2.89	.136	7.73**
CSES	Control	159.16 (44.90)	[148.74, 169.58]	162.86 (45.31)	[152.35, 173.38]	-	-	.018	1.15
	MoodKit	152.00 (45.46)	[140.86, 163.14]	175.73 (41.84)	[164.49, 186.97]	.112	14.95***	.406	37.59***
	MoodPrism	169.75 (34.21)	[158.61, 180.89]	182.48 (37.73)	[171.24, 193.72]	.025	3.08	.169	11.15**
	MoodMission	154.46 (43.37)	[142.67, 166.25]	170.95 (45.28)	[159.06, 182.85]	.042	4.86*	.191	11.60***
MHLQ	Control	16.38 (2.12)	[15.82, 16.93]	16.61 (2.22)	[16.05, 17.16]	-	-	.023	1.51
	MoodKit	16.40 (2.09)	[15.8, 16.99]	16.26 (2.34)	[15.67, 16.85]	.012	1.46	.006	.58
	MoodPrism	16.54 (2.42)	[15.94, 17.13]	16.57 (1.83)	[15.97, 17.16]	.005	.58	.001	.03
	MoodMission	16.20 (2.44)	[15.57, 16.83]	16.28 (2.6)	[15.65, 16.91]	.002	.18	.001	.06

Note: *$p < .05$, ** $p < .01$, *** $p < .001$

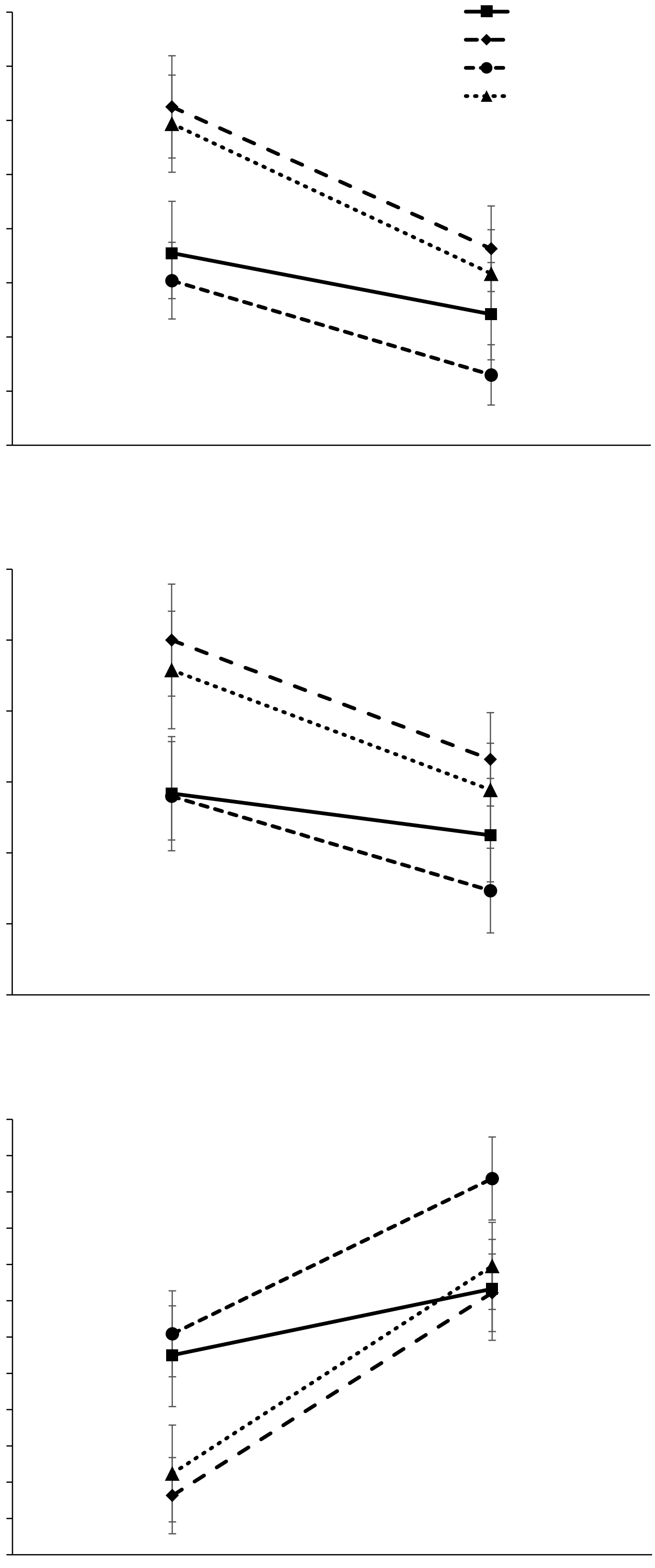


Figure 2. Baseline and 30-day assessment means on the primary outcome measures.

Table 3

Standardized Indirect Effects and [95% Confidence Intervals] from Mediation Analyses

App compared to Waitlist	Outcome measure	Mediator CSE	 ESA	 MHL
MoodKit	PHQ-9	-.217* [-.370, -.081]	-.020 [-.085, .015]	-.006 [-.049, .021]
	GAD-7	-.206* [-.360, -.082]	-.029 [-.098, .022]	.010 [-.055, .027]
	WEMWBS	.238* [.101, .391]	.044 [-.009, .125]	.011 [-.014, .069]
MoodPrism	PHQ-9	-.113* [-.261, -.007]	-.011 [-.099, .053]	-.003 [-.049, .016]
	GAD-7	-.122* [-.256, -.012]	-.060 [-.189, .007]	-.012 [-.061, .027]
	WEMWBS	.119* [.024, .225]	.063* [.002, .160]	.000 [-.017, .033]
MoodMission	PHQ-9	-.165* [-.337, -.006]	-.008 [-.053, .018]	-.004 [-.063, .038]
	GAD-7	-.152* [-.320, -.011]	-.011 [-.071, .037]	-.007 [-.067, .055]
	WEMWBS	.133* [.031, .241]	.020 [-.029, .086]	-.002 [-.032, .025]

Note: *95% CI does not contain 0, so $p < .05$

Discussion

This is the first RCT to compare three different available, stand-alone MHapps with a waitlist control condition. As hypothesized, the participants who used a MHapp for the 30-day trial period experienced significant increases in mental wellbeing when compared to participants in the waitlist control condition. However, only those using MoodKit and MoodMission experienced significant reductions in depression, and none of the apps had significant effects on anxiety when compared to waitlist. These findings were not expected, as all three apps were designed to reduce both anxiety and depression. There was no significant change in anxiety for the control group and there were significant reductions in anxiety for all three MHapps. However, the absence of any group by time interactions prevents the conclusion that any of the MHapps performed better than the waitlist condition. The absence of statistical significance may be due to limited power of the design and the use of a community sample. As the first RCT of its kind, the present study makes a useful contribution to the literature, and these findings are notable, given the adult community sample.

MoodKit and MoodMission were associated with significant increases in CSE and, as hypothesised, MoodPrism yielded a smaller effect on CSE than the other two more coping-focused MHapps. However, it was predicted that all apps would increase CSE by some significant degree, and this was not found for MoodPrism. As expected, participants in the MoodPrism group experienced significant increases in ESA, but participants in the MoodKit and MoodMission groups did not. Again, it was predicted that all apps would increase ESA by some significant degree, and this was not found for MoodKit and MoodMission. While all three MHapps allowed participants to rate their mood and review a log of their mood over time, it was hypothesized that the MoodPrism group would experience the greatest gains in ESA as it had the most dedicated mood-tracking functionality. The absence of ESA effects in MoodKit and MoodMission groups may be due to participants not utilizing the mood-tracking features within each app. As no app usage data were collected for the present study, analysis of the effects of each discrete tool was not possible, but points towards considerations for future studies.

The results showed no change in MHL across any of the MHapp conditions. MHL is a knowledge-based construct rather than a state or trait-based construct (Jorm, 2012), and therefore measures are usually tailored to quiz participants on the specific information contained in interventions (e.g., Reavley, Morgan, & Jorm, 2014). The current study used three different MHapps, each with different information on mental health, so it is possible that the MHL measure used did not adequately fit the variety of psychoeducation. Alternatively, the MHapps may have not contained sufficient psychoeducational features to generate changes on the measure of MHL used. For example, MoodMission's Missions each have a "Why This Helps" section, which explains the utility of each activity within the CBT model. However, including more information about the rates of mental illness in the community into the apps' content may have had more of an impact on the measure of MHL, as questions in the measure assess this knowledge. No suitable measures for MHL have been psychometrically developed, so this study used the MHLQ created for other MHapp studies (Bakker & Rickard, 2017a, 2017b). The low Cronbach's alpha score for the MHLQ may have also contributed to the lack of findings, but as a test of knowledge, internal reliability is less relevant as a construct than for a single construct scale. The MHLQ was likely a multidimensional test, with items about a range of distinct knowledge areas, so it is entirely possible that some individuals will have knowledge of some topics tested but not others. A psychometrically validated, multidimensional measure would have been better to include, if one existed.

The detected depression effects and absent anxiety effects may be due to the smaller effect sizes observed in the literature for anxiety than depression (Firth et al., 2017a, 2017b).

There have been fewer RCTs published that have shown effects of MHapps on anxiety, and those using community samples have not reported anxiety effects (e.g. Howells et al., 2014). It is also possible that MoodKit and MoodMission’s behavioural activation strategies were more effective on depression than the mood-tracking features of MoodPrism. However, further study is required to discriminate the origins of these discrepancies by investigating MHapp therapeutic processes in greater detail.

Depression and anxiety scores in the MoodKit group were significantly greater than those in the control group for the baseline assessment. This should be noted, as previous research has suggested that the effect of MHapp interventions can be moderated by baseline depression and anxiety (Bakker & Rickard, 2017a, 2017b). Participants who are clinically depressed or anxious may experience mental health improvements of a comparatively greater magnitude because they a) have more scope to improve their scores to a nonclinical level, and b) may find the interventions more applicable to their current mental state. While there is no direct evidence that the current findings are biased in such a way, the findings for MoodKit should be interpreted with this potential limitation.

Findings from the mediation analyses confirm that CSE played a significant role in mediating the mental health and wellbeing effects for each of the MHapp groups. This was found for all apps across depression, anxiety, and wellbeing, even in the absence of group by time interactions in comparison to the control group. This suggests that a major way the MHapp interventions worked was by increasing participants’ confidence in their ability to cope and their overall coping skill. This finding was consistent despite the large differences in functionality between each of the MHapps. This is supported by findings from Bakker and Rickard (2017b), which found a mediating effect of CSE between engagement with MoodMission and mental health outcomes, but only for participants who had subclinical or moderate, not severe, levels of depression or anxiety. It was also found that ESA mediated increases in wellbeing experienced by the MoodPrism group. This too is supported by a previous study, with Bakker and Rickard (2017a) finding that ESA mediated the relationship between mental health outcomes and engagement with MoodPrism, as was expected from the mood-tracking app.

The current RCT design offers different insights to Bakker and Rickard’s (2017a, 2017b) investigations, as these examined the quality of engagement with the app in users who were not specifically recruited for research purposes and had downloaded the app naturally from the app store. The current RCT’s participants were aware that they had been recruited into a study which may have provided a certain level of motivation at the outset, meaning that the effects of the app were less dependent on the quality of their engagement with the app. Furthermore, despite using a community sample, the proportion of participants who scored in the clinical range on depression and anxiety measures was higher than community norms. This suggests that help-seeking for current mental health problems was a factor motivating participation. Individuals who are considering or actively seeking mental health support are the intended market for MHapps, so the sample was appropriate to use for the current study of self-guided MHapps.

The use of a waitlist condition should be considered when interpreting these findings. Torous and Firth (2016) propose a digital placebo effect, in which measurable mental health effects may be generated from the simple act of downloading a MHapp. To overcome this, some studies have used “active” controls, with participants using a “dummy” version of the app or some other “light touch” intervention (e.g. Arean et al., 2016). This was not possible for the current study due to the nature of the apps, the style of recruitment that could set up expectations for accessing a functional and interactive MHapp, and the potential frustration this may have caused participants who were allocated the dummy app. An app that frustrates users may even have negative impacts on measures of mental health which would arguably be a more serious confound as it could create false positive effects for the other apps where no true effect occurs (Hassenzahl, Diefenbach, & Göritz, 2010). Another way to overcome this digital placebo effect may be to use a different study design that measures the relationship between intervention engagement and outcomes (Carpenter et al., 2016). Bakker and Rickard reported findings that linked app engagement with mental health and wellbeing improvements, for both MoodPrism (Bakker and Rickard, 2017a) and MoodMission (Bakker & Rickard, 2017b). This suggests that the MHapp effects found in this study were not solely due to the digital placebo effect, and were attributable to the interventions contained within the MHapps.

Research on MHapps has generally used time as the independent variable rather than usage or number of engagements (e.g., Howells et al., 2014; Kuhn et al., 2017). This is to reflect the naturalistic use of MHapps which are downloaded and then intermittently used throughout an individual's daily routine. Different patterns of engagement are used by different MHapp intervention paradigms, so often cannot be compared objectively. For example, the daily mood surveys completed by MoodPrism participants may have involved more "screen time" than using MoodMission to discover new coping strategies and then completing Missions off-app. This makes time passed rather than time engaged with the intervention a more helpful independent variable, especially when comparing across the literature (Kazantzis, Brownfield, Mosely, Usatoff, & Flighty, 2017). This study used a period of 30 days for the apps to exert effects, as this is a period used in other RCTs (e.g. Enock, Hofmann, & McNally, 2014; Kauer et al., 2012; Roepke et al., 2015).

In addition to the other limitations previously noted, there were also different modes of assessment administered across groups. The MoodPrism and MoodMission groups completed the measures on the apps themselves, as the measures were already built into the apps and users were required to complete them to "unlock" the intervention. In contrast, the waitlist and MoodKit groups completed the measures using separate online assessments. While evidence suggests that there should not be a discernible difference between administration of assessments via mobile app or online (Brodey, Gonzalez, Elkin, Sasiela, & Brodey, 2017; Watts et al., 2013), there may have been small effects related to the unique formats used by each MHapp. As the formats remained constant between the baseline and final assessments, it is expected that these effects were minimized. Another difference between the groups was the perceived cost of the apps. Although codes were provided to participants to access MoodKit, it is possible that participants perceived the app to be more valuable, in comparison to MoodPrism and MoodMission which were displayed on the app store as free to download. This increased perception of value may have increased engagement or perceived benefits for the MoodKit group (West et al., 2012; Zeithaml, 1988), but this was not possible to verify using the data collected.

While the effect sizes found in this RCT appear small when compared to clinical treatments for depression and anxiety, they are within the expected range for low-intensity, nonclinical interventions. As Bennett-Levy et al. (2010) point out, the small effect sizes of low-intensity interventions can translate into large public health gains. By preventing small scale emotional problems from developing into clinical disorders, low-intensity interventions can reduce the incidence of depression by up to 50% (Barrera, Torres, & Muñoz, 2007). This can have exponential effects on the wellbeing of the individual and those around them, as they are better able to maintain work obligations, emotionally support their friends and family, respond to stressors with resilience, and reflect on their competence doing all of this.

The present RCT supports the growing literature that MHapps can effectively reduce depression and increase mental wellbeing in a community sample. The findings suggest that MHapps like MoodKit, MoodPrism, and MoodMission can offer effective support within a stepped-care clinical framework and may offer preventative benefits. In addition, the present study contributed uniquely in the investigation of the underlying mechanisms of three different MHapps, and suggests that despite each app's distinct functionality, the MHapps studied improved participants' confidence in their ability to cope with stress and adversity by using specific strategies. The use of a MHapp in itself may be considered a coping strategy. The MHapp interventions currently available are not positioned to replace professional clinical supports, but the evidence indicates that some can be useful tools for improving mental health and wellbeing. The strengths of MHapps are being realized as more mobile-based interventions are developed and their use becomes more commonplace among smartphone users.

References

Ahrnsbrak, R., Bose, J., Hedden, S. L., Lipari, R. N., & Park-Lee, E. (2017). *Key Substance Use and Mental Health Indicators in the United States: Results from the 2016 National Survey on Drug Use and Health* (No. HHS Publication No. SMA 17-5044, NSDUH Series H-52). Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Retrieved from https://www.samhsa.gov/data/

Anton, M. T., & Jones, D. J. (2017). Adoption of technology-enhanced treatments: Conceptual and practical considerations. *Clinical Psychology: Science and Practice*, *24*(3), 223–240. https://doi.org/10.1111/cpsp.12197

Arean, P. A., Hallgren, K. A., Jordan, J. T., Gazzaley, A., Atkins, D. C., Heagerty, P. J., & Anguera, J. A. (2016). The use and effectiveness of mobile apps for depression: Results from a fully remote clinical trial. *Journal of Medical Internet Research*, *18*(12), e330. https://doi.org/10.2196/jmir.6482

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2016). Mental health smartphone apps: Review and evidence-based recommendations for future developments. *JMIR Mental Health*, *3*, e7. https://doi.org/10.2196/mental.4984

Bakker, D., & Rickard, N. (2017a). Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism. *Journal of Affective Disorders*, *227*, 432–442. https://doi.org/10.1016/j.jad.2017.11.016

Bakker, D., & Rickard, N. (2017b). *Engagement with a cognitive behavioral therapy mobile phone app predicts changes in mental health and well-being: MoodMission*. Manuscript submitted for publication.

Barlow, D. H., Farchione, T. J., Bullis, J. R., Gallagher, M. W., Murray-Latin, H., Sauer-Zavala, S., … Cassiello-Robbins, C. (2017). The Unified Protocol for transdiagnostic treatment of emotional disorders compared with diagnosis-specific protocols for anxiety disorders: A randomized clinical trial. *JAMA Psychiatry*, *74*(9), 875–884. https://doi.org/10.1001/jamapsychiatry.2017.2164

Barrera, A. Z., Torres, L. D., & Muñoz, R. F. (2007). Prevention of depression: the state of the science at the beginning of the 21st Century. *International Review of Psychiatry (Abingdon, England)*, *19*(6), 655–670. https://doi.org/10.1080/09540260701797894

Barrett, L., Gross, J., Christensen, T., & Benvenuto, M. (2001). Knowing what you’re feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. *Cognition and Emotion*, *15*, 713–724. https://doi.org/10.1080/02699930143000239

Benka, J., Nagyova, I., Rosenberger, J., Macejova, Z., Lazurova, I., Klink, J. V. der, … Dijk, J. V. (2014). Is coping self-efficacy related to psychological distress in early and established rheumatoid arthritis patients? *Journal of Developmental and Physical Disabilities*, *26*, 285–297. https://doi.org/10.1007/s10882-013-9364-y

Bennett-Levy, J., Richards, D. A., & Farrand, P. (2010). Low intensity CBT interventions: A revolution in mental health care. In J. Bennett-Levy, D. Richards, P. Farrand, H. Christensen, K. Griffiths, D. Kavanagh, … J. Proudfoot (Eds.), *Oxford Guide to Low Intensity CBT Interventions* (1st ed., pp. 3–18). Oxford: Oxford University Press.

Blankers, M., Koeter, M. W. J., & Schippers, G. M. (2010). Missing data approaches in eHealth research: Simulation study and a tutorial for nonmathematically inclined researchers. *Journal of Medical Internet Research*, *12*(5), e54. https://doi.org/10.2196/jmir.1448

Brijnath, B., Protheroe, J., Mahtani, K. R., & Antoniades, J. (2016). Do web-based mental health literacy interventions improve the mental health literacy of adult consumers? Results from a systematic review. *Journal of Medical Internet Research, 18*(6), e165. https://doi.org/10.2196/jmir.5463

Brodey, B. B., Gonzalez, N. L., Elkin, K. A., Sasiela, W. J., & Brodey, I. S. (2017). Assessing the equivalence of paper, mobile phone, and tablet survey responses at a community mental health center using equivalent halves of a 'gold-standard' depression item bank. *JMIR Mental Health*, *4*(3), e36. https://doi.org/10.2196/mental.6805

Carpenter, J., Crutchley, P., Zilca, R. D., Schwartz, H. A., Smith, L. K., Cobb, A. M., & Parks, A. C. (2016). Seeing the "big" picture: Big data methods for exploring relationships between usage, language, and outcome in internet intervention data. *Journal of Medical Internet Research, 18*(8), e241. https://doi.org/10.2196/jmir.5725

Chesney, M. A., Neilands, T. B., Chambers, D. B., Taylor, J. M., & Folkman, S. (2006). A validity and reliability study of the coping self-efficacy scale. *British Journal of Health Psychology*, *11*, 421–437. https://doi.org/10.1348/135910705X53155

Donker, T., Griffiths, K. M., Cuijpers, P., & Christensen, H. (2009). Psychoeducation for depression, anxiety and psychological distress: A meta-analysis. *BMC Medicine*, *7*, 79. https://doi.org/10.1186/1741-7015-7-79

Donker, T., Petrie, K., Proudfoot, J., Clarke, J., Birch, M.-R., & Christensen, H. (2013). Smartphones for smarter delivery of mental health programs: A systematic review. *Journal of Medical Internet Research, 15*, e247. https://doi.org/10.2196/jmir.2791

Enock, P. M., Hofmann, S. G., & McNally, R. J. (2014). Attention bias modification training via smartphone to reduce social anxiety: A randomized, controlled multi-session experiment. *Cognitive Therapy and Research*, *38*(2), 200–216. https://doi.org/10.1007/s10608-014-9606-z

Field, A. (2013). *Discovering statistics using SPSS* (4th ed.). London: Sage.

Firth, J., Torous, J., Nicholas, J., Carney, R., Pratap, A., Rosenbaum, S., & Sarris, J. (2017a). The efficacy of smartphone-based mental health interventions for depressive symptoms: A meta-analysis of randomized controlled trials. *World Psychiatry*, *16*(3), 287–298. https://doi.org/10.1002/wps.20472

Firth, J., Torous, J., Nicholas, J., Carney, R., Rosenbaum, S., & Sarris, J. (2017b). Can smartphone mental health interventions reduce symptoms of anxiety? A meta-analysis of randomized controlled trials. *Journal of Affective Disorders*, *218*(Supplement C), 15–22. https://doi.org/10.1016/j.jad.2017.04.046

Grist, R., Porter, J., & Stallard, P. (2017). Mental health mobile apps for preadolescents and adolescents: A systematic review. *Journal of Medical Internet Research*, *19*(5), e176. https://doi.org/10.2196/jmir.7332

Hassenzahl, M., Diefenbach, S., & Göritz, A. (2010). Needs, affect, and interactive products – Facets of user experience. *Interacting with Computers*, *22*(5), 353–362. https://doi.org/10.1016/j.intcom.2010.04.002

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (1 edition). New York: The Guilford Press.

Hayes, A. F., & Rockwood, N. J. (2016). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy*. https://doi.org/10.1016/j.brat.2016.11.001

Hayes, S. C., & Hofmann, S. G. (2017). The third wave of cognitive behavioral therapy and the rise of process-based care. *World Psychiatry*, *16*(3), 245–246. https://doi.org/10.1002/wps.20442

Hayes, S. C., & Hofmann, S. G. (Eds.). (2018). *Process-based CBT: The science and core clinical competencies of Cognitive Behavioral Therapy* (1 edition). Oakland CA: New Harbinger.

Hill, C. L. M., & Updegraff, J. A. (2012). Mindfulness and its relationship to emotional regulation. *Emotion*, *12*, 81–90. https://doi.org/10.1037/a0026355

Hochheimer, C. J., Sabo, R. T., Krist, A. H., Day, T., Cyrus, J., & Woolf, S. H. (2016). Methods for evaluating respondent attrition in web-based surveys. *Journal of Medical Internet Research*, *18*(11), e301. https://doi.org/10.2196/jmir.6342

Hofmann, S. G. (2015). *Emotion in therapy: From science to practice*. New York, NY: Guilford Press.

Howells, A., Ivtzan, I., & Eiroa-Orosa, F. J. (2014). Putting the “app” in happiness: A randomised controlled trial of a smartphone-based mindfulness intervention to enhance wellbeing. *Journal of Happiness Studies*. https://doi.org/10.1007/s10902-014-9589-1

Jorm, A. F. (2012). Mental health literacy: Empowering the community to take action for better mental health. *American Psychologist*, *67*, 231–243. https://doi.org/10.1037/a0025957

Kauer, S. D., Reid, S. C., Crooke, A. H. D., Khor, A., Hearps, S. J. C., Jorm, A. F., … Patton, G. (2012). Self-monitoring using mobile phones in the early stages of adolescent depression: Randomized controlled trial. *Journal of Medical Internet Research*, *14*, e67. https://doi.org/10.2196/jmir.1858

Kazantzis, N. (2018). Introduction to the special issue on processes of Cognitive Behavioral Therapy: Does “necessary, but not sufficient” still capture it? *Cognitive Therapy and Research*, *42*(2), 115–120. https://doi.org/10.1007/s10608-018-9891-z

Kazantzis, N., Brownfield, N. R., Mosely, L., Usatoff, A. S., & Flighty, A. J. (2017). Homework in Cognitive Behavioral Therapy: A systematic review of adherence assessment in anxiety and depression (2011–2016). *Psychiatric Clinics of North America*, *40*(4), 625–639. https://doi.org/10.1016/j.psc.2017.08.001

Kazantzis, N., Luong, H. K., Usatoff, A. S., Impala, T., Yew, R. Y., & Hofmann, S. G. (in press). The processes of cognitive behavioral therapy: A review of meta-analyses. *Cognitive Therapy & Research.*

Kessler, R. C., Chiu, W. T., Demler, O., Merikangas, K. R., & Walters, E. E. (2005). Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication. *Archives of General Psychiatry*, *62*(6), 617–627. https://doi.org/10.1001/archpsyc.62.6.617

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*, 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kuhn, E., Kanuri, N., Hoffman, J. E., Garvert, D. W., Ruzek, J. I., & Taylor, C. B. (2017). A randomized controlled trial of a smartphone app for posttraumatic stress disorder symptoms. *Journal of Consulting and Clinical Psychology*, *85*(3), 267–273. https://doi.org/10.1037/ccp0000163

Mennin, D. S., Ellard, K. K., Fresco, D. M., & Gross, J. J. (2013). United we stand: Emphasizing commonalities across cognitive-behavioral therapies. *Behavior Therapy*, *44*, 234–248. https://doi.org/10.1016/j.beth.2013.02.004

MoodMission Pty Ltd. (2017). MoodMission (Version 1.1.2) [Mobile application software]. Retrieved May 23, 2017, from https://itunes.apple.com/au/app/moodmission/id1140332763?mt=8

MoodPrism. (2016). MoodPrism (Version 1.0.15) [Mobile application software]. Retrieved May 23, 2017, from https://play.google.com/store/apps/details?id=au.com.monash.moodprism&hl=en

Morris, M. E., Kathawala, Q., Leen, T. K., Gorenstein, E. E., Guilak, F., Labhard, M., & Deleeuw, W. (2010). Mobile therapy: Case study evaluations of a cell phone application for emotional self-awareness. *Journal of Medical Internet Research*, *12*, e10. https://doi.org/10.2196/jmir.1371

Nicholas, J., Larsen, M. E., Proudfoot, J., & Christensen, H. (2015). Mobile apps for bipolar disorder: A systematic review of features and content quality. *Journal of Medical Internet Research*, *17*(8), e198. https://doi.org/10.2196/jmir.4581

O'Toole, M., Jensen, M., Fentz, H., Zachariae, R., & Hougaard, E. (2014). Emotion differentiation and emotion regulation in high and low socially anxious individuals: An experience-sampling study. *Cognitive Therapy and Research*, *38*, 428–438. https://doi.org/10.1007/s10608-014-9611-2

Philip, E. J., Merluzzi, T. V., Zhang, Z., & Heitzmann, C. A. (2013). Depression and cancer survivorship: Importance of coping self-efficacy in post-treatment survivors. *Psycho-Oncology, 22,* 987–994. https://doi.org/10.1002/pon.3088

Pritchard, C., & Gow, K. (2012). Coping self-efficacy and psychological distress in flood victims. In K. Gow & M. J. Celinski (Eds.), *Individual trauma: Recovering from deep wounds and exploring the potential for renewal* (pp. 207–219). Hauppauge, NY, US: Nova Science.

Reavley, N. J., Morgan, A. J., & Jorm, A. F. (2014). Development of scales to assess mental health literacy relating to recognition of and interventions for depression, anxiety disorders and schizophrenia/psychosis. *Australian and New Zealand Journal of Psychiatry*, *48*, 61–69. https://doi.org/10.1177/0004867413491157

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. https://doi.org/10.2196/mental.6202

Roepke, A. M., Jaffee, S. R., Riffle, O. M., McGonigal, J., Broome, R., & Maxwell, B. (2015). Randomized controlled trial of SuperBetter, a smartphone-based/internet-based self-help tool to reduce depressive symptoms. *Games for Health Journal*, *4*(3), 235–246. https://doi.org/10.1089/g4h.2014.0046

Sirois, F. M., & Hirsch, J. K. (2013). Associations of psychological thriving with coping efficacy, expectations for future growth, and depressive symptoms over time in people with arthritis. *Journal of Psychosomatic Research*, *75*, 279–286. https://doi.org/10.1016/j.jpsychores.2013.06.004

Slade, M. (2010). Mental illness and well-being: the central importance of positive psychology and recovery approaches. *BMC Health Services Research*, *10*, 26. https://doi.org/10.1186/1472-6963-10-26

Smith, A., Benight, C., & Cieslak, R. (2013). Social support and postdeployment coping self-efficacy as predictors of distress among combat veterans. *Military Psychology*, *25*, 452–461. https://doi.org/10.1037/mil0000013

Spitzer, R. L., Kroenke, K., Williams, J. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, *166*, 1092–1097. https://doi.org/10.1001/archinte.166.10.1092

Stewart-Brown, S., & Janmohamed, K. (2008). Warwick-Edinburgh Mental Well-being Scale. *User Guide. Version*, *1*. Retrieved from http://www.cppconsortium.nhs.uk/admin/files/1343987601WEMWBS%20User%20Guide%20Version%201%20June%202008.pdf

Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., … Stewart-Brown, S. (2007). The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Development and UK validation. *Health and Quality of Life Outcomes*, *5*, 63. https://doi.org/10.1186/1477-7525-5-63

Thorne, K. J., Andrews, J. J. W., & Nordstokke, D. (2013). Relations among children's coping strategies and anxiety: The mediating role of coping efficacy. *The Journal of General Psychology*, *140*, 204–223. https://doi.org/10.1080/00221309.2013.792235

Thriveport LLC. (2016). MoodKit - Mood Improvement Tools (Version 3.1) [Mobile application software]. Retrieved May 23, 2017, from https://itunes.apple.com/au/app/moodkit-mood-improvement-tools/id427064987?mt=8

Torous, J., & Firth, J. (2016). The digital placebo effect: mobile mental health meets clinical psychiatry. *The Lancet Psychiatry*, *3*(2), 100–102. https://doi.org/10.1016/S2215-0366(15)00565-9

van Straten, A., Hill, J., Richards, D. A., & Cuijpers, P. (2015). Stepped care treatment delivery for depression: a systematic review and meta-analysis. *Psychological Medicine; Cambridge*, *45*(2), 231–246. http://dx.doi.org.ezproxy.lib.monash.edu.au/10.1017/S0033291714000701

Watts, S., Mackenzie, A., Thomas, C., Griskaitis, A., Mewton, L., Williams, A., & Andrews, G. (2013). CBT for depression: A pilot RCT comparing mobile phone vs. computer. *BMC Psychiatry*, *13*, 49. https://doi.org/10.1186/1471-244X-13-49

West, J. H., Hall, P. C., Hanson, C. L., Barnes, M. D., Giraud-Carrier, C., & Barrett, J. (2012). There's an app for that: Content analysis of paid health and fitness apps. *Journal of Medical Internet Research*, *14*(3). https://doi.org/10.2196/jmir.1977

Whiteford, H. A., Degenhardt, L., Rehm, J., Baxter, A. J., Ferrari, A. J., Erskine, H. E., … Vos, T. (2013). Global burden of disease attributable to mental and substance use disorders: findings from the Global Burden of Disease Study 2010. *The Lancet*, *382*(9904), 1575–1586. https://doi.org/10.1016/S0140-6736(13)61611-6

Williams, C., & Martinez, R. (2008). Increasing access to CBT: Stepped care and CBT self-help models in practice. *Behavioural and Cognitive Psychotherapy*, *36*, 675–683. https://doi.org/10.1017/S1352465808004864

World Health Organization. (2004). *Promoting mental health: Concepts, emerging evidence, practice*. Geneva: World Health Organization.

World Health Organization. (2017). WHO | Depression. Retrieved March 30, 2017, from http://www.who.int/mediacentre/factsheets/fs369/en/

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2–22. https://doi.org/10.2307/1251446

[i] Converted to Hedge's *g* by Firth et al. (2017a) from original η_p^2 = .030

[ii] Converted to Hedge's *g* by Firth et al. (2017a) from original d = 0.67

CHAPTER 8: INTEGRATED DISCUSSION

The first publicly successful online therapy programs, such as MoodGYM (Twomey & O'Reilly, 2017), underwent rigorous research and evaluation before being released to the public. However, when mental health apps (MHapps) first appeared on the iTunes and Google Play app stores, they lacked any supporting evidence for the mental health improvement claims that they made. A precedent was set that MHapps did not need to be researched before they were released to the public (Chou et al., 2017). Now there are thousands of mental health apps available, and only a handful have been subjected to any form of research (Firth et al., 2017a, 2017b). Not only does this limit the number of MHapps available that are known to be effective, but it also means that the underlying mechanisms used by MHapps have remained unstudied, hindering future developments and improvement in the field.

This thesis aimed to progress the field of mental health apps by developing new insights into whether they work, how they work, and how they might be improved. This was achieved by first reviewing the field of mental health apps, then contributing to the design and development of two new apps (MoodPrism and MoodMission), and finally evaluating the apps' effects on mood, anxiety, and mental wellbeing. In evaluating the apps, it was found that participants with depression or anxiety who used MoodPrism and engaged in its reflection-focussed, mood-tracking features experienced improvements in mental health and wellbeing. Analyses suggested that increases in emotional self-awareness (ESA) mediated these effects. Furthermore, participants who engaged in short cognitive behavioural therapy (CBT) strategies to cope with distress via the problem-focussed app MoodMission experienced increases in wellbeing. In contrast to MoodPrism, analyses suggested that increases in coping self-efficacy (CSE) mediated these effects for participants who were experiencing moderate symptomatology. Comparing these apps against another publicly available mental health app (MoodKit) and a waitlist control group in a randomised controlled trial (RCT) suggested that providing participants with an evidence-based MHapp significantly improved their mental health and wellbeing, potentially by increasing CSE. Across all these studies, the effects on depression and anxiety were mixed and, in part, depended on the clinical status of the participants, but the increases in mental wellbeing were much more consistent across groups and apps. Overall, these findings support the efficacy of the MHapps tested, and reveal important considerations regarding the underlying mechanisms of MHapps in general. The main findings of this thesis' empirical papers are summarised in Table 1.

One contrasting finding across the studies concerned MoodMission's effect on depression. In Chapter 6, no direct relationship between app engagement and depression was found. However, Chapter 7's RCT found a significant Group by Time interaction for depression and significant decreases in depression for the MoodMission group. The discrepancy between the two studies' findings could be the result of the studies' different methodologies. For example, the participants in the effectiveness study who naturalistically downloaded the app from the app store may have approached the use of MoodMission differently to those who were allocated to use the app in the RCT. Another likelihood is that the relationship between app engagement and depression is more complicated than the relationship between app engagement and wellbeing. This is suggested by the finding that CSE significantly mediated the engagement-depression relationships, despite the lack of a direct effect. Engagement with MoodMission increased CSE, which in turn decreased depression, but overall there was no effect of engagement on depression. As speculated in Chapter 6, this could be due to other, unmeasured mediators masking the direct effect. The RCT found that MoodMission had efficacy in increasing wellbeing and reducing depression. The established reliability and impact of the RCT design throughout psychological and medical research should be accounted for when considering this evidence (Begg et al., 1996). This, together with the indirect effect of app engagement on depression and anxiety via CSE, enables the conclusion that MoodMission use can be an effective tool for relieving low moods.

The studies reported in Chapters 4 and 6 used a devised measure of engagement taken from the feedback questionnaire administered to participants in the 30-day assessment. As discussed in the chapters, this measure of “quality” of engagement was chosen over “quantity” of engagement variables like number of times the app was accessed, or time spent using the app. This was because patterns of app use could be influenced by a range of factors independent to or confounded with app engagement. For example, an individual who uses their phone a lot, who uses their phone for distraction from anxiety, or who requires more time to read would show conflated engagement ratings on these variables. While the engagement measure chosen avoids these confounds, a potential limitation to consider is the influence of app likeability. An individual who likes the app and has a more positive attitude to the app may be more likely to respond with a high engagement score. As discussed in Chapter 4, the engagement measure used can be thought of as analogous to measures of client engagement or therapeutic relationship, as these predict treatment outcomes in in-person CBT (Holdsworth et al., 2014; Kazantzis et al., 2015; Sucala et al., 2012). Such measures could also be confounded by how much individuals like their therapist or the content of the therapy. However, this starts to raise questions about the nature and importance of likability in CBT interventions and how different it really is from engagement, especially given the importance the individual’s intrinsic motivation to commit to therapeutic change. More research is needed to develop more reliable measures of therapeutic engagement that can be used for MHapp interventions and are consistent with CBT models and theory.

Mediation analyses were included throughout this thesis to investigate the mechanisms each MHapp intervention used to generate therapeutic change. The mediator variables were chosen because they were positioned in the theoretical model between engaging with the intervention and the hypothesised mental health and wellbeing improvements. For example, using MoodMission to learn and practise coping strategies should theoretically improve confidence in coping ability and CSE. This, in turn, may help individuals cope with anxiety and low moods. The mediation analyses supported the majority of the hypothesised relationships but could not affirm causality for the overall hypothesised model. More research is needed to clarify and affirm the time-order processes involved and the direction of relationships between engagement, ESA/CSE, and mental health outcomes.

This discussion will relate the findings obtained in this thesis to theory in an effort to provide a theory-driven understanding of MHapp effects and means for their improvement. The methods used in this thesis will also be discussed to provide insight into methods for future MHapp studies. Finally, broad recommendations will be made for MHapp use and development, accounting for factors outside the scope of this thesis' findings, such as app promotion, accessibility, software development, and organisational guiding values.

Table 1

Summary of Empirical Findings

				Significant Effects on Outcomes			Significant Mediators		
Design	Chapter	App	Sample	Depression	Anxiety	Wellbeing	Depression	Anxiety	Wellbeing
Regression between app engagement and outcomes	4	MoodPrism	Whole	✓	✓	✓	-	-	-
			Nonclinical	-	-	✓	-	-	-
			Clinical	-	✓	✓	ESA	ESA	ESA
	6	MoodMission	Whole	-	-	✓	CSE	CSE	CSE
			Nonclinical	-	-	✓	-	-	CSE
			Moderate clinical	-	-	✓	CSE	CSE	CSE
			Severe clinical	-	-	✓	-	-	-
RCT	7	MoodKit		✓	-	✓	CSE	CSE	CSE
		MoodPrism		-	-	✓	CSE	CSE	CSE, ESA
		MoodMission		✓	-	✓	CSE	CSE	CSE

Theoretical Implications

The novelty of MHapp interventions means there has been limited opportunity to establish a single theoretical framework to understand their effects. However, two well-established theories were described in the introductory paper of this thesis as important for the MHapp field; cognitive behavioural therapy (CBT) theory and self-determination theory (SDT). CBT is a theory of achieving therapeutic outcomes in mental health, so it is useful to understand the bottom-up mechanisms that MHapps use to instigate therapeutic change. Alternatively, SDT is a theory of motivation, so it is useful for understanding top-down interactions that enhance motivation to engage in therapeutic processes. In addition to these two theories, Gross' (2002) Emotion Regulation Theory can be helpful to assess the overall direction of the intervention in the kinds of emotion regulation strategies it encourages, and the Behavioural Health Continuum of Care model is helpful to understand the broader population-level impacts of highly accessible MHapps. Discussion of MoodPrism and MoodMission within each of these four theories aims to reveal: a) the theoretical mechanisms underlying each MHapp's effects; b) how the intervention structures that exist within other MHapps may relate to these theories; and c) how MHapps can be better designed to enhance the theory-based mechanisms of change.

Cognitive Behavioural Therapy

CBT covers a large variety of different interventions for a variety of psychological problems. This thesis' introductory paper made reference to Mennin, Ellard, Fresco, and Gross' (2013) definition of the commonalities underlying CBT interventions, including a common goal and three main change processes. Reflecting on how these relate to MoodPrism and MoodMission can reveal the theoretical processes that these, and other CBT-based apps, use to generate mental health improvements.

The common goal of all CBT interventions is behavioural adaptation (Mennin et al., 2013). This is the process by which an organism becomes more suited to thriving in its environment. The goals that an individual wishes to achieve become easier to pursue, and they maximise the use of their own resources in their self-guided endeavours. Most CBT interventions are aimed at ameliorating dysfunction, because they are treatments for psychological disorders, but behavioural adaptation can also be achieved by improving functioning beyond what is already achieved. This goal is shared by the majority of MHapps, which aim to help users better deal with cognitive, behavioural, or emotional problems. However, not all MHapps use CBT change principles.

CBT works through three basic change principles, including context engagement, attention change, and cognitive change (Mennin et al., 2013). Not all individual aspects of a CBT intervention need to engage all three change principles, but the intervention as a whole should aim to utilise all three. Context engagement refers to a process of using new experiences to alter older, more habitual, maladaptive patterns of thought, feeling, and behaviour. For example, behavioural activation treatments aim to redirect depressed individuals out of depressive patterns by engaging them in activities that are much more physiologically and behaviourally exciting (Dimidjian et al., 2014). Similarly, exposure techniques help individuals face fears that they have avoided for a long time (Peterman, Read, Wei, & Kendall, 2015). Therefore, any MHapp that is promoting a new mode of reacting, behaving, thinking, or feeling may be using context engagement, particularly if that new mode is in opposition to the individual's established routines. Apps that solely reinforce existing behaviours or thought patterns and do not attempt to change them are not using context engagement.

MoodPrism aims to promote an awareness for an individual of their own emotional state and own emotional history. It also provides users with mental health information that they may not have considered before. The context engagement used by MoodPrism is focussed on changing the relationship between the user and their moods. This is not as active as MoodMission, which suggests new coping strategies and wellbeing activities to users that they may not have considered before. Mission suggestions are tailored to an individual’s state, so, for example, behavioural activation missions are more likely to be suggested to users reporting depressive symptoms. Tailoring uses context engagement by suggesting Missions that are counteractive of the user’s current state.

Attention change is the second CBT change principle outlined by Mennin et al. (2013), and involves practising the reorientation of attention in more adaptive directions. This allows individuals to break out of psychological vicious cycles, or “problem maintaining circles” (PMCs; Bakker, 2008), by focussing their attention on thoughts, feelings, or behaviours that are outside of the cycle. Acceptance strategies also involve attention change, as an individual focusses their cognitive attention on thoughts that accept and do not perpetuate the problem.

Using MoodPrism may foster a change in an individual’s attention onto different aspects of their emotions and situations. For example, when a user is prompted to complete a daily mood report, they are reminded to pay attention to their current emotional state. Similarly, when MoodMission suggests a series of Missions to a user, this can move attention away from the problem towards a solution. The Missions themselves also often contain attention change components. For example, mindfulness Missions guide an individual to attend to various physical sensations or other neutral stimuli, and thought stopping Missions redirect attention away from unhelpful thoughts.

Cognitive change is the final change principle listed by Mennin et al. (2013), and refers to the practice of taking different perspectives on events and generating alternative thoughts, which may lead to alternative interpretations and beliefs. Cognitive reframing interventions engage cognitive change by recontextualising events in ways that lead to fewer maladaptive emotional or behavioural responses. Many CBT techniques that focus on cognitive change involve keeping an objective record of experiences, usually by noting down thoughts and feelings on a worksheet or in a diary, and making numbered ratings of intensity via subjective units of distress (SUDs) scales (Kazantzis, MacEwan, & Dattilio, 2005).

MoodPrism's mood diary may help users change their perspective on events by reflecting on their emotional experiences. Subjective recollection is marred by biases that may increase maladaptive perceptions of the past (Platt, Waters, Schulte-Koerne, Engelmann, & Salemink, 2017), so MoodPrism's diary can help users by presenting them with a more objective, less biased record. Furthermore, depression can negatively bias an individual's recollection (Becker & Leinenger, 2011), so keeping an objective account of emotional states over time may correct those cognitive biases.

MoodMission requires users to report their level of distress using a SUDs scale before completing a Mission, and when they report their distress again after, they are reminded of their initial pre-Mission rating. This may help to promote an individual's conceptualisation of themselves as someone who is able to lower their own distress through use of a strategy, which in turn should improve CSE. In this way, MoodMission's intervention structure is promoting cognitive change. Many Missions employed by MoodMission also engage cognitive change, such as the Missions that coach users through cognitive reframing exercises commonly employed in CBT, or prompt users to record three good things about themselves or their day.

The mediators investigated in this thesis included CSE, ESA, and mental health literacy (MHL). However, only CSE and ESA significantly mediated app engagement and wellbeing outcomes, suggesting that the apps did not exert effects by increasing user MHL. CSE and ESA are both strongly implicated in CBT theory, and many core CBT techniques are aimed at improving coping skills and emotional awareness. While increasing an individual's knowledge about mental health may improve recognition of symptoms, increase help-seeking, or reduce stigma (Jorm, 2012), it does not directly engage any of the three CBT change processes. This may explain the lack of a mediating effect observed for the outcome variables.

Emotion Regulation Theory

Gross (2002) outlines a theory of emotion regulation that is compatible with Mennin et al.'s (2013) understanding of CBT, but further emphasises the importance of emotion down-regulation in overcoming stressors and coping with anxiety or low moods. The theory stipulates two main kinds of strategies for down-regulating emotion; cognitive reappraisal and expressive suppression. MHapps can aid individuals in engaging either reappraisal or suppression strategies, and understanding the costs and benefits of each can inform MHapp design.

Cognitive reappraisal refers to changing the associated thoughts and meanings of emotion-triggering situations (Gross, 2002). In the CBT model, thoughts precede emotions (Beck, 2011), so changing cognitions can change the emotions triggered. For example, if an individual notices symptoms of anxiety, like elevated heart rate and shallow breathing, they may worry about the symptoms and trigger an increase in anxiety, forming a "vicious cycle" and leading to a panic attack (Clark, 1986). Alternatively, the individual could reappraise the symptoms as evidence of excitement rather than anxiety, and down-regulate the distress (Brooks, 2014).

Rather than modulating the cognitive interpretation of the situation, expressive suppression strategies are used by individuals to directly restrict their emotional responses after they have been triggered by cognitions (Gross, 2002). This is akin to maintaining a "poker face" while experiencing emotion (Vanderhasselt, Kühn, & De Raedt, 2013). Evidence suggests that expressive suppression is not as effective as cognitive reappraisal in both short and long-term emotion regulation, and suppressive efforts can inadvertently suppress positive emotions in addition to negative emotions.

Emotion Regulation Theory can be useful for assessing the overall direction of an intervention towards either cognitive reappraisal or expressive suppression. For maximum benefit, individuals who engage with a MHapp should be encouraged to reappraise the thoughts and triggers leading up to an emotion, rather than be encouraged to actively suppress their feelings. CBT interventions are designed with this direction in mind (Mennin et al., 2013), as were the MHapps included in this thesis.

MoodPrism's features may assist with reappraisal through improving ESA. An increase in ESA allows individuals to better reflect on the precipitants, maintaining factors, responses, and overall quality of their emotions, which can aid reappraisal in subsequent triggering situations (Paivio, 2013). MoodMission additionally coach's individuals in CBT strategies that aim to intervene in emotion regulation before expressive suppression can be used. Furthermore, increasing an individual's CSE encourages cognitions of empowerment and "I can deal with this situation", which is a key reappraisal strategy (Barlow, Allen, & Choate, 2004). Both apps avoid interactions that may lead to suppression. Both encourage openness in reporting emotional states, with no negative consequences for reporting negative emotions. None of MoodMission's Missions are suppression based.

Beyond MHapps, the general use of smartphones and apps may actually decrease the use of expressive suppression strategies. Removing an individual's smartphone increases their reliance on suppression strategies (J. Elhai, Hall, & Erwina, 2017; Hoffner & Lee, 2015). This may be because smartphones are commonly used for reappraisal strategies, such as social support and information organisation. However, apps designed for mental health purposes may be more explicit and active in the training of reappraisal strategies as remedies for psychological distress.

Self-Determination Theory

Self-determination theory (SDT; Deci & Ryan, 1985) is well-suited to understanding interventions that are self-guided or require the individual's motivation to practise strategies and engage in change principles (Kazantzis & L'Abate, 2005). SDT emphasises three human needs that encourage intrinsic motivation and personal growth; the need for autonomy, for competence, and for relatedness. An intervention should aim to foster and serve these needs, as this will both increase an individual's motivation to engage with it and increase the individual's potential for psychological thriving (Deci & Ryan, 2012).

Autonomy refers to an individual's need to be in control of their own destiny. This should decrease hopelessness and reinforce a belief that they are empowered to achieve their desired goals. Interventions which are overly prescriptive and dictate behaviours to individuals may suppress autonomy (Hagger & Chatzisarantis, 2009). Allowing an individual to create their own goals and choose their means and methods to achieve them can foster autonomy (Seligman & Csikszentmihalyi, 2000). Often then a collaborative therapeutic relationship is pursued, as this creates an environment where an individual's autonomy is respected and fostered, but they are provided the necessary guidance to make productive decisions (Tee & Kazantzis, 2011).

Self-guided MHapps, in a sense, already encourage autonomy by being a resource that individuals access independently and when they choose to. However, the stricter the interaction rules imposed by a MHapp, the more likely autonomy will be suppressed. For example, if an intervention dictates that an individual must engage with it at a certain time every day for a certain duration, this may decrease their self-perceived autonomy. However, if a MHapp allows the user to choose between a range of session lengths and they can start a session whenever they like, autonomy is being facilitated.

The user interface and overall design of a MHapp may have impacts on perceived autonomy of the user (Wendel, 2013). For example, if a MHapp does not allow the user to navigate back to previous screens, or allow the user to always return to an app home screen wherever they are in the app, the user may feel restricted and without autonomy. This may lead to frustration and eventual deletion of the app. Alternatively, if the user is free to navigate from section to section and screen to screen, autonomy is being facilitated. Guidance may be provided by the app, either implicitly through choice of interactions (e.g. button placement) or explicitly through instructions in text, but it is ultimately up to the user to autonomously interact with the app's interface (Galitz, 2007).

MoodPrism allows users to complete a daily mood survey once a day, at any point as long as it is after the randomly timed push notification reminder. The user must complete all questions in the daily mood survey for it to register and show in their mood diary. Once unlocked, the mood diary can be opened and explored at any point, and the user is in control of the resolution in which they view it (e.g. months, weeks, days) and the information available for each entry. These interactional design choices give a user autonomy, but ultimately the restrictions of the research design limit this autonomy. For example, for more autonomy users should be able to record as many mood surveys as they like every day, at any time, and in as much detail as they would like.

MoodMission is more flexible in its approach to interaction design, offering users the ability to report mood and complete Missions regardless of the time. There are also options on each of the reporting screens to effectively "skip" the step and proceed to the next screen. Users are informed upon onboarding that the more information they provide to MoodMission, the better the app can tailor Mission suggestions, so they are given a rationale to complete the reporting screens. However, it is ultimately up to the user what the length or depth of their engagement will be.

Within SDT, *competence* refers to an individual’s need for self-improvement through development of skills and mastery (Ryan & Deci, 2000). This gives the impression of progress being made through life in pursuit of personal values. In much the same way, interventions can give the impression of progress being made by helping individuals reflect on their achievements and realise the developments made in their skills. For example, the subjective outcome tracking in Feedback Informed Treatment (FIT; Prescott, Maeschalck, & Miller, 2017) provides a way for individuals to reflect on their progress over time and realise personal improvements.

Gamification is the term often given to app-based rewards, such as points and badges, which are meant to reinforce to the user their achievements and progression through the app (Kapp, 2012). To properly facilitate competence, these rewards need to be relevant and aligned with the user’s motivations and goals (Burke, 2014). While MoodPrism does not incorporate traditional gamification features like badges, it does give the user an impression of progress as they complete more mood reports and fill out their colourful mood diary. Additional feedback is also unlocked at milestones, so the more mood reports that are completed, the more feedback is provided. In this way, the impression of progress is completely based on quantity rather than quality of engagement, so may only be partly aligned with the users’ goals. Alternatively, MoodMission includes a badges and ranking system that tracks both quantity and quality of a user’s engagement. Rankings are based purely on number of Missions completed, while badges are awarded based on how well the Missions perform and the use of a variety of different Missions. The Mission Log also allows users to review all their completed Missions in an autonomous fashion, so they can remind themselves of the progress made.

Within SDT, *relatedness* refers to an individual’s need for connectedness to others through trusting and caring relationships, but also encompasses a need to belong (Ryan &

Deci, 2000). This may be a sense of belonging to social groups, to broader communities, or even to ideals and values. This gives the individual a sense that they are not isolated, but are instead part of something bigger and greater. Individuals experiencing mental health issues often feel rejected by others around the, and by society based on the stigmas of mental illness or behaviours perceived to be related to mental illness. Interventions which work against stigmas by normalising mental health issues may therefore improve an individual's relatedness by reducing real and perceived isolation (Cacioppo, Hawkley, Norman, & Berntson, 2011).

MoodPrism and MoodMission do not require or seek clinical diagnoses, reducing the influence of stigma and increasing accessibility. Both apps use nonclinical, non-stigmatising language in an effort to reframe mental health issues and inspire hopefulness. For example, MoodMission's Missions are fairly normal, everyday activities, which makes them more achievable, and promotes the perception that regular solutions are require for regular problems. Alternatively, an activity like hypnosis is so unusual that individuals may perceive it to be a "serious" treatment, which in turn may promote the belief that there is something truly "wrong" with them. This may suppress relatedness and therefore increase the impact of self-stigma. The relatable, commonplace activities and language used in Missions were chosen to increase relatedness and reduce stigma. Furthermore, many Missions involve social contact in an effort to enhance trusting and caring relationships with others.

Behavioural Health Continuum of Care

The Behavioural Health Continuum of Care model (see Figure 1) outlines the stages of intervention for behavioural health issues, including mental health (Institute of Medicine, 1994; Rickwood, 2010; World Health Organization, 2004a). It emphasises three other stages in addition to the treatment stage of intervention, including the promotion, prevention, and recovery stages.

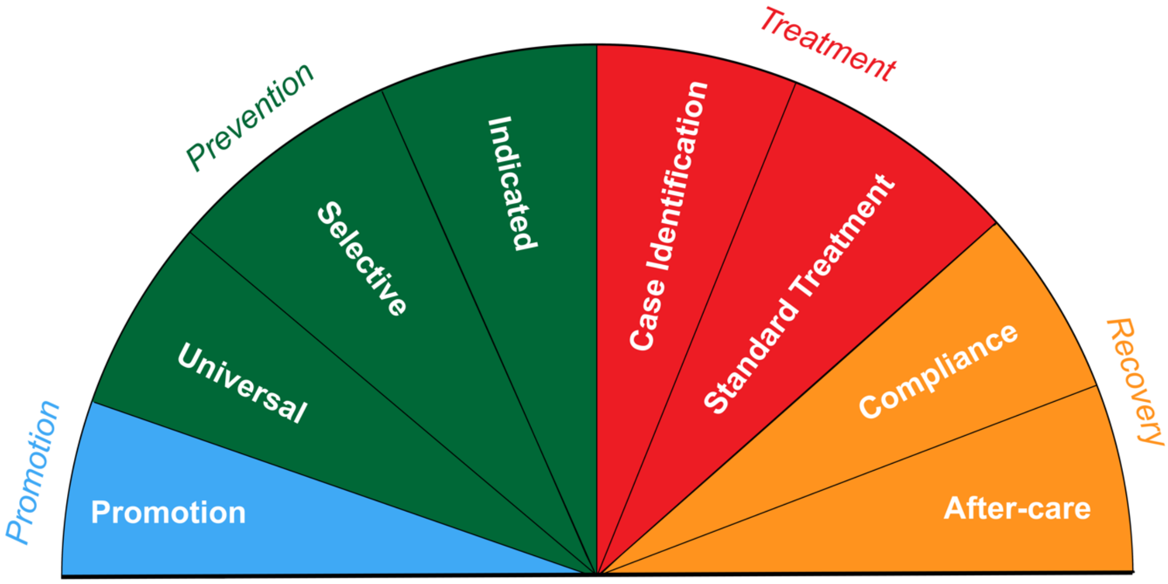


Figure 1. Behavioural Health Continuum of Care model of interventions

Within the prevention stage, there are three different kinds of preventative interventions. Universal prevention interventions are targeted at all or most individuals within a population, such as promotional campaigns that deliver health messages across a wide range of broadcast media. For example, television advertisements that quote statistics about the prevalence of anxiety and recommend seeking support from health professionals would be universal prevention interventions.

Selective prevention interventions are more narrowly targeted towards groups that may be more at risk for developing a disorder. For example, a school program that aims to increase student's mental health literacy (MHL) would be considered selective because it is targeting school children when they are vulnerable to developing problematic views about mental distress (Black Dog Institute, 2016). By educating them about difficult emotions and ways of coping with stress, the students may be better equipped to prevent small emotional problems from developing into more complex, severe ones. This may also prevent alcohol and drug misuse, as these substances are often used to cope with distress.

The final type of prevention interventions are labelled indicated, as these are aimed to be used with individuals who have been specifically indicated to be at risk of developing a disorder requiring treatment. Indicated prevention interventions are generally more involved than universal or selective interventions, as they can resemble a type of minimal, subclinical treatment (e.g. P. Cuijpers, Muñoz, Clarke, & Lewinsohn, 2009). For example, brief problem-solving therapy delivered in group settings can help reduce distress and prevent depression in nonprofessional carers (Vázquez González et al., 2013).

Computerised interventions usually aim to be indicated prevention interventions or, more commonly, treatment and recovery stage interventions (Kenardy, McCafferty, & Rosa, 2003). This is because the individual must be motivated enough to engage in the intervention, and computerised interventions require the user to become stationary and devote their full attention to the computer for a moderately long period of time to, for example, complete a thirty-minute module. They also have to factor this into their daily routines, often scheduling in the sessions to ensure that they complete them. Individuals would have to be well motivated to engage with this sort of interaction paradigm, so those that are not at risk of or currently experiencing a mental health issue may lack motivation to engage with a computerised intervention. In contrast, mobile interventions require a lot less time and attention to engage with them. They can be used in almost any context throughout an individual’s daily routine, and the limited screen size and lack of mouse and keyboard simplify the interaction paradigm. The smaller time and attention requirements ease the motivational burden to engage with mobile interventions, and coupled with the high levels of smartphone ownership observed in the community, and the ease of accessing interactive content via the app stores, mobile paradigms are better suited than computerised paradigms for preventative interventions (Judith Proudfoot, 2013).

In the first paper presented in this thesis, the recommendation was made to target MHapps at nonclinical populations. One of the reasons for this recommendation was to enable the MHapp to serve as a prevention intervention. A clinical approach may be appropriate in treatment interventions, but is not appropriate when engaging users who may not be experiencing any clinically significant distress. The interaction paradigms used by both MoodPrism and MoodMission were designed to be flexible enough to allow use as universal and selective prevention interventions. The time and attention requirements were aimed to be low enough for engagement with users who were not motivated by a need for treatment, and instead were looking for a tool to understand themselves better, or help in times of stress.

Although prevention of mental illness was not measured by the studies in this thesis (partly because of the short pre-post time scale used), the findings reinforce the appropriateness of MHapps being used for preventative purposes. All studies were conducted with community samples, unlike past research that has recruited participants experiencing clinical distress (e.g. Kauer et al., 2012; Kuhn et al., 2017; Roepke et al., 2015). While the effects on depression and anxiety were mixed and, in part, depended on the clinical status of the participants, the increases in mental wellbeing were much more consistent across groups and apps. This suggests that despite the absence of depressive or anxious symptoms, users can still gain benefits from using MHapps, as increased mental wellbeing can prevent mental ill health (Slade, 2010). Another factor that supports MHapps as preventative interventions is the presence of effects in the nonclinical and moderate clinical groups, but not in the severe clinical group of MoodMission participants. This suggests that participants who were experiencing more severe symptomatology were unable to derive measurable benefit from the app, suggesting that they should be seeking treatment interventions rather than using a preventative one.

Broader Implications for the Field

The MHapp field is evolving in important and distinct ways as it becomes more established. This thesis has examined the entire lifecycle of a MHapp from design, to development, evaluation, and launch, and this has enabled a comprehensive perspective on some of the field's broader challenges. It is important to discuss these in addition to the study findings, as they are influential to the future of the field.

Research paradigms are being challenged in the field of digital mental health. RCTs have long been upheld by researchers as the gold standard of research designs. However, RCTs neglect a lot of important metrics of intervention success. A traditional RCT is able to provide an evaluation of an intervention's therapeutic efficacy, but can neglect the importance of real-world implementation, effectiveness, time and financial efficiency, and user engagement. For example, the participants in the RCT reported in this thesis first signed up to a research study on mental health apps, and were then given instructions on how to download an app. This process can create sampling bias and Hawthorne effects, which can artificially inflate engagement with the interventions (McCambridge et al., 2014). An individual who downloads a MHapp naturally off the app store has fewer reasons to keep engaged with the app because they do not experience pressure to satisfy researchers, and they have not made a conscious commitment to sign up for a research study. This thesis acknowledged these shortcomings and therefore supplemented the pursuit of an RCT with usability and engagement studies, achieving a broad spectrum of validation across multiple methodologies and metrics.

Great care and attention was also given to user engagement and the process of delivery in the development of the MHapps, rather than solely focussing on the intervention content. In the same way that therapists can become preoccupied with therapy content (which activities to pursue with clients), rather than considering therapy process (the best way to engage the client in therapy and build a strong therapeutic alliance; Kazantzis, Dattilio, & Dobson, 2017), researchers can become preoccupied with the content or structure of text-based modules in internet interventions rather than considering interface design, user experience design, graphic design, and other aspects that influence the user's relationship with the intervention. The user’s relationship does not just determine their overall level of engagement, but may profoundly change their learning outcomes because the meaning of the content may be altered. For example, users may be more likely to interpret their mental health issues as clinical, medical illnesses if an intervention takes graphic design cues from clinical, hospital environments, while an intervention that looks and feels like a video game may lighten the user’s attitude to typically stigmatised issues.

Throughout the development process of MoodPrism and MoodMission, large differences in approach to projects were noted between the software developers and the researchers. These issues are typical of the field, and are evident in the differences in design between MHapps that are directed by researchers or academics (e.g. Blue Watch; Deakin University, 2017), and those that are directed by entrepreneurs or businesses (e.g. Pacifica; Pacifica Labs Inc., 2016). Each party values different outcomes and uses different metrics to track those outcomes. In broad terms, researchers, academics, and clinicians are usually primarily motivated by therapeutic outcomes. This is why evidence from RCTs is so dominant in clinical decision making. Alternatively, those from business professions are more inclined to value usage, uptake, and ultimately revenue. The app’s primary purpose is to be used, because the more it is used, the more revenue can be generated from in-app purchases, subscriptions, advertising, and other models of commercialisation. It is therefore common for researchers to overlook the importance of maximising usability, and common for businesses to overlook the importance of ensuring therapeutic outcomes. However, both goals are important. It is important for an intervention to be efficacious and usable, because without either the intervention has limited real-world effectiveness. The evidence presented in this thesis demonstrated the usability (Chapter 5, Appendix X), effectiveness (Chapters 4 and 6), and efficacy (Chapter 7) of both MoodPrism and MoodMission, and hopefully more MHapps can undergo the same multimethod evaluation process in the future.

One frustration often reported by scientifically-minded clinicians and consumers is the lack of clarity about which MHapps are truly evidence-based in their design, and also which have supporting outcome study evidence for their use. At present, services like Psyberguide (2017) and ReachOut Australia (2017) aim to evaluate the therapeutic quality of MHapps to better inform clinician and consumer choices. However, the majority of smartphone users may never research their choice of MHapp, instead relying on a search of the app store to provide them with an app for “depression” or “stress”. There is currently no accreditation system for MHapps or the claims they make. This places an important ethical responsibility on app stores and MHapp promoters to only make claims that they can substantiate with evidence (Grundy et al., 2017; Weckert & Lucas, 2013). However, this is rarely observed and the majority of the top-downloaded MHapps do not have published evidence that supports their claims.

Ultimately MHapps are developed to improve the mental health and wellbeing of smartphone users. With this in mind, the process of choosing and downloading a MHapp is of crucial importance to achieving the overall goal. It is therefore worth considering systems to guide clinicians and consumers towards good decisions. For example, endorsement of certain evidence-based MHapps could be made by peak mental health bodies, such as beyondblue or NIH. Endorsement or financial support by organisations that enable the delivery of mental health services, such as Medicare or the NHS, may help even more with implementation. Preventative MHapps would benefit most from endorsement or promotion by organisations outside of the health system. For example, schools and universities are in a position to educate students about the importance of using preventative mental health strategies, such as particular apps. The same could be achieved by businesses who wish to support the mental health of their employees.

Recommendations for Stakeholders

To conclude this thesis, a series of recommendations have been compiled for various mental health app stakeholders. These draw from the past and current research findings, and from the observations and experiences gleaned while undertaking this research and development. The recommendations discussed in the first paper of this thesis apply broadly across MHapps and helped guide the development of MoodPrism and MoodMission. The recommendations listed here are those specific for each stakeholder group, so should be considered in conjunction with the first paper's recommendations. Together they guide the practical utilisation of MHapps in various stakeholder contexts.

End Users

Finding a MHapp can be a daunting, overwhelming, or potentially unsatisfying task for an individual roaming the app store. Many apps make claims about "curing" mental illness or use techniques that users with average mental health literacy may not realise lack supportive evidence. The consumer guides that rate MHapps (e.g. PsyberGuide, 2017; ReachOut Australia, 2017), are not widely accessed by the public, so until changes are made to introduce an official certification system within the app store or something similar, it may be more efficient for users to be guided by certain principles when choosing MHapps. Organisations that promote mental health information should be involved in the dissemination of this guidance.

Users should start by checking to see whether the app refers to evidence or research supporting its effectiveness. Users should be sceptical about any outlandish claims made, and should turn to trusted experts for advice. If there is an absence of direct experimental evidence, the app should be based on a supported intervention theory, like CBT. This thesis has found support for apps offering mood-tracking and short CBT strategies, so apps with these features should be considered. It is recommended that users seek apps that are comprehensive in scope, not just providing one coping strategy or targeting one mental health issue, but offering a suite of different tools, packaged in an engaging behavioural plan.

Clinicians

MHapps can be powerful tools for clinicians to use in their clinical practice. Clinicians may include psychologists, general practitioners, medical physicians, social workers, occupational therapists, physiotherapists, or any health professional who works with clients, patients, consumers, or service providers to achieve health outcomes. For the sake of brevity, the word “client” will be used in this discussion to refer to all individuals who receive health services.

Before recommending a MHapp to a client who may benefit, whether the app is an appropriate intervention should first be assessed. If the client would be more comfortable with a different intervention modality, such as pen and paper notepads or worksheets, then these should be considered first. The client should already be motivated to use technology as part of treatment before apps are considered.

Simply informing clients about the existence of a MHapp may not be enough for them to take all the necessary steps to meaningfully engage with it. Attending to the client’s motivation to use the MHapp can increase the likelihood of independent client engagement, just like any self-guided or “homework” intervention. Motivation can be increased by considering the SDT needs for intrinsic motivation; autonomy, competence, and relatedness.

Autonomy can be enhanced by guiding an individual to find and download the MHapp on their own device. Furthermore, simple barriers, like finding the app on the app store and then completing the onboarding process may prevent a client from starting engagement. Therefore, it can be helpful to coach the client through the downloading and onboarding process while they are present in consultation.

Coaching the client through a few minutes of use may improve the individual's sense of competence, increasing motivation by improving familiarity and decreasing anxiety about using it. While a well-designed app will guide clients into using it correctly, some clients may need further guidance from the clinician for them to maximise the effectiveness of their autonomous use.

As with any intervention referral or recommendation, discussing the MHapp in inclusive, non-stigmatising terms can aid with promoting relatedness. The clinician may wish to discuss how other people use the MHapp, or how they have used it themselves, depending on the appropriateness of self-disclosure. Online communities of other users can also be explored by the client to foster relatedness.

Providing good guidance requires a clinician to be familiar with the MHapp themselves. Self-practice of CBT involves the clinician using CBT techniques themselves to: a) improve their own behavioural, cognitive, and emotional responses while working with clients; and b) improve their insight into the experience of using the CBT techniques (Bennett-Levy, Thwaites, Haarhoff, & Perry, 2015). For example, a CBT therapist may record their own negative automatic thoughts that they notice throughout their day, and challenge them later by generating and practising alternative thoughts. In much the same way, it would be helpful for clinicians who are recommending the use of MHapps to clients to exercise self-practice, using the MHapp in their daily lives. Notes about any strengths or difficulties should be made and considered when introducing the MHapp.

As clinicians note strengths and difficulties, they should consider providing feedback directly to the developers of the MHapp. Unlike other intervention modalities, such as printed workbooks, MHapps are more capable of adjustment and reiteration. Developers are often eager to improve their products, and the feedback of a user, particularly one who is a health professional, is very valuable. The rapid iteration process used by most developers allows small fixes to be made and updates to be released, so feedback-informed improvements can be made quickly.

MHapps are being developed specifically as adjuncts to specific therapies. For example, dialectical behaviour therapy (DBT) clinicians and clients can use the DBT Coach app as part of therapy to help clients practise skills in vivo (Rizvi, Dimeff, Skutch, Carroll, & Linehan, 2011). Acceptance and commitment therapy (ACT) is able to be similarly enhanced using the ACT Daily app (Levin, Haeger, Pierce, & Cruz, 2017). Further work is needed to investigate how CBT and other therapies can be enhanced with the addition of an app, so clinicians are encouraged to pursue such studies. For example, with a few small changes MoodMission could be used by clinicians and clients to set and track CBT homework activities.

App Developers

As already discussed, developing a MHapp is a complex process of balancing the need for a slick, attractive, superficially engaging product, with the need for an intervention that is scientifically rigorous and engages psychological change mechanisms. This means that developers should consider their expertise and motivations, decide on what side of the balance they fall, and seek collaborators whose expertise and motivations fall on the opposite side of the balance. For example, if a software developer with no psychological expertise wishes to develop a MHapp, they should seek collaboration with a mental health clinician or expert. Once a relationship is formed, clear and open communication should be maintained between the parties to avoid misunderstandings. App developers should also be aware of the unique legal and policy requirements of MHapps, and seek guidance in matters of privacy, security, suitability of content, advertising, finance, and, if applicable, medical device status (Grundy et al., 2017).

The app development process usually has several milestones that can be treated as review points to avoid unnecessary work in making changes. For example, once the app's user interface is sketched out into "wireframe" diagrams, all development parties should confirm the wireframe before continuing to further stages, such as graphic design or building. If decisions made early on the project are changed later in the project, all the project stages will need to be repeated to incorporate the changes.

As there are already many existing digital treatments and MHapps available, these should be reviewed for design inspiration. Existing apps may have features that could be adapted, or visual designs that are particularly pleasing or appropriate. Branding principles should be considered, and opinions sought from product design and graphic design experts. Unless patents or trademarks have been taken against certain designs, a lot of what already exists can be used as valid inspiration for new and improved products. Developers should not be afraid of emulating existing designs, and if there are any areas where guidelines are not clear, legal and expert advice should be sought.

Organisations

MHapps can be used by organisations to support the mental health and wellbeing of their members. As discussed with reference to universal preventative interventions, MHapps are highly scalable in the number of people they can support, the quantity and quality of the support, and the breadth of mental health issues they can support or detect to refer users for further help-seeking. Organisations are encouraged to seek apps that are compatible with their organisational culture, while still retaining evidence-based and effective techniques, and keeping the mental health and wellbeing of the user as the goal. Some writers have accused corporate culture of encouraging the use of techniques usually used for mental health, but instead "hijacking" them to serve corporate goals (Halliwell, 2014). For example, Target, Ford, and Google encourage their employees to exercise mindfulness, but with an aim to improve the quantity and quality of their work, rather than to support mental health and wellbeing (Pinsker, 2015). Mental health professionals may argue that, ethically, the use of MHapps within organisations should always be first and foremost to support the mental health and wellbeing of members, with improvements to their work or participation being a secondary goal.

Researchers

As researchers embrace methodologies that use mobile technologies, there are a number of unique challenges, particularly in mental health. Research aims must be achieved while still upholding ethical obligations to participants. Some of the most pressing challenges include data security, supporting participant welfare, recruitment strategies, participant engagement, appropriate evaluation approaches, funding for technical development, and the maintenance of platforms following the conclusion of research.

Maintaining the security of data collected by apps can be a confusing and frustrating process for researchers. However, there are three steps that were noted during this project which could simplify the process. Firstly, it should be decided whether the data set collected needs to be identifiable. Deidentified data have fewer security and legal requirements than identifiable data, i.e. data linked to participant names, email addresses, or other personally identifying information. Secondly, the location of the data storage and what it entails for security should be clarified. For example, some university ethics committees prefer data to be stored on local servers, located on the university campus, as they assume that this is more secure than a server located off campus. This creates technical challenges, as the server performance then becomes reliant on campus hardware, with little scalability and often limited maintenance. Most apps instead use leased virtual servers, leveraging the power and scalability of the hardware located in data facilities owned by large companies like Amazon, Microsoft, or Google. These vault-like facilities are securely encrypted, and are physically much more secure than a server on campus (Google, 2017). Furthermore, specific facilities that are located within certain countries can be used to maintain legal requirements. This may need to be explained to ethics committees to prevent misguided compromises or project delays. Thirdly, legal and technical advice should always be sought before finalising security plans.

It is an ethical obligation to provide appropriate support to participants who require it. For example, researchers who are conducting interviews with participants in a mental health setting should conduct suicide risk assessments and follow up with appropriate intervention. While it was recommended in paper one that MHapps provide other support options, including crisis supports, some researchers may be resistant to adding anything “extra” to the MHapp that might act as an additional intervention to the one being studied. For example, some ecological momentary assessment studies rely on apps to collect data in a way that does not provide any feedback or intervention to the participant, as this may interfere with the clarity of the ecological measurements. However, if an app takes measurements that are linked to increased risk for suicide or self-harm, such as a measure of depression or hopelessness, it would be ethical to reflect that back to the participant and encourage help-seeking.

MHapps can be expensive to develop in a research context, as there is usually the need to seek outside expert advice and hire the services of a private app development firm. Furthermore, once the app is built, usually after extensive and unforeseeable delays, there will be a number of ongoing costs to update and maintain the app. Coordinating all the development tasks and involved parties can be time intensive, especially if changes are made to the app after design milestones have passed. The field of mobile mental health app research, and indeed the broader field of internet interventions, is currently in a transitional state from relying strictly on research funds to being partly commercialised. The value of commercialisation is being realised by researchers who want the interventions they are developing to be more widely used beyond strict research contexts. For the development of MoodMission, the majority of funding was derived from crowdfunding, in which financial support was sought from individuals, with reciprocal rewards delivered through the online platform Pozible (2017). This not only made the project possible financially, but also helped with promotion and the building of an online community to support the app. For example, individuals who pledged to the campaign were offered the opportunity to test the app before it was released and provide feedback to guide improvements. This online community also helped with recruitment.

Researchers may have to rethink traditional recruitment strategies when using a MHapp. Researchers are encouraged to investigate marketing strategies for other, similar health apps to develop fresh strategies. For example, social media platforms are powerful recruitment tools, but only if the strategy is carefully planned and adaptively flexible (Kaplan & Michael Haenlein, 2010). It is recommended that social media experts are consulted to develop a comprehensive strategy.

Once participants are recruited, they must engage with the MHapp in a way that is satisfactory for both research needs and supportive needs. In addition to the strategies already outlined in this thesis, it is recommended that researchers consider the length, complexity and interactivity of the assessment process used in MHapp research. A compromise must be made between making the assessments long enough to be useful for the researchers and short enough to be achievable for the participant. Overly complex assessments may frustrate participants, and administration via mobile device may pose problems for validity. It is recommended that assessments be made as interactive as possible to hold participants' attention and reward their engagement.

Reporting improvements in mental health variables is one way to evaluate the effectiveness of MHapps. However, adding economic evaluation may be more favourable to justify future MHapp development (see Paganini, Teigelkötter, Buntrock, & Baumeister, 2018). Demonstrating the social and economic advantages of developing massively scalable interventions that can prevent or treat mental health issues can help secure government funding and power evidence-based policy changes (Layard & Clark, 2014).

After a MHapp is launched and research is underway, there are ongoing costs in the maintenance of the platform. These costs will continue after the research has concluded if the app continues to be available. It is important for successful MHapps to remain available because: a) there are only a few MHapps available with evidence-backing; b) resources have been devoted to establishing an intervention, which should then be shared to justify the resources; c) often more research questions can be investigated using a MHapp platform, so researchers should have the opportunity to pursue these without the trouble of developing an entire new platform, and d) evidence-backed MHapps are valuable for enhancing public mental health and for further research, as some questions can only be answered by using a known-effective or known-acceptable app as an experimental or a control condition. It is recommended that researchers investigate funding and support models that allow the ongoing maintenance of MHapp projects.

Conclusion

This thesis reports on the development of two new publicly available and evidence-backed MHapps that incorporated innovative mobile-optimised interactions and were based on psychological theory, including CBT. Evaluation of these apps demonstrated that wellbeing was promoted after 30 days' use of either app, and while somewhat mixed, evidence was also obtained that each app reduced depression and anxiety levels, particularly for users who already reported moderated depression or anxiety. Considerable insight was also obtained into how these apps worked; the effects of the reflection-focussed app MoodPrism were mediated by increasing ESA, and the effects of the problem-focussed app MoodMission were mediated by increasing CSE.

Over the coming years, more MHapps will be developed, released, and reiterated. They have the potential to be important tools in the campaign against mental illness; the leading cause of disability and global disease burden (World Health Organization, 2017). Prior to the publication of the studies in this thesis, there was no compilation of evidence-based recommendations for MHapp development, most of the empirical literature supported interventions that were not accessible to the public, and there was little understanding of the mechanisms underlying the effects of different MHapps. The findings reported in this thesis advance research on MHapps by providing a blueprint for app developers and researchers to produce evidence-based apps that are functional and engaging. Importantly, the studies reported here demonstrate that digital technologies can significantly contribute to public health by offering sustainable and complementary support for mental health outside professional health care clinics.

References

ABS. (2007). *National survey of mental health and wellbeing: Summary of results* (No. 4326.0). Canberra: Australian Bureau of Statistics.

ADAA. (2017). Facts & statistics | Anxiety and Depression Association of America, ADAA. Retrieved December 5, 2017, from https://adaa.org/about-adaa/press-room/facts-statistics

Agarwal, S., LeFevre, A. E., Lee, J., L'Engle, K., Mehl, G., Sinha, C., & Labrique, A. (2016). Guidelines for reporting of health interventions using mobile phones: mobile health (mHealth) evidence reporting and assessment (mERA) checklist. *BMJ*, *352*, i1174. https://doi.org/10.1136/bmj.i1174

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review*, *30*(2), 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

Andrews, G., Cuijpers, P., Craske, M. G., McEvoy, P., & Titov, N. (2010). Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: A meta-analysis. *PLoS ONE*, *5*, e13196. https://doi.org/10.1371/journal.pone.0013196

Andrews, G., & Williams, A. D. (2014). Internet psychotherapy and the future of personalized treatment. *Depression and Anxiety*, *31*(11), 912–915. https://doi.org/10.1002/da.22302

Anton, M. T., & Jones, D. J. (2017). Adoption of technology-enhanced treatments: Conceptual and practical considerations. *Clinical Psychology: Science and Practice*, *24*(3), 223–240. https://doi.org/10.1111/cpsp.12197

Arean, P. A., Hallgren, K. A., Jordan, J. T., Gazzaley, A., Atkins, D. C., Heagerty, P. J., & Anguera, J. A. (2016). The use and effectiveness of mobile apps for depression: Results from a fully remote clinical trial. *Journal of Medical Internet Research, 18*(12), e330. https://doi.org/10.2196/jmir.6482

Aung, M. H., Matthews, M., & Choudhury, T. (2017). Sensing behavioral symptoms of mental health and delivering personalized interventions using mobile technologies. *Depression and Anxiety*, *34*(7), 603–609. https://doi.org/10.1002/da.22646

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2016). Mental health smartphone apps: Review and evidence-based recommendations for future developments. *JMIR Mental Health*, *3,* e7. https://doi.org/10.2196/mental.4984

Bakker, D., Kazantzis, N., Rickwood, D., & Rickard, N. (2017). *Development and pilot evaluation of smartphone delivered cognitive behavior therapy strategies for mood and anxiety related problems: MoodMission*. Manuscript submitted for publication.

Bakker, D., & Rickard, N. (2017a). Engagement in mobile phone app for self-monitoring of emotional wellbeing predicts changes in mental health: MoodPrism. *Journal of Affective Disorders*. https://doi.org/10.1016/j.jad.2017.11.016

Bakker, D., & Rickard, N. (2017b). *Engagement with a cognitive behavioral therapy mobile phone app predicts changes in mental health and well-being: MoodMission*. Manuscript submitted for publication.

Bakker, G. (2008). *Practical CBT: Using functional analysis and standardised homework in everyday therapy*. Bowen Hills, Qld.: Australian Academic Press.

Ballegooijen, W. van, Cuijpers, P., Straten, A. van, Karyotaki, E., Andersson, G., Smit, J. H., & Riper, H. (2014). Adherence to internet-based and face-to-face cognitive behavioural therapy for depression: A meta-analysis. *PLoS One*, *9,* e100674. https://doi.org/10.1371/journal.pone.0100674

Barlow, D. H., Allen, L. B., & Choate, M. L. (2004). Toward a unified treatment for emotional disorders. *Behavior Therapy*, *35*, 205–230. https://doi.org/10.1016/S0005-7894(04)80036-4

Barlow, D. H., Farchione, T. J., Bullis, J. R., Gallagher, M. W., Murray-Latin, H., Sauer-Zavala, S., … Cassiello-Robbins, C. (2017). The Unified Protocol for transdiagnostic treatment of emotional disorders compared with diagnosis-specific protocols for anxiety disorders: A randomized clinical trial. *JAMA Psychiatry*, *74*(9), 875–884. https://doi.org/10.1001/jamapsychiatry.2017.2164

Baron, K. G., Duffecy, J., Reid, K., Begale, M., & Caccamo, L. (2018). Technology-Assisted Behavioral Intervention to Extend Sleep Duration: Development and Design of the Sleep Bunny Mobile App. *JMIR Mental Health*, *5*(1), e3. https://doi.org/10.2196/mental.8634

Barrett, L., Gross, J., Christensen, T., & Benvenuto, M. (2001). Knowing what you're feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. *Cognition and Emotion*, *15*, 713–724. https://doi.org/10.1080/02699930143000239

Batterham, P. J., & Calear, A. L. (2017). Preferences for internet-based mental health interventions in an adult online sample: Findings from an online community survey. *JMIR Mental Health*, *4*(2), e26. https://doi.org/10.2196/mental.7722

Beck, J. S. (2011). *Cognitive behavior therapy: Basics and beyond* (2nd ed.). New York: The Guilford Press.

Becker, M. W., & Leinenger, M. (2011). Attentional selection is biased toward mood-congruent stimuli. *Emotion*, *11*, 1248–1254. https://doi.org/10.1037/a0023524

Begg, C., Cho, M., Eastwood, S., Horton, R., Moher, D., Olkin, I., … Stroup, D. F. (1996). Improving the quality of reporting of randomized controlled trials: The CONSORT statement. *JAMA*, *276*(8), 637–639. https://doi.org/10.1001/jama.1996.03540080059030

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, *29*(5), 585–609. https://doi.org/10.1016/j.jbusvent.2013.07.003

Benka, J., Nagyova, I., Rosenberger, J., Macejova, Z., Lazurova, I., Klink, J. V. der, … Dijk, J. V. (2014). Is coping self-efficacy related to psychological distress in early and established rheumatoid arthritis patients? *Journal of Developmental and Physical Disabilities*, *26*, 285–297. https://doi.org/10.1007/s10882-013-9364-y

Bennett-Levy, J., Thwaites, R., Haarhoff, B., & Perry, H. (2015). *Experiencing CBT from the inside out: A self-practice/self-reflection workbook for therapists*. New York, NY: Guilford Press.

BinDhim, N. F., Alanazi, E. M., Aljadhey, H., Basyouni, M. H., Kowalski, S. R., Pont, L. G., … Alhawassi, T. M. (2016). Does a mobile phone depression-screening app motivate mobile phone users with high depressive symptoms to seek a health care professional's help? *Journal of Medical Internet Research*, *18*(6), e156. https://doi.org/10.2196/jmir.5726

Black Dog Institute. (2016). *Prevention of depression and anxiety in Australian schools*. Sydney: Black Dog Institute.

Blankers, M., Koeter, M. W. J., & Schippers, G. M. (2010). Missing data approaches in eHealth research: Simulation study and a tutorial for nonmathematically inclined researchers. *Journal of Medical Internet Research*, *12*(5), e54. https://doi.org/10.2196/jmir.1448

Bolognesi, F., Baldwin, D. S., & Ruini, C. (2014). Psychological interventions in the treatment of generalized anxiety disorder: A structured review. *Journal of Psychopathology*, *20*(2), 111–126.

Borkovec, T. D., Newman, M. G., Pincus, A. L., & Lytle, R. (2002). A component analysis of cognitive-behavioral therapy for generalized anxiety disorder and the role of interpersonal problems. *Journal of Consulting and Clinical Psychology*, *70*(2), 288–298. https://doi.org/10.1037/0022-006X.70.2.288

Bower, P., & Gilbody, S. (2005). Stepped care in psychological therapies: access, effectiveness and efficiency. *The British Journal of Psychiatry*, *186*(1), 11–17. https://doi.org/10.1192/bjp.186.1.11

Bradford, S., & Rickwood, D. (2015). Young people’s views on electronic mental health assessment: Prefer to type than talk? *Journal of Child and Family Studies*, 1213-1221. https://doi.org/10.1007/s10826-014-9929-0

Brijnath, B., Protheroe, J., Mahtani, K. R., & Antoniades, J. (2016). Do web-based mental health literacy interventions improve the mental health literacy of adult consumers? Results from a systematic review. *Journal of Medical Internet Research*, *18*(6), e165. https://doi.org/10.2196/jmir.5463

Brodey, B. B., Gonzalez, N. L., Elkin, K. A., Sasiela, W. J., & Brodey, I. S. (2017). Assessing the equivalence of paper, mobile phone, and tablet survey responses at a community mental health center using equivalent halves of a ‘gold-standard’ depression item bank. *JMIR Mental Health*, *4*(3), e36. https://doi.org/10.2196/mental.6805

Brooks, A. W. (2014). Get excited: reappraising pre-performance anxiety as excitement. *Journal of Experimental Psychology. General*, *143*(3), 1144–1158. https://doi.org/10.1037/a0035325

Brown, M., Glendenning, A., Hoon, A. E., & John, A. (2016). Effectiveness of web-delivered acceptance and commitment therapy in relation to mental health and well-being: A systematic review and meta-analysis. *Journal of Medical Internet Research*, *18*(8). https://doi.org/10.2196/jmir.6200

Burke, B. (2014). *Gamify: How gamification motivates people to do extraordinary things*. Brookline, MA: Bibliomotion.

Butler, A. C., Chapman, J. E., Forman, E. M., & Beck, A. T. (2006). The empirical status of cognitive-behavioral therapy: A review of meta-analyses. *Clinical Psychology Review*, *26*(1), 17–31. https://doi.org/10.1016/j.cpr.2005.07.003

Cacioppo, J. T., Hawkley, L. C., Norman, G. J., & Berntson, G. G. (2011). Social isolation. *Annals of the New York Academy of Sciences*, *1231*(1), 17–22. https://doi.org/10.1111/j.1749-6632.2011.06028.x

Callan, J. A., Wright, J., Siegle, G. J., Howland, R. H., & Kepler, B. B. (2017). Use of computer and mobile technologies in the treatment of depression. *Archives of Psychiatric Nursing*, *31*(3), 311–318. https://doi.org/10.1016/j.apnu.2016.10.002

Carpenter, J., Crutchley, P., Zilca, R. D., Schwartz, H. A., Smith, L. K., Cobb, A. M., & Parks, A. C. (2016). Seeing the “big” picture: Big data methods for exploring relationships between usage, language, and outcome in internet intervention data. *Journal of Medical Internet Research*, *18*(8), e241. https://doi.org/10.2196/jmir.5725

Chesney, M. A., Neilands, T. B., Chambers, D. B., Taylor, J. M., & Folkman, S. (2006). A validity and reliability study of the coping self-efficacy scale. *British Journal of Health Psychology*, *11*, 421–437. https://doi.org/10.1348/135910705X53155

Chou, T., Bry, L. J., & Comer, J. S. (2017). Overcoming traditional barriers only to encounter new ones: Doses of caution and direction as technology-enhanced treatments begin to “go live.” *Clinical Psychology: Science and Practice*, *24*(3), 241–244. https://doi.org/10.1111/cpsp.12196

Clark, D. M. (1986). A cognitive approach to panic. *Behaviour Research and Therapy*, *24*(4), 461–470. https://doi.org/10.1016/0005-7967(86)90011-2

Comello, M. L. G., Qian, X., Deal, A. M., Ribisl, K. M., Linnan, L. A., & Tate, D. F. (2016). Impact of game-inspired infographics on user engagement and information processing in an eHealth program. *Journal of Medical Internet Research*, *18*(9), e237. https://doi.org/10.2196/jmir.5976

comScore. (2015). *comScore Reports March 2015 U.S. Smartphone Subscriber Market Share*. Retrieved from http://www.comscore.com/Insights/Market-Rankings/comScore-Reports-March-2015-US-Smartphone-Subscriber-Market-Share

Cooney, G. M., Dwan, K., Greig, C. A., Lawlor, D. A., Rimer, J., Waugh, F. R., … Mead, G. E. (2013). Exercise for depression. *Cochrane Database of Systematic Reviews*, *9*, CD004366. https://doi.org/10.1002/14651858.CD004366.pub6

Craske, M. G., & Barlow, D. H. (2014). Panic disorder and agoraphobia. In D. H. Barlow (Ed.), *Clinical handbook of psychological disorders: A step-by-step treatment manual* (5th ed., pp. 1–61). New York: Guilford Publications.

Cuijpers, P., Berking, M., Andersson, G., Quigley, L., Kleiboer, A., & Dobson, K. S. (2013). A meta-analysis of cognitive-behavioural therapy for adult depression, alone and in comparison with other treatments. *Canadian Journal of Psychiatry*, *58*(7), 376–385. https://doi.org/10.1177/070674371305800702

Cuijpers, P., Cristea, I. A., Weitz, E., Gentili, C., & Berking, M. (2016). The effects of cognitive and behavioural therapies for anxiety disorders on depression: A meta-analysis. *Psychological Medicine; Cambridge*, *46*(16), 3451–3462. http://dx.doi.org.ezproxy.lib.monash.edu.au/10.1017/S0033291716002348

Cuijpers, P., Muñoz, R. F., Clarke, G. N., & Lewinsohn, P. M. (2009). Psychoeducational treatment and prevention of depression: The “Coping with Depression” course thirty years later. *Clinical Psychology Review*, *29*, 449–458. https://doi.org/10.1016/j.cpr.2009.04.005

Cumming, G. (2011). *Understanding the new statistics: Effect sizes, confidence intervals, and meta-analysis*. New York: Routledge.

Dahne, J., Kustanowitz, J., & Lejuez, C. W. (2017). Development and preliminary feasibility study of a brief behavioral activation mobile application (Behavioral Apptivation) to be used in conjunction with ongoing therapy. *Cognitive and Behavioral Practice*. https://doi.org/10.1016/j.cbpra.2017.05.004

Darlington, R. B., & Hayes, A. F. (2016). *Regression analysis and linear models: Concepts, applications, and implementation* (1 edition). New York: The Guilford Press.

Deakin University. (2017). Blue Watch (Version 1.0.2) [Mobile application software]. Retrieved from https://itunes.apple.com/au/app/blue-watch/id1055310499?mt=8

Dear, B. F., Staples, L. G., Terides, M. D., Fogliati, V. J., Sheehan, J., Johnston, L., … Titov, N. (2016). Transdiagnostic versus disorder-specific and clinician-guided versus self-guided internet-delivered treatment for Social Anxiety Disorder and comorbid disorders: A randomized controlled trial. *Journal of Anxiety Disorders*, *42*, 30–44. https://doi.org/10.1016/j.janxdis.2016.05.004

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Boston, MA: Springer US.

Deci, E. L., & Ryan, R. M. (2012). Self-determination theory. In *Handbook of theories of social psychology: Volume 1* (pp. 416–437). London: SAGE Publications Ltd.

Deloitte. (2016a). 2016 Global mobile consumer survey: US edition | Deloitte US. Retrieved March 5, 2017, from https://www2.deloitte.com/us/en/pages/technology-media-and-telecommunications/articles/global-mobile-consumer-survey-us-edition.html

Deloitte. (2016b). *Mobile Consumer Survey 2015 – The Australian Cut*. Retrieved from http://landing.deloitte.com.au/rs/761-IBL-328/images/deloitte-au-tmt-mobile-consumer-survey-2015-291015.pdf

Deloitte. (2016c). *There's no place like phone: Consumer usage patterns in the era of peak smartphone*. Retrieved from http://www.deloitte.co.uk/mobileuk/

Dèttore, D., Pozza, A., & Andersson, G. (2015). Efficacy of technology-delivered cognitive behavioural therapy for OCD versus control conditions, and in comparison with therapist-administered CBT: Meta-analysis of randomized controlled trials. *Cognitive Behaviour Therapy*, *44*(3), 190–211. https://doi.org/10.1080/16506073.2015.1005660

Dimidjian, S., Martell, C. R., Herman-Dunn, R., & Hubley, C. P. (2014). Behavioral activation for depression. In D. H. Barlow (Ed.), *Clinical handbook of psychological disorders: A step-by-step treatment manual* (5th ed., pp. 353–393). New York: Guilford Publications.

Dirmaier, J., Liebherz, S., Sänger, S., Härter, M., & Tlach, L. (2016). Psychenet.de: Development and process evaluation of an e-mental health portal. *Informatics for Health and Social Care*, *41*(3), 267–285. https://doi.org/10.3109/17538157.2015.1008486

Dobson, D., & Dobson, K. S. (2009). *Evidence-based practice of cognitive-behavioral therapy*. New York: The Guilford Press.

Dogan, E., Sander, C., Wagner, X., Hegerl, U., & Kohls, E. (2017). Smartphone-based monitoring of objective and subjective data in affective disorders: Where are we and where are we going? Systematic review. *Journal of Medical Internet Research*, *19*(7), e262. https://doi.org/10.2196/jmir.7006

Donker, T., Griffiths, K. M., Cuijpers, P., & Christensen, H. (2009). Psychoeducation for depression, anxiety and psychological distress: A meta-analysis. *BMC Medicine*, *7*, 79. https://doi.org/10.1186/1741-7015-7-79

Donker, T., Petrie, K., Proudfoot, J., Clarke, J., Birch, M.-R., & Christensen, H. (2013). Smartphones for smarter delivery of mental health programs: A systematic review. *Journal of Medical Internet Research*, *15*, e247. https://doi.org/10.2196/jmir.2791

Dubad, M., Winsper, C., Meyer, C., Livanou, M., & Marwaha, S. (2018). A systematic review of the psychometric properties, usability and clinical impacts of mobile mood-monitoring applications in young people. *Psychological Medicine*, *48*, 208-228. https://doi.org/10.1017/S0033291717001659

Durbin, J., & Watson, G. S. (1951). Testing for serial correlation in least squares regression. *Biometrika*, *38*(1/2), 159–177. https://doi.org/10.2307/2332325

Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2017). Non-social features of smartphone use are most related to depression, anxiety and problematic smartphone use. *Computers in Human Behavior*, *69*, 75–82. https://doi.org/10.1016/j.chb.2016.12.023

Elhai, J., Hall, B., & Erwina, M. C. (2017). Emotion regulation’s relationships with depression, anxiety and stress due to imagined smartphone and social media loss. *Psychiatry Research*, *in press*.

Ellard, K. K., Fairholme, C. P., Boisseau, C. L., Farchione, T. J., & Barlow, D. H. (2010). Unified protocol for the transdiagnostic treatment of emotional disorders: Protocol development and initial outcome data. *Cognitive and Behavioral Practice*, *17*(1), 88–101. https://doi.org/10.1016/j.cbpra.2009.06.002

Enock, P. M., Hofmann, S. G., & McNally, R. J. (2014). Attention bias modification training via smartphone to reduce social anxiety: A randomized, controlled multi-session experiment. *Cognitive Therapy and Research*, *38*(2), 200–216. https://doi.org/10.1007/s10608-014-9606-z

Eyal, N. (2014). *Hooked: How to build habit-forming products*. Penguin Group US.

Fernandez, E., Salem, D., Swift, J. K., & Ramtahal, N. (2015). Meta-analysis of dropout from cognitive behavioral therapy: Magnitude, timing, and moderators. *Journal of Consulting and Clinical Psychology*, *83*(6), 1108–1122. https://doi.org/10.1037/ccp0000044

Field, A. (2013). *Discovering statistics using SPSS* (4th ed.). London: Sage.

Firth, J., Torous, J., Nicholas, J., Carney, R., Pratap, A., Rosenbaum, S., & Sarris, J. (2017a). The efficacy of smartphone-based mental health interventions for depressive symptoms: A meta-analysis of randomized controlled trials. *World Psychiatry*, *16*(3), 287–298. https://doi.org/10.1002/wps.20472

Firth, J., Torous, J., Nicholas, J., Carney, R., Rosenbaum, S., & Sarris, J. (2017b). Can smartphone mental health interventions reduce symptoms of anxiety? A meta-analysis of randomized controlled trials. *Journal of Affective Disorders*, *218*, 15–22. https://doi.org/10.1016/j.jad.2017.04.046

Fling, B. (2009). *Mobile design and development: Practical concepts and techniques for creating mobile sites and web apps*. Sebastopol, CA: O’Reilly Media Inc.

Franklin, J. C., Fox, K. R., Franklin, C. R., Kleiman, E. M., Ribeiro, J. D., Jaroszewski, A. C., … Nock, M. K. (2016). A brief mobile app reduces nonsuicidal and suicidal self-injury: Evidence from three randomized controlled trials. *Journal of Consulting and Clinical Psychology*, *84*(6), 544–557. https://doi.org/10.1037/ccp0000093

Galitz, W. O. (2007). *The essential guide to user interface design: An introduction to GUI design principles and techniques* (3rd ed.). Indianapolis, IN: Wiley Technology.

Garg, R., & Telang, R. (2012). Inferring app demand from publicly available data. *MIS Quarterly, Forthcoming*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1924044

Google. (2016). *How people use their devices: What marketers need to know*. Retrieved from https://www.thinkwithgoogle.com/advertising-channels/mobile/device-use-marketer-tips/

Google. (2017). Data Centers. Retrieved December 18, 2017, from https://www.google.com/about/datacenters/inside/data-security/

Grist, R., Porter, J., & Stallard, P. (2017). Mental health mobile apps for preadolescents and adolescents: A systematic review. *Journal of Medical Internet Research*, *19*(5), e176. https://doi.org/10.2196/jmir.7332

Gross, J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology*, *39*, 281–291. https://doi.org/10.1017.S0048577201393198

Grundy, Q., Parker, L., Raven, M., Gillies, D., Mintzes, B., Jureidini, J., & Bero, L. (2017). *Finding peace of mind: Navigating the marketplace of mental health apps*. Sydney: ACCAN. Retrieved from http://accan.org.au/files/Grants/ACCAN%20final%20report%20-%20Finding%20Peace%20of%20Mind_web.pdf

Hagger, M. S., & Chatzisarantis, N. L. D. (2009). Integrating the theory of planned behaviour and self-determination theory in health behaviour: A meta-analysis. *British Journal of Health Psychology*, *14*(2), 275–302.

Halliwell, E. (2014, July 25). Mindfulness: has it been hijacked by business or can it change lives? *The Guardian*. Retrieved from http://www.theguardian.com/sustainable-business/mindfulness-hijacked-business-parliamentary-inquiry

Hara, K. M., Aviram, A., Constantino, M. J., Westra, H. A., & Antony, M. M. (2017). Therapist empathy, homework compliance, and outcome in cognitive behavioral therapy for generalized anxiety disorder: partitioning within- and between-therapist effects. *Cognitive Behaviour Therapy*, *46*(5), 375–390. https://doi.org/10.1080/16506073.2016.1253605

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (1 edition). New York: The Guilford Press.

Hayes, A. F., & Rockwood, N. J. (2016). Regression-based statistical mediation and moderation analysis in clinical research: Observations, recommendations, and implementation. *Behaviour Research and Therapy, 98,* 39-57. https://doi.org/10.1016/j.brat.2016.11.001

Hayes, S. C., & Hofmann, S. G. (2017). The third wave of cognitive behavioral therapy and the rise of process-based care. *World Psychiatry*, *16*(3), 245–246. https://doi.org/10.1002/wps.20442

Hayes, S. C., & Hofmann, S. G. (Eds.). (2018). *Process-based CBT: The science and core clinical competencies of Cognitive Behavioral Therapy* (1 edition). Oakland CA: New Harbinger.

Headspace. (2015). Headspace: Meditation techniques for mindfulness, stress relief & peace of mind (Version 2.4) [Mobile application software]. Retrieved from https://itunes.apple.com/au/app/headspace-meditation-techniques/id493145008?mt=8

Heber, E., Ebert, D. D., Lehr, D., Cuijpers, P., Berking, M., Nobis, S., & Riper, H. (2017). The benefit of web- and computer-based interventions for stress: A systematic review and meta-analysis. *Journal of Medical Internet Research, 19*(2), e32. https://doi.org/10.2196/jmir.5774

Henry, J. D., & Crawford, J. R. (2005). The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample. *British Journal of Clinical Psychology, 44*(2), 227–239. https://doi.org/10.1348/014466505X29657

Hides, L., Kavanagh, D. J., Zelenko, O., Tjondronegoro, D., Stoyanov, S. R., & Cockshaw, W. (2015). *Ray's Night Out: A new iPhone app targeting alcohol use in young people*. Retrieved from https://www.youngandwellcrc.org.au/knowledge-hub/publications/raysnightout/

Hides, L., Kavanagh, D., Stoyanov, S., Zelenko, O., Tjondronegoro, D., & Mani, M. (2014). *Mobile application rating scale (MARS)*. Abbotsford, Victoria, AUS: Young and Well Cooperative Research Centre.

Hill, C. L. M., & Updegraff, J. A. (2012). Mindfulness and its relationship to emotional regulation. *Emotion, 12,* 81–90. https://doi.org/10.1037/a0026355

Hochheimer, C. J., Sabo, R. T., Krist, A. H., Day, T., Cyrus, J., & Woolf, S. H. (2016). Methods for evaluating respondent attrition in web-based surveys. *Journal of Medical Internet Research, 18*(11), e301. https://doi.org/10.2196/jmir.6342

Hoffner, C. A., & Lee, S. (2015). Mobile phone use, emotion regulation, and well-being. *Cyberpsychology, Behavior, and Social Networking, 18*(7), 411–416. https://doi.org/10.1089/cyber.2014.0487

Hofmann, S. G. (2015). *Emotion in therapy: From science to practice*. New York, NY: Guilford Press.

Hofmann, S. G., Sawyer, A. T., Witt, A. A., & Oh, D. (2010). The effect of mindfulness-based therapy on anxiety and depression: A meta-analytic review. *Journal of Consulting*, *78*, 169–183. https://doi.org/10.1037/a0018555

Holdsworth, E., Bowen, E., Brown, S., & Howat, D. (2014). Client engagement in psychotherapeutic treatment and associations with client characteristics, therapist characteristics, and treatment factors. *Clinical Psychology Review*, *34*(5), 428–450. https://doi.org/10.1016/j.cpr.2014.06.004

Howells, A., Ivtzan, I., & Eiroa-Orosa, F. J. (2014). Putting the “app” in happiness: A randomised controlled trial of a smartphone-based mindfulness intervention to enhance wellbeing. *Journal of Happiness Studies*. https://doi.org/10.1007/s10902-014-9589-1

Huguet, A., Rao, S., McGrath, P. J., Wozney, L., Wheaton, M., Conrod, J., & Rozario, S. (2016). A systematic review of cognitive behavioral therapy and behavioral activation apps for depression. *PLoS One; San Francisco*, *11*(5). http://dx.doi.org.ezproxy.lib.monash.edu.au/10.1371/journal.pone.0154248

Institute of Medicine. (1994). *Reducing risks for mental disorders: Frontiers for preventive intervention research*. Washington, DC: National Academies Press

Jacobson, N. S., Dobson, K. S., Truax, P. A., Addis, M. E., Koerner, K., Gollan, J. K., … Prince, S. E. (1996). A component analysis of cognitive-behavioral treatment for depression. *Journal of Consulting and Clinical Psychology*, *64*(2), 295–304. https://doi.org/10.1037/0022-006X.64.2.295

Jaspers, M. W. M. (2009). A comparison of usability methods for testing interactive health technologies: Methodological aspects and empirical evidence. *International Journal of Medical Informatics*, *78*(5), 340–353. https://doi.org/10.1016/j.ijmedinf.2008.10.002

Jones, N., & Moffitt, M. (2016). Ethical guidelines for mobile app development within health and mental health fields. *Professional Psychology: Research and Practice*, *47*(2), 155–162. https://doi.org/10.1037/pro0000069

Jorm, A. F. (2012). Mental health literacy: Empowering the community to take action for better mental health. *American Psychologist*, *67*, 231–243. https://doi.org/10.1037/a0025957

Jorm, A. F., Korten, A. E., Jacomb, P. A., Christensen, H., Rodger, B., & Pollitt, P. (1997). “Mental health literacy”: A survey of the public’s ability to recognise mental disorders and their beliefs about the effectiveness of treatment. *Medical Journal of Australia*, *166*, 5.

Kaplan, A. M., & Michael Haenlein. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68. https://doi.org/10.1016/j.bushor.2009.09.003

Kapp, K. M. (2012). *The gamification of learning and instruction: Game-based methods and strategies for training and education*. San Francisco, CA: Pfeiffer.

Kauer, S. D., Reid, S. C., Crooke, A. H. D., Khor, A., Hearps, S. J. C., Jorm, A. F., … Patton, G. (2012). Self-monitoring using mobile phones in the early stages of adolescent depression: Randomized controlled trial. *Journal of Medical Internet Research, 14*, e67. https://doi.org/10.2196/jmir.1858

Kazantzis, N. (2017). Introduction to the special issue on processes of Cognitive Behavioral Therapy: Does “necessary, but not sufficient” still capture it? *Cognitive Therapy and Research*.

Kazantzis, N., Brownfield, N. R., Mosely, L., Usatoff, A. S., & Flighty, A. J. (2017). Homework in Cognitive Behavioral Therapy: A systematic review of adherence assessment in anxiety and depression (2011–2016). *Psychiatric Clinics of North America*, *40*(4), 625–639. https://doi.org/10.1016/j.psc.2017.08.001

Kazantzis, N., Dattilio, F. M., & Dobson, K. S. (2017). *The Therapeutic Relationship in Cognitive-Behavioral Therapy*. Retrieved from https://www.booktopia.com.au/therapeutic-relationship-in-cognitive-behavioral-therapy-nikolaos-kazantzis/prod9781462531288.html

Kazantzis, N., Deane, F. P., & Ronan, K. R. (2005). Assessment of homework completion. In N. Kazantzis, F. P. Deane, K. R. Ronan, & L. L'Abate (Eds.), *Using homework assignments in cognitive behavior therapy* (pp. 103–122). New York: Routledge.

Kazantzis, N., & L'Abate, L. (2005). Theoretical foundations. In N. Kazantzis, F. P. Deane, K. R. Ronan, & L. L'Abate (Eds.), *Using homework assignments in cognitive behavior therapy* (pp. 8–28). New York: Routledge.

Kazantzis, N., MacEwan, J., & Dattilio, F. M. (2005). A guiding model for practice. In N. Kazantzis, F. P. Deane, K. R. Ronan, & L. L'Abate (Eds.), *Using homework assignments in cognitive behavior therapy* (pp. 359–407). New York: Routledge.

Kazantzis, N., Whittington, C., Zelencich, L., Kyrios, M., Norton, P. J., & Hofmann, S. G. (2016). Quantity and quality of homework compliance: A meta-analysis of relations with outcome in cognitive behavior therapy. *Behavior Therapy*, *47*(5), 755–772. https://doi.org/10.1016/j.beth.2016.05.002

Kenardy, J., McCafferty, K., & Rosa, V. (2003). Internet-delivered indicated prevention for anxiety disorders: A randomized dontrolled trial. *Behavioural and Cognitive Psychotherapy*, *31*, 279–289. https://doi.org/10.1017/S1352465803003047

Kinderman, P., Hagan, P., King, S., Bowman, J., Chahal, J., Gan, L., … Tai, S. (2016). The feasibility and effectiveness of Catch It, an innovative CBT smartphone app. *British Journal of Psychiatry Open*, *2*(3), 204–209. https://doi.org/10.1192/bjpo.bp.115.002436

Kliem, S., Kroger, C., & Kosfelder, J. (2010). Dialectical behavior therapy for borderline personality disorder: A meta-analysis using mixed-effects modeling. *Journal of Consulting and Clinical Psychology*, *78*(6), 936–951. https://doi.org/10.1037/a0021015

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine, 16*, 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kuester, A., Niemeyer, H., & Knaevelsrud, C. (2016). Internet-based interventions for posttraumatic stress: A meta-analysis of randomized controlled trials. *Clinical Psychology Review*, *43*, 1–16. https://doi.org/10.1016/j.cpr.2015.11.004

Kuhn, E., Kanuri, N., Hoffman, J. E., Garvert, D. W., Ruzek, J. I., & Taylor, C. B. (2017). A randomized controlled trial of a smartphone app for posttraumatic stress disorder symptoms. *Journal of Consulting and Clinical Psychology*, *85*(3), 267–273. https://doi.org/10.1037/ccp0000163

Lambert, M. J. (1989). The individual therapist's contribution to psychotherapy process and outcome. *Clinical Psychology Review*, *9*(4), 469–485. https://doi.org/10.1016/0272-7358(89)90004-4

Lambert, N. M., Fincham, F. D., & Stillman, T. F. (2012). Gratitude and depressive symptoms: The role of positive reframing and positive emotion. *Cognition and Emotion*, *26*(4), 615–633. https://doi.org/10.1080/02699931.2011.595393

Lambrecht, A., Goldfarb, A., Bonatti, A., Ghose, A., Goldstein, D. G., Lewis, R., … Yao, S. (2014). How do firms make money selling digital goods online? *Marketing Letters, 25*(3), 331–341.

Layard, R., & Clark, D. (2014). *Thrive: The power of evidence-based psychological therapies*. London: Penguin UK.

Levin, M. E., Haeger, J., Pierce, B., & Cruz, R. A. (2017). Evaluating an Adjunctive Mobile App to Enhance Psychological Flexibility in Acceptance and Commitment Therapy. *Behavior Modification*, *41*(6), 846–867. https://doi.org/10.1177/0145445517719661

Linehan, M. M., Korslund, K. E., Harned, M. S., Gallop, R. J., Lungu, A., Neacsiu, A. D., … Murray-Gregory, A. M. (2015). Dialectical behavior therapy for high suicide risk in individuals with borderline personality disorder: A randomized clinical trial and component analysis. *JAMA Psychiatry*, *72*(5), 475–482. https://doi.org/10.1001/jamapsychiatry.2014.3039

Löwe, B., Wahl, I., Rose, M., Spitzer, C., Glaesmer, H., Wingenfeld, K., … Brähler, E. (2010). A 4-item measure of depression and anxiety: Validation and standardization of the Patient Health Questionnaire-4 (PHQ-4) in the general population. *Journal of Affective Disorders*, *122*, 86–95. https://doi.org/10.1016/j.jad.2009.06.019

Luxton, D. D., McCann, R. A., Bush, N. E., Mishkind, M. C., & Reger, G. M. (2011). mHealth for mental health: Integrating smartphone technology in behavioral healthcare. *Professional Psychology: Research and Practice*, *42*(6), 505–512. https://doi.org/10.1037/a0024485

Macrodimitris, S. D., Hamilton, K. E., Backs-Dermott, B. J., & Mothersill, K. J. (2010). CBT basics: A group approach to teaching fundamental cognitive-behavioral skills. *Journal of Cognitive Psychotherapy*, *24*, 132–146. https://doi.org/10.1891/0889-8391.24.2.132

Manzoni, G., Pagnini, F., Castelnuovo, G., & Molinari, E. (2008). Relaxation training for anxiety: a ten-years systematic review with meta-analysis. *BMC Psychiatry*, *8*(1), 41. https://doi.org/10.1186/1471-244X-8-41

Mazzucchelli, T., Kane, R., & Rees, C. (2009). Behavioral activation treatments for depression in adults: A meta-analysis and review. *Clinical Psychology: Science and Practice*, *16*(4), 383–411. https://doi.org/10.1111/j.1468-2850.2009.01178.x

Mazzucchelli, T., Kane, R. T., & Rees, C. S. (2010). Behavioral activation interventions for well-being: A meta-analysis. *The Journal of Positive Psychology*, *5*(2), 105–121. https://doi.org/10.1080/17439760903569154

McCambridge, J., Witton, J., & Elbourne, D. R. (2014). Systematic review of the Hawthorne effect: New concepts are needed to study research participation effects. *Journal of Clinical Epidemiology*, *67*(3), 267–277. https://doi.org/10.1016/j.jclinepi.2013.08.015

Meinlschmidt, G., Lee, J.-H., Stalujanis, E., Belardi, A., Oh, M., Jung, E. K., … Tegethoff, M. (2016). Smartphone-based psychotherapeutic micro-interventions to improve mood in a real-world setting. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01112

Mennin, D. S., Ellard, K. K., Fresco, D. M., & Gross, J. J. (2013). United we stand: Emphasizing commonalities across cognitive-behavioral therapies. *Behavior Therapy*, *44*, 234–248. https://doi.org/10.1016/j.beth.2013.02.004

Mohr, D. C., Tomasino, K. N., Lattie, E. G., Palac, H. L., Kwasny, M. J., Weingardt, K., … Schueller, S. M. (2017). IntelliCare: An eclectic, skills-based app suite for the treatment of depression and anxiety. *Journal of Medical Internet Research*, *19*(1), e10. https://doi.org/10.2196/jmir.6645

MoodMission Pty Ltd. (2017). MoodMission (Version 1.1.2) [Mobile application software]. Retrieved May 23, 2017, from https://itunes.apple.com/au/app/moodmission/id1140332763?mt=8

MoodPrism. (2016). MoodPrism (Version 1.0.15) [Mobile application software]. Retrieved May 23, 2017, from https://play.google.com/store/apps/details?id=au.com.monash.moodprism&hl=en

Morris, M. E., Kathawala, Q., Leen, T. K., Gorenstein, E. E., Guilak, F., Labhard, M., & Deleeuw, W. (2010). Mobile therapy: Case study evaluations of a cell phone application for emotional self-awareness. *Journal of Medical Internet Research*, *12*, e10. https://doi.org/10.2196/jmir.1371

Newby, J. M., Twomey, C., Yuan Li, S. S., & Andrews, G. (2016). Transdiagnostic computerised cognitive behavioural therapy for depression and anxiety: A systematic review and meta-analysis. *Journal of Affective Disorders*, *199*, 30–41. https://doi.org/10.1016/j.jad.2016.03.018

Nicholas, J., Larsen, M. E., Proudfoot, J., & Christensen, H. (2015). Mobile apps for bipolar disorder: A systematic review of features and content quality. *Journal of Medical Internet Research*, *17*(8), e198. https://doi.org/10.2196/jmir.4581

Nielsen. (2016). Millennials are top smartphone users. Retrieved January 3, 2018, from http://www.nielsen.com/us/en/insights/news/2016/millennials-are-top-smartphone-users

Olff, M. (2015). Mobile mental health: A challenging research agenda. *European Journal of Psychotraumatology*, *6*, 27882. https://doi.org/10.3402/ejpt.v6.27882

Pacifica Labs Inc. (2016). Pacifica - Anxiety, Stress, & Depression relief based on CBT & Mindfulness on the App Store. Retrieved March 6, 2016, from https://itunes.apple.com/au/app/pacifica-anxiety-stress-depression/id922968861?mt=8

Paganini, S., Teigelkötter, W., Buntrock, C., & Baumeister, H. (2018). Economic evaluations of internet- and mobile-based interventions for the treatment and prevention of depression: A systematic review. *Journal of Affective Disorders*, *225*, 733–755. https://doi.org/10.1016/j.jad.2017.07.018

Paivio, S. C. (2013). Essential processes in emotion-focused therapy. *Psychotherapy, 50*, 341–345. https://doi.org/10.1037/a0032810

Păsărelu, C. R., Andersson, G., Nordgren, L. B., & Dobrean, A. (2017). Internet-delivered transdiagnostic and tailored cognitive behavioral therapy for anxiety and depression: A systematic review and meta-analysis of randomized controlled trials. *Cognitive Behaviour Therapy*, *46*, 1–28. https://doi.org/10.1080/16506073.2016.1231219

Peterman, J. S., Read, K. L., Wei, C., & Kendall, P. C. (2015). The art of exposure: Putting science into practice. *Cognitive and Behavioral Practice, 22*, 379-392. https://doi.org/10.1016/j.cbpra.2014.02.003

Philip, E. J., Merluzzi, T. V., Zhang, Z., & Heitzmann, C. A. (2013). Depression and cancer survivorship: Importance of coping self-efficacy in post-treatment survivors. *Psycho-Oncology*, *22*, 987–994. https://doi.org/10.1002/pon.3088

Pinsker, J. (2015). Corporations' newest productivity hack: Meditation. *The Atlantic*. Retrieved from https://www.theatlantic.com/business/archive/2015/03/corporations-newest-productivity-hack-meditation/387286/

Platt, B., Waters, A. M., Schulte-Koerne, G., Engelmann, L., & Salemink, E. (2017). A review of cognitive biases in youth depression: attention, interpretation and memory. *Cognition and Emotion*, *31*(3), 462–483. https://doi.org/10.1080/02699931.2015.1127215

Pozible. (2017). Crowdfunding for Australian artists & non-profits. Retrieved November 25, 2017, from https://pozible.com

Prescott, D. S., Maeschalck, C. L., & Miller, S. D. (2017). *Feedback-informed treatment in clinical practice: reaching for excellence*. Washington, DC: American Psychological Association.

Pritchard, C., & Gow, K. (2012). Coping self-efficacy and psychological distress in flood victims. In K. Gow & M. J. Celinski (Eds.), *Individual trauma: Recovering from deep wounds and exploring the potential for renewal* (pp. 207–219). Hauppauge, NY, US: Nova Science.

Proudfoot, J. (2013). The future is in our hands: The role of mobile phones in the prevention and management of mental disorders. *Australian & New Zealand Journal of Psychiatry*, *47*(2), 111–113. https://doi.org/10.1177/0004867412471441

Proudfoot, J., Clarke, J., Birch, M.-R., Whitton, A. E., Parker, G., Manicavasagar, V., … Hadzi-Pavlovic, D. (2013). Impact of a mobile phone and web program on symptom and functional outcomes for people with mild-to-moderate depression, anxiety and stress: a randomised controlled trial. *BMC Psychiatry*, *13*, 312. https://doi.org/10.1186/1471-244X-13-312

Proudfoot, J., Parker, G., Hadzi Pavlovic, D., Manicavasagar, V., Adler, E., & Whitton, A. (2010). Community attitudes to the appropriation of mobile phones for monitoring and managing depression, anxiety, and stress. *Journal of Medical Internet Research*, *12*, e64. https://doi.org/10.2196/jmir.1475

PsyberGuide. (2017). Home. Retrieved November 24, 2017, from https://psyberguide.org/

ReachOut. (2016). ReachOut WorryTime. Retrieved March 7, 2016, from http://au.professionals.reachout.com/reachout-worrytime

ReachOut Australia. (2017). Tools and apps. Retrieved November 24, 2017, from https://au.reachout.com/tools-and-apps/

Reavley, N. J., Morgan, A. J., & Jorm, A. F. (2014). Development of scales to assess mental health literacy relating to recognition of and interventions for depression, anxiety disorders and schizophrenia/psychosis. *Australian and New Zealand Journal of Psychiatry*, *48*, 61–69. https://doi.org/10.1177/0004867413491157

Reger, G., Hoffman, J., Riggs, D., Rothbaum, B., Ruzek, J., Holloway, K., & Kuhn, E. (2013). The “PE coach” smartphone application: An innovative approach to improving implementation, fidelity, and homework adherence during prolonged exposure. *Psychological Services*, *10*(3), 342–349. http://dx.doi.org/10.1037/a0032774

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. https://doi.org/10.2196/mental.6202

Rickwood, D. J. (2010). Promoting youth mental health through computer-mediated communication. *International Journal of Mental Health Promotion*, *12*(3), 32–44. https://doi.org/10.1080/14623730.2010.9721817

Rizvi, S. L., Dimeff, L. A., Skutch, J., Carroll, D., & Linehan, M. M. (2011). A pilot study of the DBT coach: An interactive mobile phone application for individuals with borderline personality disorder and substance use disorder. *Behavior Therapy*, *42*(4), 589–600. https://doi.org/10.1016/j.beth.2011.01.003

Roepke, A. M., Jaffee, S. R., Riffle, O. M., McGonigal, J., Broome, R., & Maxwell, B. (2015). Randomized controlled trial of SuperBetter, a smartphone-based/internet-based self-help tool to reduce depressive symptoms. *Games for Health Journal*, *4*(3), 235–246. https://doi.org/10.1089/g4h.2014.0046

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*, 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Seligman, M. E., & Csikszentmihalyi, M. (2000). Positive psychology: An introduction. *American Psychologist*, *55*, 5–14. https://doi.org/10.1037/0003-066X.55.1.5

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology, 4,* 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Shipherd, J. C., & Fordiani, J. M. (2015). The application of mindfulness in coping with intrusive thoughts. *Cognitive and Behavioral Practice*, *22*(4), 439–446. https://doi.org/10.1016/j.cbpra.2014.06.001

Morson, S. (2015). *Designing for iOS with Sketch*. Berkeley, CA: Apress.

Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis. *Journal of Clinical Psychology, 65*(5), 467–487. https://doi.org/10.1002/jclp.20593

Sirois, F. M., & Hirsch, J. K. (2013). Associations of psychological thriving with coping efficacy, expectations for future growth, and depressive symptoms over time in people with arthritis. *Journal of Psychosomatic Research*, *75*, 279–286. https://doi.org/10.1016/j.jpsychores.2013.06.004

Slade, M. (2010). Mental illness and well-being: the central importance of positive psychology and recovery approaches. *BMC Health Services Research, 10*, 26. https://doi.org/10.1186/1472-6963-10-26

Smiling Mind. (2015). Smiling Mind (Version 2.1.6) [Mobile application software]. Retrieved January 16, 2015, from https://itunes.apple.com/au/app/smiling-mind/id560442518?mt=8

Smith, A., Benight, C., & Cieslak, R. (2013). Social support and postdeployment coping self-efficacy as predictors of distress among combat veterans. *Military Psychology*, *25*, 452–461. https://doi.org/10.1037/mil0000013

Spitzer, R. L., Kroenke, K., Williams, J. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, *166*, 1092–1097. https://doi.org/10.1001/archinte.166.10.1092

Stewart-Brown, S., & Janmohamed, K. (2008). Warwick-Edinburgh Mental Well-being Scale. *User Guide. Version*, *1*. Retrieved from http://www.cppconsortium.nhs.uk/admin/files/1343987601WEMWBS%20User%20Guide%20Version%201%20June%202008.pdf

Stoll, R. D., Pina, A. A., Gary, K., & Amresh, A. (2017). Usability of a Smartphone application to support the prevention and early intervention of anxiety in youth. *Cognitive and Behavioral Practice*. https://doi.org/10.1016/j.cbpra.2016.11.002

Stoyanov, S. R., Hides, L., Kavanagh, D. J., & Wilson, H. (2016). Development and validation of the user version of the Mobile Application Rating Scale (uMARS). *JMIR MHealth and UHealth*, *4*(2), e72. https://doi.org/10.2196/mhealth.5849

Sucala, M., Cuijpers, P., Muench, F., Cardoș, R., Soflau, R., Dobrean, A., … David, D. (2017). Anxiety: There is an app for that. A systematic review of anxiety apps. *Depression and Anxiety*, *34*(6), 518–525. https://doi.org/10.1002/da.22654

SuperBetter Inc. (2014). SuperBetter (Version 1.1) [Mobile application software]. Retrieved January 13, 2015, from https://itunes.apple.com/au/app/superbetter/id536634968?mt=8

Tang, W., & Kreindler, D. (2017). Supporting homework compliance in cognitive behavioural therapy: Essential features of mobile apps. *JMIR Mental Health*, *4*(2), e20. https://doi.org/10.2196/mental.5283

Tee, J., & Kazantzis, N. (2011). Collaborative empiricism in cognitive therapy: A definition and theory for the relationship construct. *Clinical Psychology: Science and Practice*, *18*, 47–61. https://doi.org/10.1111/j.1468-2850.2010.01234.x

Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., … Stewart-Brown, S. (2007). The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Development and UK validation. *Health and Quality of Life Outcomes*, *5*, 63. https://doi.org/10.1186/1477-7525-5-63

Thorne, K. J., Andrews, J. J. W., & Nordstokke, D. (2013). Relations among children's coping strategies and anxiety: The mediating role of coping efficacy. *The Journal of General Psychology*, *140*, 204–223. https://doi.org/10.1080/00221309.2013.792235

Thriveport LLC. (2016). MoodKit - Mood Improvement Tools (Version 3.1) [Mobile application software]. Retrieved May 23, 2017, from https://itunes.apple.com/au/app/moodkit-mood-improvement-tools/id427064987?mt=8

Titov, N., Dear, B. F., Staples, L. G., Terides, M. D., Karin, E., Sheehan, J., … McEvoy, P. M. (2015). Disorder-specific versus transdiagnostic and clinician-guided versus self-guided treatment for major depressive disorder and comorbid anxiety disorders: A randomized controlled trial. *Journal of Anxiety Disorders*, *35*, 88–102. https://doi.org/10.1016/j.janxdis.2015.08.002

Torous, J., & Firth, J. (2016). The digital placebo effect: mobile mental health meets clinical psychiatry. *The Lancet Psychiatry*, *3*(2), 100–102. https://doi.org/10.1016/S2215-0366(15)00565-9

Torous, J., Friedman, R., & Keshavan, M. (2014). Smartphone ownership and interest in mobile applications to monitor symptoms of mental health conditions. *JMIR MHealth and UHealth*, *2*(1), e2. https://doi.org/10.2196/mhealth.2994

Twomey, C., & O'Reilly, G. (2017). Effectiveness of a freely available computerised cognitive behavioural therapy programme (MoodGYM) for depression: Meta-analysis. *Australian & New Zealand Journal of Psychiatry*, *51*(3), 260–269. https://doi.org/10.1177/0004867416656258

Van Ameringen, M., Turna, J., Khalesi, Z., Pullia, K., & Patterson, B. (2017). There is an app for that! The current state of mobile applications (apps) for DSM-5 obsessive-compulsive disorder, posttraumatic stress disorder, anxiety and mood disorders. *Depression and Anxiety*, *34*(6), 526–539. https://doi.org/10.1002/da.22657

van Os, J., Verhagen, S., Marsman, A., Peeters, F., Bak, M., Marcelis, M., … Delespaul, P. (2017). The experience sampling method as an mHealth tool to support self-monitoring, self-insight, and personalized health care in clinical practice. *Depression and Anxiety*, *34*(6), 481–493. https://doi.org/10.1002/da.22647

van Straten, A., Hill, J., Richards, D. A., & Cuijpers, P. (2015). Stepped care treatment delivery for depression: a systematic review and meta-analysis. *Psychological Medicine; Cambridge*, *45*(2), 231–246. http://doi.org/10.1017/S0033291714000701

Vanderhasselt, M.-A., Kühn, S., & De Raedt, R. (2013). 'Put on your poker face': neural systems supporting the anticipation for expressive suppression and cognitive reappraisal. *Social Cognitive and Affective Neuroscience*, *8*(8), 903–910. https://doi.org/10.1093/scan/nss090

Vázquez González, F. L., Otero Otero, P., Torres Iglesias, A., Hermida García, E., Blanco Seoane, V., & Díaz Fernández, O. (2013). A brief problem-solving indicated-prevention intervention for prevention of depression in nonprofessional caregivers. *Psicothema*, *25*(1), 87–92. https://doi.org/10.7334/psicothema2012.89

Vent. (2017). Vent (Version 5.7) [Mobile application software]. Retrieved from https://itunes.apple.com/WebObjects/MZStore.woa/wa/viewSoftware?id=780298346&mt=8

Vickers, A. J., & Altman, D. G. (2001). Analysing controlled trials with baseline and follow up measurements. *BMJ : British Medical Journal*, *323*(7321), 1123–1124.

Vogl, G., Ratnaike, D., Ivancic, L., Rowley, A., & Chandy, V. (2016). *One click away? Insights into mental health digital self-help by young Australians*. Sydney: EY and ReachOut Australia.

Watts, S., Mackenzie, A., Thomas, C., Griskaitis, A., Mewton, L., Williams, A., & Andrews, G. (2013). CBT for depression: A pilot RCT comparing mobile phone vs. computer. *BMC Psychiatry*, *13*, 49. https://doi.org/10.1186/1471-244X-13-49

Weckert, J., & Lucas, R. (2013). *Professionalism in the information and communication technology industry*. Canberra: ANU Press.

Wen, C. K. F., Schneider, S., Stone, A. A., & Spruijt-Metz, D. (2017). Compliance with mobile ecological momentary assessment protocols in children and adolescents: A systematic review and meta-analysis. *Journal of Medical Internet Research*, *19*(4), e132. https://doi.org/10.2196/jmir.6641

Wendel, S. (2013). *Designing for behavior change: Applying psychology and behavioral economics*. Sebastopol, California: O’Reilly Media.

Weng, L., Menczer, F., & Ahn, Y.-Y. (2013). Virality prediction and community structure in social networks. *Scientific Reports*, *3*, 2522. https://doi.org/10.1038/srep02522

Werner-Seidler, A., O’Dea, B., Shand, F., Johnston, L., Frayne, A., Fogarty, A. S., & Christensen, H. (2017). A smartphone app for adolescents with sleep disturbance: Development of the Sleep Ninja. *JMIR Mental Health*, *4*(3), e28. https://doi.org/10.2196/mental.7614

West, J. H., Hall, P. C., Hanson, C. L., Barnes, M. D., Giraud-Carrier, C., & Barrett, J. (2012). There’s an app for that: Content analysis of paid health and fitness apps. *Journal of Medical Internet Research*, *14*(3). https://doi.org/10.2196/jmir.1977

Westbrook, D., Kennerley, H., & Kirk, J. (2011). *An introduction to cognitive behaviour therapy: Skills and applications* (2nd ed.). Los Angeles: SAGE Publications Ltd.

Westen, D., Novotny, C. M., & Thompson-Brenner, H. (2004). The empirical status of empirically supported psychotherapies: Assumptions, findings, and reporting in controlled clinical trials. *Psychological Bulletin*, *130*(4), 631–663. https://doi.org/10.1037/0033-2909.130.4.631

White, J. (2010). The STEPS model: A high volume, multi-level, multi-purpose approach to address common mental health problems. In J. Bennett-Levy, D. Richards, P. Farrand, H. Christensen, K. Griffiths, D. Kavanagh, … J. Proudfoot (Eds.), *Oxford Guide to Low Intensity CBT Interventions* (1st ed., pp. 35–52). Oxford: Oxford University Press.

Winslow, B. D., Chadderdon, G. L., Dechmerowski, S. J., Jones, D. L., Kalkstein, S., Greene, J. L., & Gehrman, P. (2016). Development and clinical evaluation of an mHealth application for stress management. *Frontiers in Psychiatry*, *7*. https://doi.org/10.3389/fpsyt.2016.00130

World Health Organization. (2004a). *Prevention of mental disorders: Effective interventions and policy options*. Geneva: World Health Organization.

World Health Organization. (2004b). *Promoting mental health: Concepts, emerging evidence, practice*. Geneva: World Health Organization.

World Health Organization. (2017). WHO | Depression. Retrieved March 30, 2017, from http://www.who.int/mediacentre/factsheets/fs369/en/

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2–22. https://doi.org/10.2307/1251446

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*, 197–206. http://dx.doi.org/10.1086/651257

APPENDICES

Appendix A: Human Ethics Certificate of Approval

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

Postal – Monash University, Vic 3800, Australia
[redacted]
ABN 12 377 614 012 CRICOS Provider #00008C

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

Original Paper

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

Nikki Rickard[1,2*], BBSc (Hons), PhD; Hussain-Abdulah Arjmand[1*], BBNSc (Hons); David Bakker[1*], BPsych (Hons); Elizabeth Seabrook[1*], BPsych (Hons)

[1]Emotion and Well-being Research Unit, School of Psychological Sciences, Monash University, Clayton, Australia

[2]Centre for Positive Psychology, Melbourne Graduate School of Education, University of Melbourne, Melbourne, Australia

[*]all authors contributed equally

Corresponding Author:
Nikki Rickard, BBSc (Hons), PhD
Emotion and Well-being Research Unit
School of Psychological Sciences
Monash University
Building 18
Wellington Rd
Clayton, 3800
Australia
Phone: 61 400 191 768
Fax: 61 3 9905 3948
Email: nikki.rickard@monash.edu

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.

(JMIR Ment Health 2016;3(4):e49) doi:10.2196/mental.6202

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.

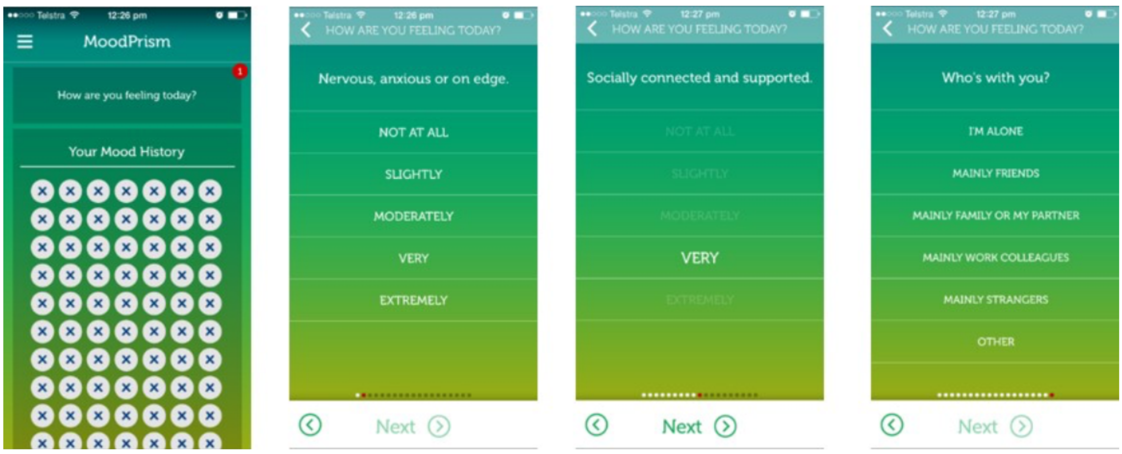


Figure 2. Screenshots showing examples of longer psychological questionnaires.

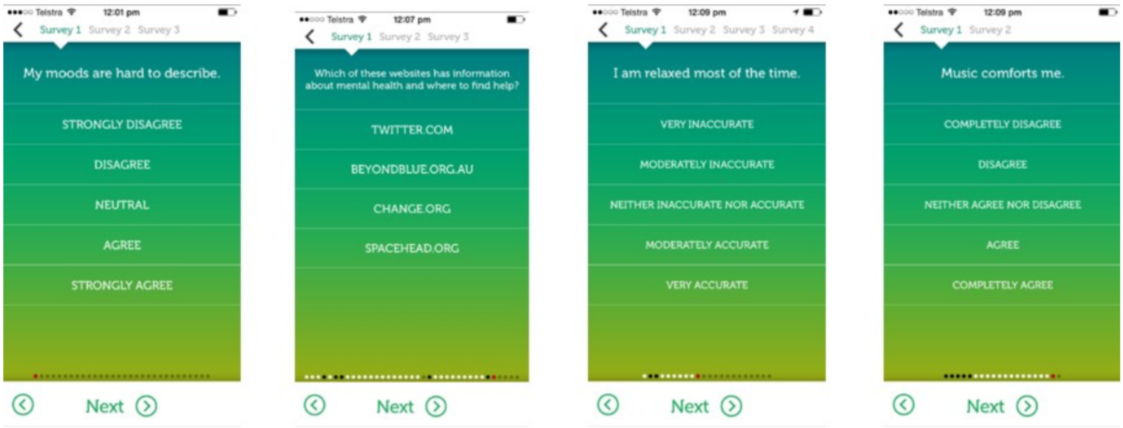


Table 1. Qualitative feedback: questions guiding qualitative feedback forums.

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.

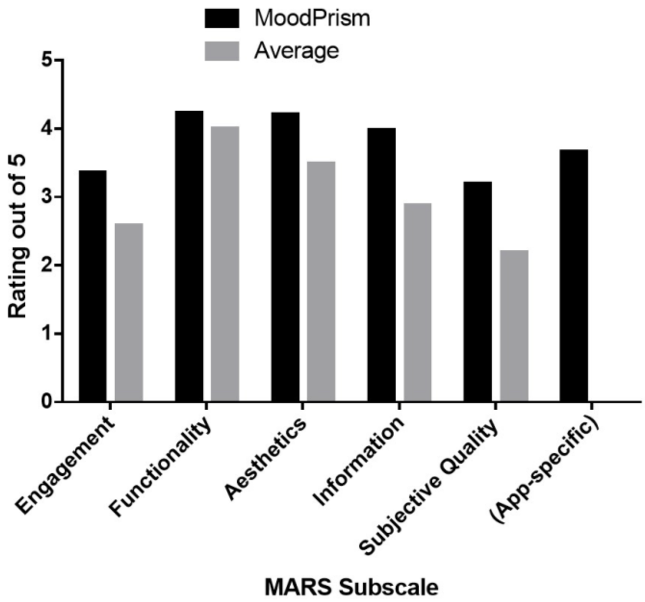
Feedback about the functionality and usability of the app was obtained from 11 beta-testers, who completed a standard survey of app usability, the MARS. The results are presented in Figure 3.

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.

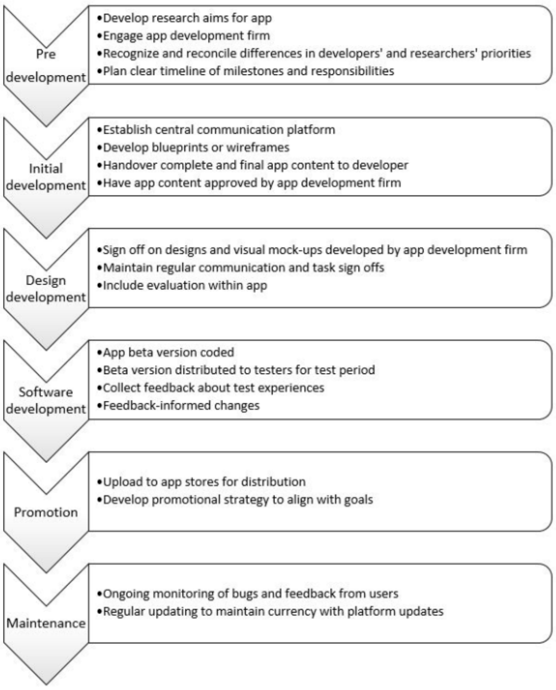
Fourth, methods to evaluate the app should be included within the app itself. Commercial apps can contain simple "thumbs up" or star ratings, but this is unlikely to be sufficiently informative for research or practitioner needs. Importantly, it is helpful to obtain assessments of the various aspects 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

This research was funded by *beyondblue*.

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]

References

1. St John T, Leon L, McCulloch A. Childhood and adolescent mental health: understanding the lifetime impacts. The Mental Health Foundation. 2015. [FREE Full text] [doi: 10.1023/A:1007219227883]
2. Greenspoon PJ, Saklofske DH. Toward an integration of subjective well-being and psychopathology. Social Indicators Research. 2001. (1) p. 81 URL: http://link.springer.com/article/10.1023/A:1007219227883 [WebCite Cache ID 6m18x9BBy]
3. Westerhof GJ, Keyes CL. Mental illness and mental health: the two continua model across the lifespan. J Adult Dev 2010 Jun;17(2):110-119 [FREE Full text] [doi: 10.1007/s10804-009-9082-y] [Medline: 20502508]

4. Diener E, Chan MY. Happy people live longer: subjective well-being contributes to health and longevity. Appl Psychol Health Well-being 2011;3(1):1-43. [doi: 10.1111/j.1758-0854.2010.01045.x]
5. Fredrickson BL. What good are positive emotions? Rev Gen Psychol 1998 Sep;2(3):300-319 [FREE Full text] [doi: 10.1037/1089-2680.2.3.300] [Medline: 21850154]
6. Folkman S, Moskowitz JT. Positive affect and the other side of coping. Am Psychol 2000 Jun;55(6):647-654. [Medline: 10892207]
7. Garland EL, Fredrickson B, Kring AM, Johnson DP, Meyer PS, Penn DL. Upward spirals of positive emotions counter downward spirals of negativity: insights from the broaden-and-build theory and affective neuroscience on the treatment of emotion dysfunctions and deficits in psychopathology. Clin Psychol Rev 2010 Nov;30(7):849-864 [FREE Full text] [doi: 10.1016/j.cpr.2010.03.002] [Medline: 20363063]
8. Isen AM. Positive affect. In: Dalgeish T, Power MJ, editors. Handboook of Cognition and Emotion. New York: Wiley; 1999:521-539.
9. Tugade MM, Fredrickson BL, Barrett LF. Psychological resilience and positive emotional granularity; examining the benefits of positive emotions on coping and health. J Pers 2004;72(6):1161-1190. [doi: 10.1111/j.1467-6494.2004.00294.x]
10. Goodwin GM. Time in the course of major depressive disorder. Medicographia 2010;32:126-132. [FREE Full text]
11. National Institute for Health and Care Excellence. Depression: management of depression in primary and secondary care. 2016. URL: https://www.nice.org.uk/guidance/CG23 [accessed 2016-06-15] [WebCite Cache ID 6iGxgM1FJ]
12. McDermott B, Baigent M, Chanen A. beyondblue Expert Working Committee Clinical Practice Guidelines: Depression in Adolescents and Young Adults. Melbourne: beyondblue; 2010.
13. Hetrick SE, Thompson A, Yuen K, Finch S, Parker AG. Is there a gap between recommended and 'real world' practice in the management of depression in young people? A medical file audit of practice. BMC Health Services 2012;12:178. [doi: 10.1186/1472-6963-12-178]
14. Morrato EH, Libby AM, Orton HD, Degruy 3rd FV, Brent DA, Allen R, et al. Frequency of provider contact after FDA advisory on risk of pediatric suicidality with SSRIs. Am J Psychiatry 2008 Jan;165(1):42-50. [doi: 10.1176/appi.ajp.2008.165.7.A42] [Medline: 17986680]
15. Cooper PJ, Goodyer I. A community study of depression in adolescent girls: I. Estimates of symptom and syndrome prevalence. Br J Psychiatry 1993;163:369-74, 379-80. [Medline: 8401968]
16. Rickwood D, Deane FP, Wilson CJ, Ciarrochi JV. Young people's help-seeking for mental health problems. Aust eJournal Adv Ment Health 2005;4(3):218-251. URL: http://ro.uow.edu.au/hbspapers/2106/ [WebCite Cache ID 6m19KUttx]
17. Rickwood DF, Deane FP, Wilson CJ. When and how do young people seek professional help for mental health problems? Med J Aust 2007;187(7 Suppl):S35-S39. [Medline: 17908023]
18. Burns JR, Rapee RM. Adolescent mental health literacy: young people's knowledge of depression and help seeking. J Adolesc 2006 Apr;29(2):225-239. [doi: 10.1016/j.adolescence.2005.05.004] [Medline: 15996727]
19. Jorm AF, Wright A, Morgan AJ. Where to seek help for a mental disorder? National survey of the beliefs of Australian youth and their parents. Med J Aust 2007 Nov 19;187(10):556-560. [Medline: 18021042]
20. aan het Rot M, Hogenelst K, Schoevers RA. Mood disorders in everyday life: a systematic review of experience sampling and ecological momentary assessment studies. Clin Psychol Rev 2012;32(6):510-523. [Medline: 22721999]
21. Myin-Germeys I, Oorschot M, Collip D, Lataster J, Delespaul P, van Os J. Experience sampling research in psychopathology: opening the black box of daily life. Psychol Med 2009 Sep;39(9):1533-1547. [doi: 10.1017/S0033291708004947] [Medline: 19215626]
22. Telford C, McCarthy-Jones S, Corcoran R, Rowse G. Experience Sampling Methodology studies of depression: the state of the art. Psychol Med 2012 Jun;42(6):1119-1129. [doi: 10.1017/S0033291711002200] [Medline: 22008511]
23. Peeters F, Berkhof J, Delespaul P, Rottenberg J, Nicolson NA. Diurnal mood variation in major depressive disorder. Emotion 2006;6(3):383-391. [doi: 10.1037/1528-3542.6.3.383] [Medline: 16938080]
24. Kenardy J, Fried L, Kraemer H, Taylor CB. Psychological precursors of panic attacks. Br J Psychiatry 1992 May;160:668-673. [Medline: 1591576]
25. Ben-Zeev D, Young MA. Accuracy of hospitalized depressed patients' and healthy controls' retrospective symptom reports: an experience sampling study. J Nerv Ment Dis 2010;198(4):280-285. [Medline: 20386257]
26. Miller G. The smartphone psychology manifesto. Perspect Psychol Sci 2012 May;7(3):221-237. [doi: 10.1177/1745691612441215] [Medline: 26168460]
27. Randall WM, Rickard NS. Development and trial of a mobile Experience Sampling Method (m-ESM) for personal music listening. Music Perception Interdisciplinary J 2012;31(2):157-170. URL: http://mp.ucpress.edu/content/31/2/157 [WebCite Cache ID 6m19NQVP0] [doi: 10.1525/mp.2013.31.2.157]
28. Reid SC, Kauer SD, Khor AS, Hearps SJ, Sanci LA, Kennedy AD, et al. Using a mobile phone application in youth mental health - an evaluation study. Aust Fam Physician 2012 Sep;41(9):711-714. [Medline: 22962650]
29. Harrison V, Proudfoot J, Wee PP, Parker G, Pavlovic DH, Manicavasagar V. Mobile mental health: review of the emerging field and proof of concept study. J Ment Health 2011 Dec;20(6):509-524. [doi: 10.3109/09638237.2011.608746] [Medline: 21988230]

30. Google. Our mobile planet: United States of America. 2013 May. URL: http://services.google.com/fh/files/misc/omp-2013-us-en.pdf [WebCite Cache ID 6a5EeTpp5]
31. Proudfoot J, Parker G, Hadzi PD, Manicavasagar V, Adler E, Whitton A. Community attitudes to the appropriation of mobile phones for monitoring and managing depression, anxiety, and stress. J Med Internet Res 2010;12(5):e64 [FREE Full text] [doi: 10.2196/jmir.1475] [Medline: 21169174]
32. Quine S, Bernard D, Booth M, Kang M, Usherwood T, Alperstein G, et al. Health and access issues among Australian adolescents: a rural-urban comparison. Rural Remote Health 2003;3(3):245 [FREE Full text] [Medline: 15882102]
33. Poushter J. Smartphone ownership and Internet usage continues to climb in emerging economies. Pew Research Center. 2016 Feb 22. URL: http://www.pewglobal.org/2016/02/22/smartphone-ownership-and-internet-usage-continues-to-climb-in-emerging-economies/ [accessed 2016-06-14] [WebCite Cache ID 6iGxlcA5V]
34. Burns JM, Durkin LA, Nicholas J. Mental health of young people in the United States: what role can the internet play in reducing stigma and promoting help seeking? J Adolesc Health 2009 Jul;45(1):95-97. [doi: 10.1016/j.jadohealth.2008.12.006] [Medline: 19541256]
35. Rickwood D. Promoting youth mental health through computer-mediated communication. Int J Ment Health Promotion 2010;12(3):32-44.
36. Bakker D, Kazantzis N, Rickwood D, Rickard NS. Mental health smartphone apps: review and evidence-based recommendations for future developments. JMIR Ment Health 2016;3(1):e7. [doi: 10.2196/mhealth.4984] [Medline: 26932350]
37. Donker T, Petrie K, Proudfoot J, Clarke J, Birch MR, Christensen H. Smartphones for smarter delivery of mental health programs: a systematic review. J Med Internet Res 2013;15(11):e247. [doi: 10.2196/jmir.2791] [Medline: 24240579]
38. Reid SC, Kauer SD, Hearps SJ, Crooke AH, Khor AS, Sanci LA, et al. A mobile phone application for the assessment and management of youth mental health problems in primary care: health service outcomes from a randomised controlled trial of mobiletype. BMC Fam Pract 2013 Jun 19;14:84 [FREE Full text] [doi: 10.1186/1471-2296-14-84] [Medline: 23782796]
39. Lathia N, Pejovic V, Rachuri KK, Mascolo C, Musolesi M, Rentfrow PJ. Smartphones for large scale behavior change interventions. IEEE CS. 2013 URL: http://www.cs.bham.ac.uk/~pejovicv/docs/Lathia2013IEEEPervasive.pdf [accessed 2016-11-02] [WebCite Cache ID 6li61Flsy]
40. LiKamWa R, Liu Y, Lane N, Zhong L. MoodScope: building a mood sensor from smartphone usage patterns. In: Proceedings of the 11th Annual International Conference on Mobile Systems, Applications, and Services. 2013 Presented at: MobiSys'13th Annual International Conference on Mobile Systems, Applications, and Services; Jun; 2013; Taipei, Taiwan p. 25-28. [doi: 10.1145/2462456.2464449]
41. Asselbergs J, Ruwaard J, Ejdys M, Schrader N, Sijbrandij M, Riper H. Mobile phone-based unobtrusive ecological momentary assessment of day-to-day mood: an explorative study. J Med Internet Res 2016 Mar;18(3):e72 [FREE Full text] [doi: 10.2196/jmir.5505] [Medline: 27025287]
42. Nielsen. A Nielsen report on the myths and realities of teen media trends. 2009. URL: http://blog.nielsen.com/nielsenwire/reports/nielsen_howteensusemedia_june09.pdf./ [accessed 2016-06-14] [WebCite Cache ID 6iGxr2fFg]
43. DeChoudhury CM, Gamon M, Counts X, Horvitz E. Predicting depression via social media. Microsoft. 2013. URL: http://research.microsoft.com/apps/pubs/default.aspx?id=192721 [accessed 2016-06-15] [WebCite Cache ID 6iGy6SKTF]
44. Kross E, Verduyn P, Demiralp E, Park J, Lee DS, Lin N, et al. Facebook use predicts declines in subjective well-being in young adults. PLoS One 2013;8(8):e69841 [FREE Full text] [doi: 10.1371/journal.pone.0069841] [Medline: 23967061]
45. Motl RW, Birnbaum AS, Kubik MY, Dishman RK. Naturally occurring changes in physical activity are inversely related to depressive symptoms during early adolescence. Psychosom Med 2004;66(3):336-342. [Medline: 15184692]
46. Thayer RE, Newman JR, McClain TM. Self-regulation of mood: strategies for changing a bad mood, raising energy, and reducing tension. J Pers Soc Psychol 1994 Nov;67(5):910-925. [Medline: 7983582]
47. De Choudhury CM. Predicting postpartum changes in emotion and behavior via social media. In: CHI '13 Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2013 Presented at: Conference on Human Factors in Computing Systems; 2013; Paris, France p. 3267-3276. [doi: 10.1145/2470654.2466447]
48. Miranda D. Music listening and mental health: variations on internalizing psychopathology. In: Macdonald R, Kreutz G, Mitchell L, editors. Music, Health, and Well-being. Oxford: Oxford University Press; 2012.
49. North A, Hargreaves D. The Social and Applied Psychology of Music. Oxford: Oxford University Press; 2008.
50. Primack BA, Silk JS, DeLozier CR, Shadel WG, Dillman Carpentier FR, Dahl RE, et al. Using ecological momentary assessment to determine media use by individuals with and without major depressive disorder. Arch Pediatr Adolesc Med 2011 Apr;165(4):360-365 [FREE Full text] [doi: 10.1001/archpediatrics.2011.27] [Medline: 21464384]
51. Ooi KE, Lech M, Allen NB. Multichannel weighted speech classification system for prediction of major depression in adolescents. IEEE Trans Biomed Eng 2013 Feb;60(2):497-506. [doi: 10.1109/TBME.2012.2228646] [Medline: 23192475]
52. Scherer K, Bänziger T, Roesch EB. Blueprint for Affective Computing: A Sourcebook. Oxford: Oxford University Press; 2010.

53. Weninger F, Eyben F, Schuller BW, Mortillaro M, Scherer KR. On the acoustics of emotion in audio: what speech, music, and sound have in common. Front Psychol 2013;4:292 [FREE Full text] [doi: 10.3389/fpsyg.2013.00292] [Medline: 23750144]
54. Calvo RA, D'Mello S, Gratch J, Kappas A. The Oxford Handbook of Affective Computing. Oxford: Oxford University Press; 2015.
55. Keyes CL. Mental illness and/or mental health? Investigating axioms of the complete state model of health. J Consult Clin Psychol 2005 Jun;73(3):539-548. [doi: 10.1037/0022-006X.73.3.539] [Medline: 15982151]
56. Suldo SM, Shaffer EJ. Looking beyond psychopathology: the dual-factor model of mental health in youth. School Psychology Review 2008;37:52-68.
57. Huppert FA. Psychological well-being: evidence regarding its causes and consequences. Appl Psychol Health Well-Being 2009;1(2):137-164.
58. Scherer K. Ways to study the nature and frequency of our daily emotions: reply to the commentaries on 'Emotions in everyday life'. Soc Sci Inf 2004;43:667-689.
59. Kapp KM. The gamification of learning and instruction: Game-Based Methods and Strategies for Training and Education. 1st edition. San Francisco, CA: Pfeiffer; 2012.
60. Pennebaker JW, Chung C, Ireland M, Gonzales A, Booth RJ. The LIWC 2007 Application. LIWC. 2016. URL: http://liwc.wpengine.com/ [accessed 2016-06-15] [WebCite Cache ID 6iGySPeBZ]
61. Kroenke K, Spitzer RL, Williams JB, Lōwe B. An ultra-brief screening scale for anxiety and depression: the PHQ-4. Psychosomatics 2009;50(6):613-621. [doi: 10.1176/appi.psy.50.6.613] [Medline: 19996233]
62. Mehrabian A, Russell J. An Approach to Environmental Psychology. 1st edition. Cambridge, MA: MIT Press; 1974.
63. Russell JA. A circumplex model of affect. J Pers Soc Psychol 1980;39(6):1161-1178.
64. Bech P, Kjoller OR, Rasmussen NK. Measuring well-being rather than the absence of distress symptoms: a comparison of the SF-36 Mental Health subscale and the WHO-Five Well-Being Scale. Int J Methods Psychiatr Res 2003;12(2):85-91. [Medline: 12830302]
65. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. J Gen Intern Med 2001 Sep;16(9):606-613 [FREE Full text] [Medline: 11556941]
66. beyondblue. beyondblue: Depression, Anxiety URL: https://www.beyondblue.org.au/ [WebCite Cache ID 6ld91qVDK]
67. Headspace. Welcome to headspace. URL: https://headspace.org.au/ [WebCite Cache ID 6ld94wTcH]
68. Monash University. Privacy policy. 2016 URL: http://www.privacy.monash.edu/ [accessed 2016-06-15] [WebCite Cache ID 6iGxIibho]
69. The British Psychological Society. Research guidelines & policy documents. 2016 URL: http://www.bps.org.uk/publications/policy-and-guidelines/research-guidelines-policy-documents/research-guidelines-poli [accessed 2016-06-15] [WebCite Cache ID 6iGxZE8ft]
70. Stoyanov S, Hides L, Kavanagh D, Zelenko O, Tjondronegoro D, Mani M. Mobile App Rating Scale: a new tool for assessing the quality of health mobile apps. JMIR mHealth uHealth 2015;3(1):e27. [doi: 10.2196/mhealth.3422] [Medline: 25760773]
71. Picard RW, Vyza E, Healey J. Toward machine emotional intelligence: analysis of affective physiological state. IEEE Trans Pattern Analysis Machine Intell 2001;23(10):1175-1191.
72. Young and Well Cooperative Research Centre. Young and Well: researching the role of technology to improve the mental health and wellbeing of young people. 2016. URL: http:// www.youngandwellcrc.org.au [WebCite Cache ID 6iGyrSPAQ]
73. Bakker G. Practical CBT: Using Functional Analysis and Standardised Homework in Everyday Therapy. Bowen Hills, Qld: Australian Academic Press; 2008.
74. Kazantzis N, MacEwan J, Dattilio FM. A guiding model for practice. In: Kazantzis N, Deane FP, Ronan KR, L'Abate L, editors. Using Homework Assignments in Cognitive Behavior Therapy. New York: Routledge; 2005:359-407.
75. Bennett K, Reynolds J, Christensen H, Griffiths KM. e-hub: an online self-help mental health service in the community. Med J Aust 2010;192(11 Suppl):S48-S52. [Medline: 20528710]
76. McGorry P, Bates T, Birchwood M. Designing youth mental health services for the 21st century: examples from Australia, Ireland, the UK. Br J Psychol 2013;202(s54):s30-s35. [doi: 10.1192/bjp.bp.112.119214]
77. Rickwood DJ, Telford NR, Mazzer KR, Parker AG, Tanti CJ, McGorry PD. The services provided to young people through the headspace centres across Australia. Med J Aust 2015 Jun 1;202(10):533-536. [Medline: 26021365]
78. Ellison N, Boyd DM. Sociality through social network sites. In: Dutton WF, editor. The Oxford Handbook of Internet Studies. Oxford: Oxford University Press; 2013:151-172.
79. Kramer AD, Guillory JE, Hancock JT. Experimental evidence of massive-scale emotional contagion through social networks. In: Proc Natl Acad Sci U S A. 2014 Jun 17 Presented at: Proceedings of the National Academy of Sciences, United States; 2014 Jun 17; p. 8788-8790. [doi: 10.1073/pnas.1320040111]
80. Park G, Schwartz HA, Eichstaedt JC, Kern ML, Kosinski M, Stillwell DJ, et al. Automatic personality assessment through social media language. J Pers Soc Psychol 2015;108(6):934-952. [doi: 10.1037/pspp0000020] [Medline: 25365036]

81. Davila J, Hershenberg R, Feinstein BA, Gorman K, Bhatia V, Starr LR. Frequency and quality of social networking among young adults: associations with depressive symptoms, rumination, and corumination. Psychol Popular Media Cult 2012;1(2):72-86. [doi: 10.1037/a0027512]
82. Feinstein BA, Bhatia V, Hershenberg R, Davila J. Another venue for problematic interpersonal behavior: the effects of depressive and anxious symptoms on social networking experiences. J Soc Clin Psychol 2012 Apr;31(4):356-382. [doi: 10.1521/jscp.2012.31.4.356]
83. Valkenburg PM, Peter J, Schouten AP. Friend networking sites and their relationship to adolescents' well-being and social self-esteem. Cyberpsychol Behav 2006 Oct;9(5):584-590. [doi: 10.1089/cpb.2006.9.584] [Medline: 17034326]
84. Seabrook E, Kern M, Rickard NS. Social networking sites, depression, and anxiety: a systematic review. JMIR Mental Health 2016 (forthcoming).
85. Bonanno GA. Loss, trauma, and human resilience: have we underestimated the human capacity to thrive after extremely aversive events? Am Psychol 2004 Jan;59(1):20-28. [doi: 10.1037/0003-066X.59.1.20] [Medline: 14736317]
86. Preotiuc-Pietro D, Eichstaedt JC, Park G, Sap M, Smith L, et al. The role of personality, age, and gender in tweeting about mental illness. 2015 Presented at: Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality: NAACL; 2015; Denver Colorado.
87. Bonanno GA, Diminich ED. Annual research review: positive adjustment to adversity—trajectories of minimal-impact resilience and emergent resilience. J Child Psychol Psychiatry 2013 Apr;54(4):378-401 [FREE Full text] [doi: 10.1111/jcpp.12021] [Medline: 23215790]
88. Dumont M, Provost MA. Resilience in adolescents: protective role of social support, coping strategies, self-esteem, and social activities on experience of stress and depression. Journal of Youth and Adolescence 1999;28:343. [doi: 10.1023/A:1021637011732]
89. Herman-Stahl M, Petersen AC. The protective role of coping and social resources for depressive symptoms among young adolescents. J Youth Adolescence 1996;25:733. [doi: 10.1007/BF01537451]
90. Noor NM, Alwi A. Stressors and well-being in low socio-economic status Malaysian adolescents: the role of resilience resources. Asian Journal of Social Psychology 2013;16:292-306. [doi: 10.1111/ajsp.12035]
91. Bonanno GA, Field NP, Kovacevic A, Kaltman S. Self-enhancement as a buffer against extreme adversity: civil war in Bosnia and traumatic loss in the United States. Personality and Social Psychology Bulletin 2002;28(2):184-196. [doi: 10.1177/0146167202282005]
92. Ryff CD, Singer B. From social structure to biology: integrative science in pursuit of human healthwell-being. In: Snyder CR, Lopez SJ, editors. Hanbook of Positive Psychology. New York: Oxford University Press; 2002:541-555.
93. Ryff CD, Singer BH, Dienberg Love G. Positive health: connecting well-being with biology. Philos Trans Royal Soc Lond B Biol Sci 2004;359(1449):1383-1394. [doi: 10.1098/rstb.2004.1521] [Medline: 15347530]
94. Meeker M, Wu L. Slideshare. 2013. Meeker M, Wu L. KPCB Internet trends 2013. Slideshare. 2013. URL: http://www.slideshare.net/kleinerperkins/kpcb-internet-trends-2013 [accessed 2016-06-14] [WebCite Cache ID 6iGyXnxlH]

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

Edited by J Strauss; submitted 14.06.16; peer-reviewed by M Prietula, D Rickwood, J Asselbergs, S Rubinelli, TR Soron; comments to author 10.07.16; revised version received 10.08.16; accepted 04.10.16; published 23.11.16

Please cite as:
Rickard N, Arjmand HA, Bakker D, Seabrook E
Development of a Mobile Phone App to Support Self-Monitoring of Emotional Well-Being: A Mental Health Digital Innovation
JMIR Ment Health 2016;3(4):e49
URL: http://mental.jmir.org/2016/4/e49/
doi:10.2196/mental.6202
PMID:27881358

Multimedia Appendix 1: Details on 3 forms of data (automatic, experience sampling, and psychological surveys) collected from MoodPrism.

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[a] 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	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	**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]
Music library	For each song in the user's music library - Song Title - Genre - Artist - Album - Last Played - Play count - Rating - Release date - Duration			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: Patien

[d]GAD-7: Gener

55. Keyes, C.L., Mental illness and/or mental health? Investigating axioms of the complete state model of health. Journal of Consulting and Clinical Psychology 2005;73(3): p. 539-548.

59. Kroenke, K., et al., An ultra-brief screening scale for anxiety and depression: the PHQ-4. Psychosomatics 2009;50(6): p. 613-21.

60. Mehrabian, A., Russell, J.A. An approach to environmental psychology (1 ed.). Cambridge, Mass.: MIT Press, 1974.

61. Russell, J. A. A circumplex model of affect. Journal of Personality and Social Psychology 1980;39:1161–1178.

62. Bech, P., O.R. Kjoller, and N.K. Rasmussen, Measuring well-being rather than the absence of distress symptoms: a comparison of the SF-36 Mental Health subscale and the WHO-Five Well-Being Scale. International J Methods Psychiatr Res, 2003. 12(2): p. 85-91.

63. Robins, R. W., Hendin, H. M., Trzesniewski, K. H. Measuring global self-esteem: Construct validation of a single-item measure and the Rosenberg Self-Esteem Scale. Personality and Social Psychology Bulletin 2001;27:151-161.

64. Cheng, C. Assessment of major life events for Hong Kong adolescents: The Chinese adolescent life event scale. American Journal of Community Psychology 1997;25(1):17-33.

65. Coddington, R. D. The significance of life events as etiologic factors in the diseases of children—II. A study of a normal population. Journal of Psychosomatic Research 1972; 16(3):205-213.

66. Newcomb, M. D., Huba, G. J., Bentler, P. M. A multidimensional assessment of stressful life events among adolescents: Derivation and correlates. Journal of Health and Social Behavior 1981;22:400-415.

67. Swearingen, E. M., Cohen, L. H. Measurement of adolescents' life events: The junior high life experiences survey. American Journal of Community Psychology 1985;13(1):69-85.

68. Waaktaar, T., Borge, A. I. H., Fundingsrud, H. P., Christie, H. J., Torgersen, S. The role of stressful life events in the development of depressive symptoms in adolescence—A longitudinal community study. Journal of adolescence 2004;27(2):153-163.

69. Holmes, T.H., Rahe, R.H. The Social Readjustment Rating Scale. J Psychosom Res 1967;11(2): 213–8

70. Zimet, G.D., et al., The Multidimensional Scale of Perceived Social Support. Journal of Personality Assessment 1988;52(1):30-41.

71. Reynolds, W.M. Development of reliable and valid short forms of the Marlowe-Crowne social desirability scale. Journal of Clinical Psychology 2006;38(1):119-125.

72. Donnellan, M.B., Oswald, F., Baird, B., Lucas, R.E., et al The Mini-IPIP Scales: Tiny-Yet-Effective Measures of the Big Five Factors of Personality. Psychological Assessment, 2006 ;18(2), 192-203

73. Rosenberg, M. Society and the adolescent self-image. Princeton, NJ: Princeton University Press, 1965.

74. Mas-Herrero, E. et al. Individual differences in music reward experiences. Music Perception 2013; 31(2):118-138.

75. Young and Well Cooperative Research Centre. 2016-06-14. URL:http://www.youngandwellcrc.org.au (Accessed: 2016-06-14. (Archived by WebCite® at http://www.webcitation.org/6iGyrSPAQ)

76. Kauer, S.D. et al. Self-monitoring Using Mobile Phones in the Early Stages of Adolescent Depression: Randomized Controlled Trial. Journal of Medical Internet Research 2012;14(3):e67

77. Tennant, R. et al The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Ddevelopment and UK validation. Health and Quality of Life Outcomes 2007;5:63

78. Kroenke K, Spitzer RL, Williams JBW. The PHQ-9: Validity of a brief depression severity measure. J Gen Intern Med 2001;16: 606-613.

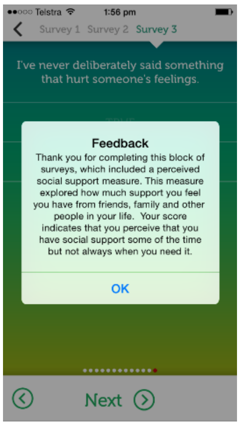
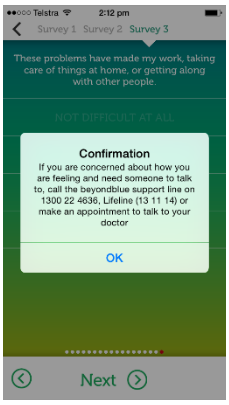
79. Spitzer RL, Kroenke K, Williams JBW, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch Intern Med 2006;166:1092-1097.

80. Reavley, N.J., Morgan, A.J, Jorm, F. F., Development of scales to assess mental health literacy relating to recognition of and interventions for depression, anxiety disorders and schizophrenia/psychosis. Australian and New Zealand Journal of Psychiatry 2014; 48(1):61-9.

81. Smith, B.W. et al The Brief Resilience Scale: Assessing the ability to bounce back. International Journal of Behavioral Medicine 2008;15:194-200.

82. Chesney, M.A., et al. A validity and reliability study of the coping self-efficacy scale. Br J Health Psychol 2006;11(3): 421-437

Multimedia Appendix 2: Feedback generated by the subjects while using MoodPrism.

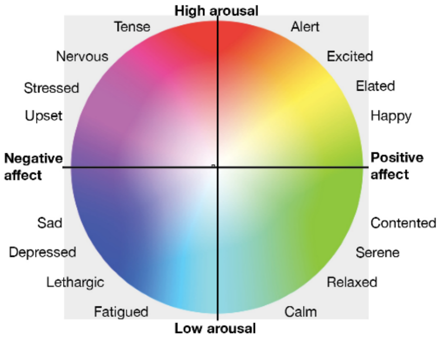
Feedback type	Trigger	Scoring	Sample
Psychological surveys			
Normative feedback	When block of surveys completed	Scoring based on published guidelines, and feedback based on published normative data). For example: (<45) in the lower range of positive health scores (less than 75% of people) (45-50) on 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)	
Risk assessment			
Prompt to seek mental health support	Red flag high score	PHQ or GAD score above 15 (as per published recommendations)	

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.

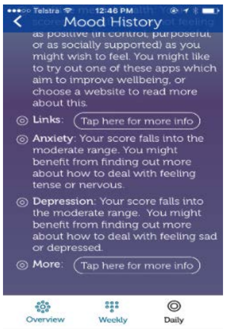
Based on 2-dimensional (arousal and valence) circumplex model of emotion (see below); color coding based on subjective convention.



Overview:

Weekly view:

Daily detail:

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”	
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 C: Emotional Self-Awareness Scale – Revised

Labels on 5 point rating options:

0 = Never
1 = Very Little
2 = Sometimes
3 = Often
4 = A lot

Reversals: 1, 3, 7, 11, 12, 14, 15, 20, 23, 27, 29

1. My moods are hard to describe
2. It’s important to me to understand what my feelings mean
3. It's hard for me to tell what mood I’m in
4. I analyse my personality to try to understand why I’m upset
5. Expressing emotion is easy
6. I usually know why I feel the way I do
7. I often have trouble deciding what will improve my mood
8. I know how I feel about most things
9. I go away by myself and think about why I feel a certain way
10. I can talk about my mood to others
11. I don't know why I feel the way I feel
12. I don't really think about why I behave as I do
13. I often 'self-talk' to think about feelings
14. I’m often confused about how I feel about things
15. I’m often aware of being emotional, but I can’t describe the emotion
16. I often take time to reflect on how I feel
17. I often know what caused my mood
18. I’m usually aware of my emotions
19. I like to go someplace alone to think about my feelings
20. I don't often think about my feelings
21. I often think about ways to make myself feel better
22. I know exactly how I'm feeling
23. Sometimes I can't figure out how to make myself feel better
24. When feeling bad, I try to deal with my problems and concerns
25. I can tell others how I’m feeling
26. I usually have clear idea about how my feelings affect how I act
27. It’s difficult to make sense of the way I feel
28. I find it easy to write down how I feel
29. It's difficult to communicate what I feel
30. I think about recent events to try to understand why I’m upset

Appendix D: Mental Health Literacy Questionnaire

Correct answers (**bolded**) are awarded 1 point.
Some answers (*italicised*) are awarded 0.5 points.

Mary is 30 years old. She has been feeling unusually sad and miserable for the last few weeks. Even though she is tired all the time, she has trouble sleeping nearly every night. Mary doesn't feel like eating and has lost weight. She can't keep her mind on her work and puts off making decisions. Even day-to-day tasks seem too much for her. This has come to the attention of her boss, who is concerned about Mary's lowered productivity.

1. What do you think is wrong with Mary?
    - **a.** Heart problems
    - **b. Depression**
    - **c.** Anxiety
    - **d.** Laziness

2. How helpful do you think each of the following would be for Mary? [rate each on a scale of 5 point rating scale with lowest labelled "Most harmful", then "Harmful", midpoint labelled "neutral", then "Helpful" and highest labelled "Most helpful"]

Item	Correct Answers
a. Visiting a chemist (pharmacist)	**Neutral, Helpful, Most helpful**
b. Asking help from close friends	**Helpful, Most helpful**
c. Having alcohol to relax	**Most harmful,** *Harmful*
d. Using an online or phone counselling service	**Helpful, Most helpful**
e. Contacting a psychologist	*Helpful*, **Most helpful**
f. Vitamins and minerals, or herbal tonics	**Harmful, Neutral, Helpful**
g. Being admitted to a psychiatric ward of a hospital	**Most harmful, Harmful**, *Neutral*
h. Visiting a GP	**Helpful, Most helpful**

John is a 15 year old living with his parents. Since starting at a new school last year he has become even more shy than usual and has made only one friend. He would really like to make more friends but is scared that he'll do or say something embarrassing when he's around others. Although John's work is OK he becomes incredibly nervous, trembles, blushes and seems like he might vomit if he has to answer a question or speak in front of the class. At home, John is quite talkative with his family, but becomes quiet if anyone he doesn't know well comes over. He never answers the phone and he refuses to attend social gatherings. He knows his fears are unreasonable but he can't seem to control them and this really upsets him.

3. What do you think is wrong with John?
    - **a.** Heart problems
    - **b.** Depression
    - **c. Anxiety**
    - **d.** Laziness

4. How helpful do you think each of the following would be for John? [rate each on a scale of 5 point rating scale with lowest labelled “Most harmful”, then “Harmful”, midpoint labelled “neutral”, then “Helpful” and highest labelled “Most helpful”]

Item	Correct Answers
a. Visiting a chemist (pharmacist)	**Neutral, Helpful, Most helpful**
b. Asking help from close friends	**Helpful, Most helpful**
c. Having alcohol to relax	**Most harmful,** *Harmful*
d. Using an online or phone counselling service	**Helpful, Most helpful**
e. Contacting a psychologist	*Helpful*, **Most helpful**
f. Vitamins and minerals, or herbal tonics	**Harmful, Neutral, Helpful**
g. Being admitted to a psychiatric ward of a hospital	**Most harmful, Harmful**, *Neutral*
h. Visiting a GP	**Helpful, Most helpful**

5. What is the most common mental condition in Australia?
   - Schizophrenia
   - Bipolar disorder
   - **Depression**
   - **Anxiety**

6. What is the best way of treating depression?
   - **Therapy with a trained practitioner**
   - Drinking alcohol
   - Just getting motivated
   - An exercise program

7. Which of these websites has information about mental health and where to find help?
   - twitter.com
   - **beyondblue.org.au**
   - change.org
   - spacehead.org

8. What is a headspace centre?
   - A part of the hospital
   - A part of the brain
   - A mental health service for people of all ages
   - **A health service for young people and their families**

9. Is anger a normal human emotion?
   - No, and it is never helpful
   - No, but it is sometimes helpful
   - Yes, but it is never helpful
   - **Yes, and it is sometimes helpful**

10. Is feeling anxious normal?
    - No, and it is never helpful
    - No, but it is sometimes helpful
    - Yes, but it is never helpful
    - **Yes, and it is sometimes helpful**

11. Which is *not* a sign of depression:
   - Tiredness, lack of energy and motivation
   - Feelings of unhappiness and irritability
   - **Hearing things that aren’t there**
   - Feeling worried or tense

Appendix E: Additional MoodMission Screenshots

Figure E.1. Example MoodMission onboarding screens.

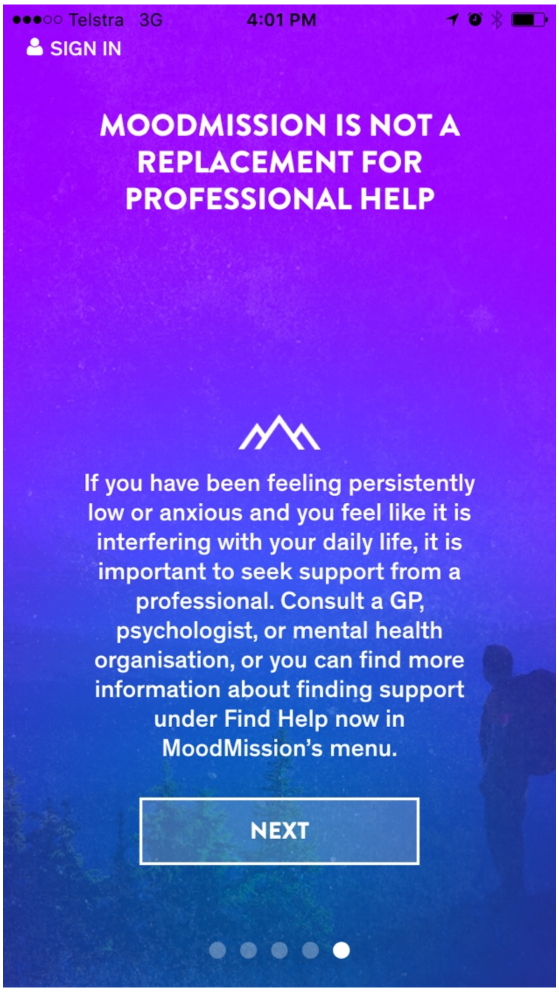


Figure E.2. Example MoodMission survey screens.

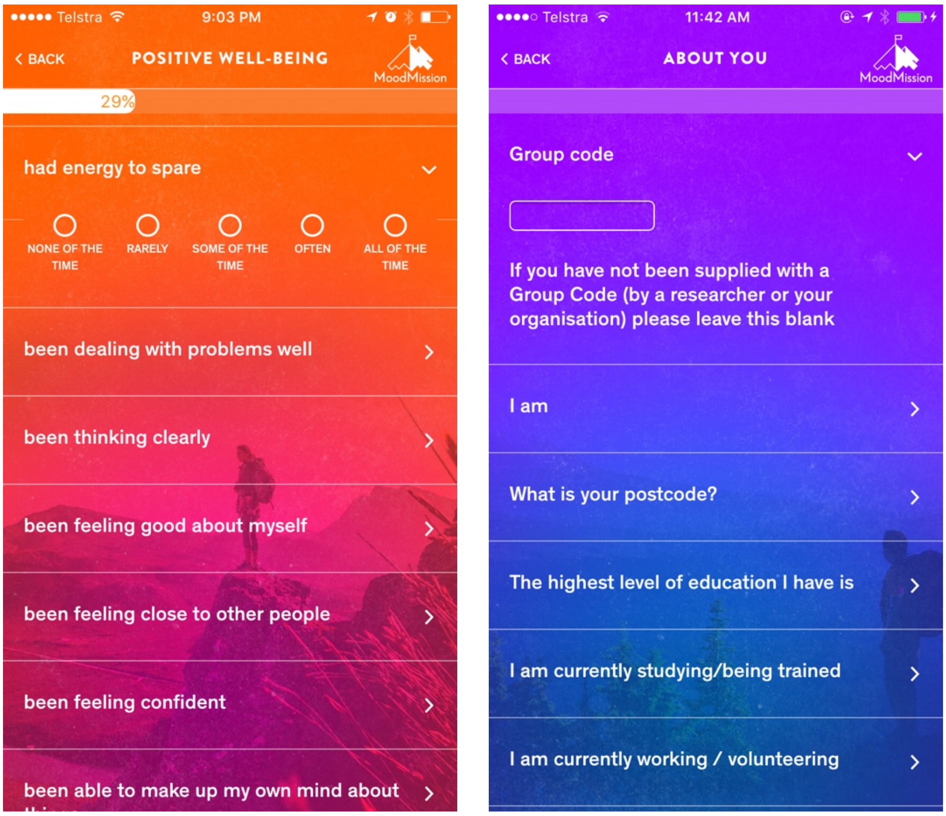


Figure E.3. Example MoodMission Mission Log screens.

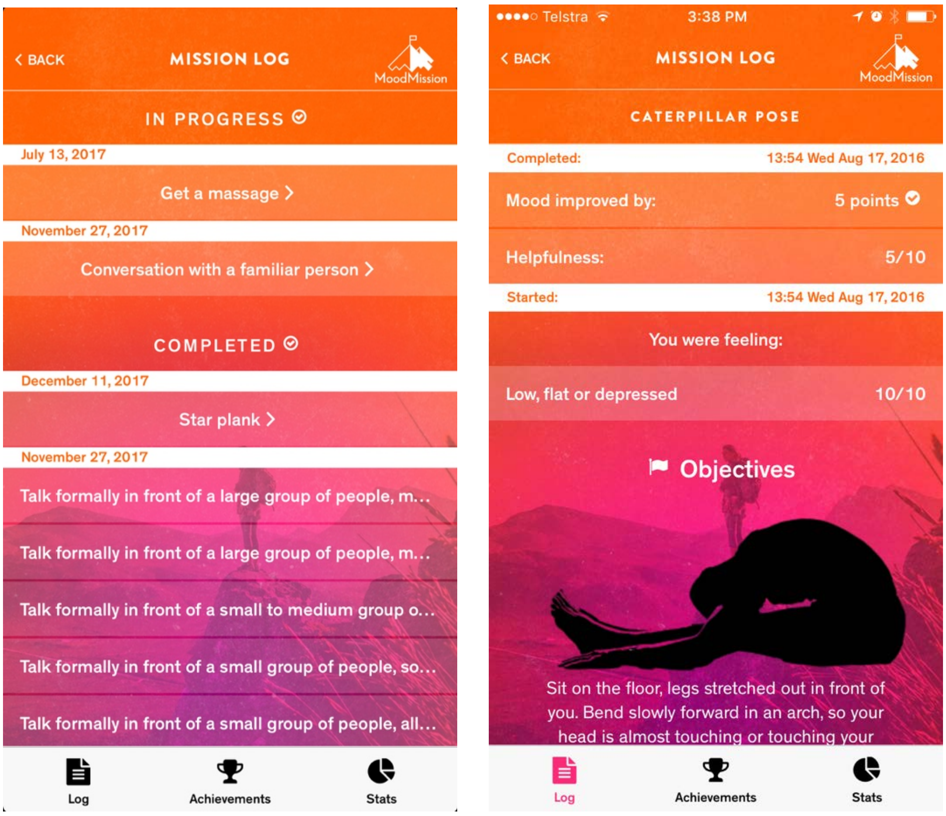


Figure E.4. Example MoodMission Stats and Achievements screens.

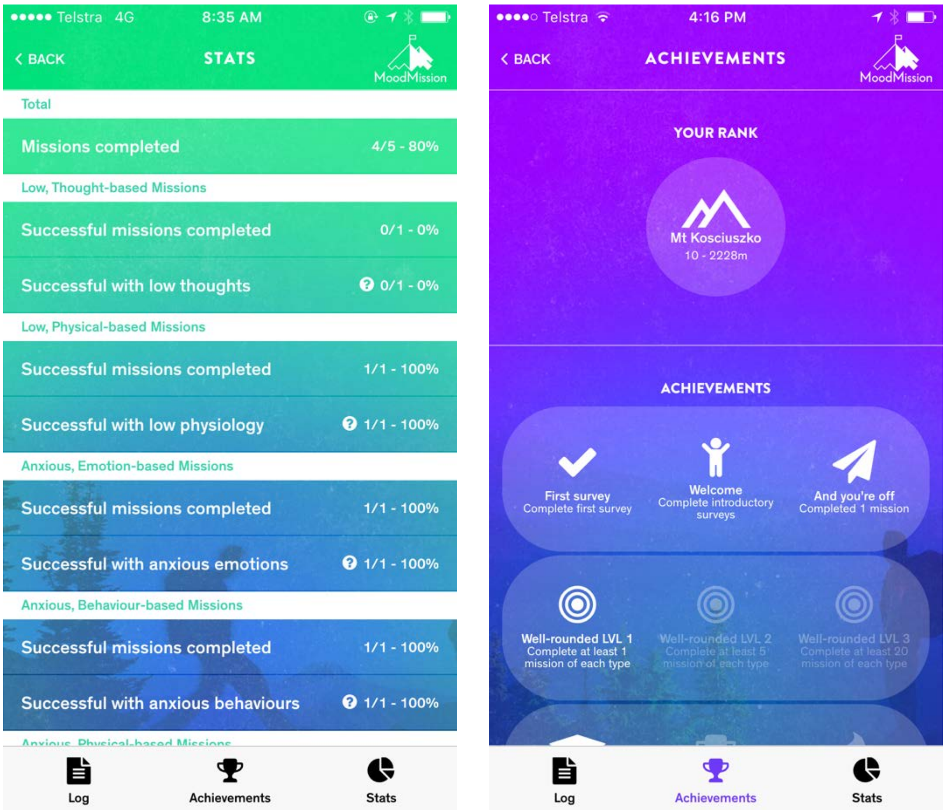


Figure E.4. Additional example MoodMission Mission screens.