Behaviour Research and Therapy 109 (2018) 75–83

Contents lists available at ScienceDirect

Behaviour Research and Therapy

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

A randomized controlled trial of three smartphone apps for enhancing public mental health

David Bakker[a,*], Nikolaos Kazantzis[a,b], Debra Rickwood[c], Nikki Rickard[a,d]

[a] School of Psychological Sciences and Monash Institute of Cognitive and Clinical Neurosciences, Monash University, Australia
[b] Cognitive Behaviour Therapy Research Unit, Monash University, Australia
[c] Psychology Department, Faculty of Health, University of Canberra, Australia
[d] Centre for Positive Psychology, University of Melbourne, Australia

ARTICLE INFO

Keywords:
Technology
Anxiety
Depression
Cognitive behavioural therapy
Randomized controlled trial
Mobile

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.

1. Introduction

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

* Corresponding author.
E-mail address: david.bakker@monash.edu (D. Bakker).

https://doi.org/10.1016/j.brat.2018.08.003
Received 7 February 2018; Received in revised form 5 August 2018; Accepted 10 August 2018
Available online 11 August 2018

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.

1.1. 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 $M = 40$, $SD = 11$), $g = 0.38$[1], 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., $g = 1.12$[2], 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.

1.2. 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.

1.3. 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 publicly 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).

1.4. 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 (Hofmann, 2015; Slade, 2010; World Health Organization, 2004). 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, 2017; 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

[1] Converted to Hedge's g by Firth et al. (2017a) from original $\eta_p^2 = 0.030$.

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

health over time, and the app provides relevant links to mental health resources. Bakker and Rickard (2017) 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, 2018).

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, 2017) and MoodMission (Bakker & Rickard, 2018), 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., 2017b, 2017a). 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., 2017b, 2017a), 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).

2. Method

2.1. 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. ($\kappa 2 = 0.54$, 95% CI = 0.43–0.64; 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 $\alpha = .05$ 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. To account for attrition rates, an aim of $n = 78$ per group was set for recruitment.

2.2. 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 $\alpha = 0.89$ (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 $\alpha = 0.90$. The GAD-7 has high internal reliability, Cronbach's $\alpha = 0.92$ (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 $\alpha = 0.92$.

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 = 0.91 (Tennant et al., 2007). In this study, Cronbach's α = 0.92.

2.3. Secondary measures - potential mediators

The Emotional Self-Awareness Scale – Revised (ESAS-R; Bakker & Rickard, 2018), 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 = 0.92.

The Coping Self-Efficacy Scale (CSES; Chesney et al., 2006) was used to assess CSE, and in this study, Cronbach's α = 0.96. 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, 2017) and MoodMission (Bakker & Rickard, 2018) 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 = 0.53.

2.4. Procedure

Flow of the participants through the study is illustrated in Fig. 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.

2.5. 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

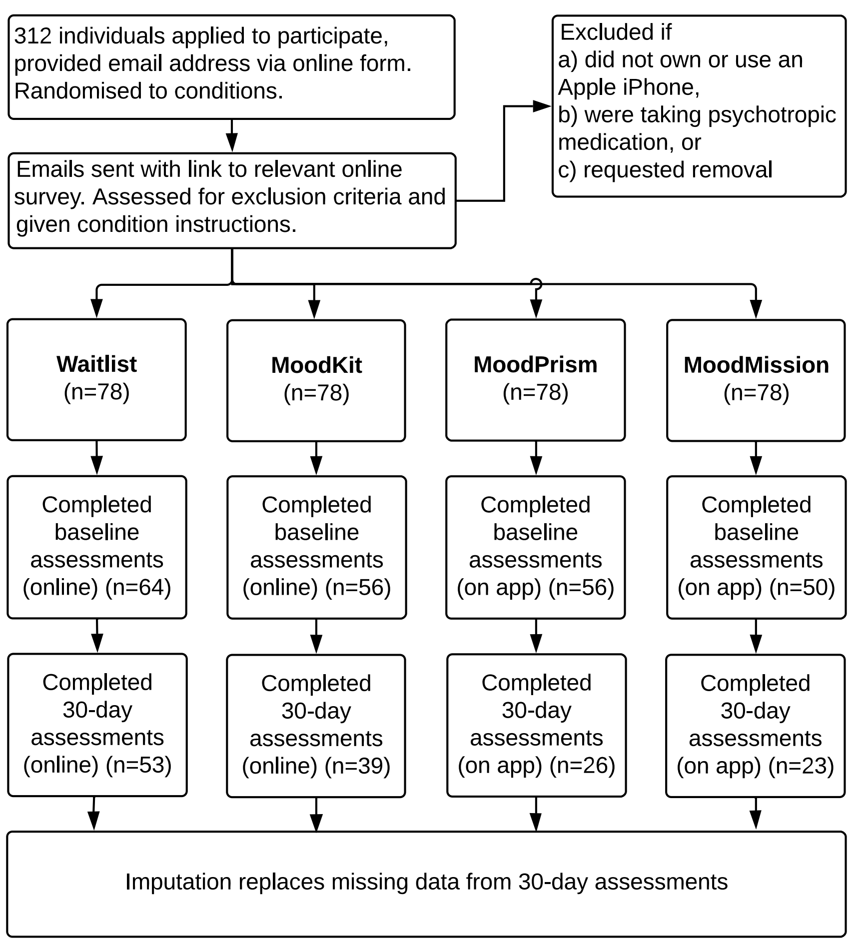

Fig. 1. CONSORT flow diagram.

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.

3. Results

3.1. Preliminary analyses

A 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 45–56, and the current study found a median of 42 with an inter-quartile range of 37–50, indicating lower levels of wellbeing.

3.2. Comparison of group effects

Means for all groups on the primary outcome measures are displayed in Fig. 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.

3.3. 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

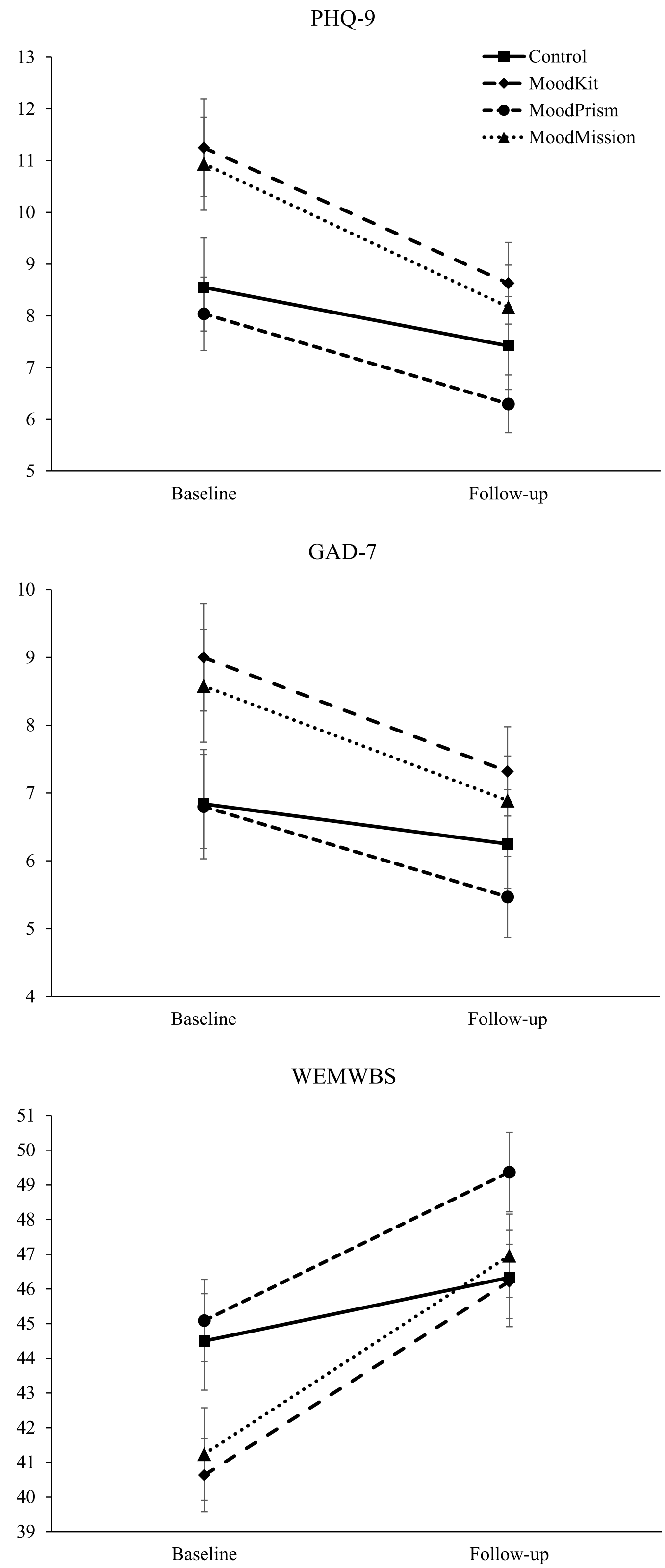

Fig. 2. Baseline and 30-day assessment means on the primary outcome measures.

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

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 $p < .05$.

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.

4. 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 hypothesized, 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, 2017, 2018). 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., 2017b, 2017a). 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, 2017, 2018). 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 (2018), 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 (2017) 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 (2017, 2018) 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 as a potential limitation 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 limitation, 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 & Rickard, 2017) and MoodMission (Bakker & Rickard, 2018). 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. This represents a limitation of the current study and other studies investigating self-guided interventions. 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, which overcomes limitations of differing engagement patterns 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., et al. (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. (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., & Rickard, N. (2018). *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., et al. (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, 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 & Emotion, 15*, 713–724. https://doi.org/10.1080/02699930143000239.

Benka, J., Nagyova, I., Rosenberger, J., Macejova, Z., Lazurova, I., Klink, J. V. der, et al. (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, (Eds.). *Oxford guide to low intensity CBT interventions* (pp. 3–18). (1st ed.). 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., et al. (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., et al. (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*(Suppl. 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, 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.

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.

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., et al. (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. (2018). The processes of cognitive behavioral therapy: A review of meta-analyses. *Cognitive Therapy and Research* (in press).
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.
MoodKit, 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.
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., et al. (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.
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. https://doi.org.ezproxy.lib.monash.edu.au/10.1017/S0033291714000701.
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.
Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., et al. (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.
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.
Watts, S., Mackenzie, A., Thomas, C., Griskaitis, A., Mewton, L., Williams, A., et al. (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., et al. (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.