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ORIGINAL ARTICLE

Engagement with a cognitive behavioural therapy mobile phone app predicts changes in mental health and wellbeing: MoodMission

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Objective: There is an abundance of evidence supporting the efficacy of computerised cognitive behavioural 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 wellbeing. 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.
Conclusions: Engaging with an app that provides CBT strategies can increase mental wellbeing, and coping self-efficacy may mediate effects of the app in individuals experiencing moderate depression or anxiety.

KEYWORDS
anxiety, cognitive behavioural therapy, computer/internet technology, depression, mobile

1 | INTRODUCTION

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 Organisation, 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 (Australian Bureau of Statistics, 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). Potential advantages of MHapps over cCBT programs include ease of access across time and environment, collection of more types of data, and more immediate and satisfying interactions. However, cCBT programs may be better at delivering large amounts of written content and may be faster, cheaper, and easier to develop technically (Bakker et al., 2016). 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 were maintained over, for example, a 30-day period. Comparative measurements of depression, anxiety, and mental wellbeing 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, as measured by the 9-item Patient Health Questionnaire (PHQ-9), and anxiety, measured by the 7-item Generalised Anxiety Disorder scale (GAD-7). 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 multi-purpose 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 summarised 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

WHAT IS ALREADY KNOWN ON THIS TOPIC

1. There is good evidence supporting the effectiveness of computerised cognitive behavioural therapy (CBT) for depression and anxiety.
2. Amongst the mental health apps available to the public, very few have had experimental validation, and fewer still have been shown to be effective amongst a community sample.
3. MoodMission is an app that recommends CBT strategies based on mood.

WHAT THIS PAPER ADDS

1. Engagement with MoodMission predicted increases in mental wellbeing.
2. Coping self-efficacy mediated the effects on depression, anxiety, and wellbeing, and participants who were moderately depressed or anxious experienced these effects.
3. Apps like MoodMission may prevent depressive and anxiety disorders and serve as an adjunct to clinical treatments.

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 (Dahne, Kustanowitz, & Lejuez, 2017; e.g., 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 wellbeing, 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. Investigating these mediators is important to deduce what app features make a MHapp effective, and how MHapps can be improved by including or refining these features (Bakker et al., 2016). 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" (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.

Bakker, Kazantzis, Rickwood, and Rickard (2018a) conducted a RCT comparing a waitlist control group to three MHapps, "MoodMission," "MoodPrism," and "MoodKit," over 30 days. It was found that all three app groups experienced increases in mental wellbeing, and MoodMission and MoodKit users experienced decreases in depression. Mediated regressions revealed that these effects were mediated via CSE rather than MHL or ESA. While this RCT suggested that the apps have efficacy, real-world effectiveness remains unknown. The participants used in the RCT signed up to a study, and thus may not represent the typical MHapp user that naturalistically finds the app while searching the app store.

To measure the real-world effects of using MHapps outside of clinical trials, some have suggested investigating and quantifying positive relationships between app usage and mental health outcomes (Carpenter et al., 2016; Yeager & Benight, 2018). This can help avoid "digital placebo effects," which occur when merely the installation of a MHapp can bias individuals' responses towards favourable mental health outcomes (Torous & Firth, 2016). Bakker and Rickard (2017) detail how app engagement may be more useful than raw usage to consider for this relationship, as usage can be influenced by a high rate of general phone use, procrastination, boredom, emotion-focused coping, or anxiety. For example, an individual who accesses an app a lot because they use their phone a lot on their morning commute as a distraction device may not be receiving the same "dose" of the intervention as someone who accesses the app a lot because they are committed to its use and feel like they are getting something out of the experience. Measuring app engagement in terms of quality rather than quantity is similar to measuring client engagement or therapeutic relationship in psychotherapy, which is predictive of treatment outcomes (Holdsworth, Bowen, Brown, & Howat, 2014; Kazantzis, Cronin, Norton, Lai, & Hofmann, 2015). Short self-report surveys are used to measure therapeutic engagement (Joe, Broome, Rowan-Szal, & Simpson, 2002), and similarly, items on a short feedback questionnaire can be used to measure a user's engagement with the MHapp, whereby if app engagement ratings are positively associated with mental health and wellbeing outcomes, it suggests the MHapp has efficacy.

The current study aimed to investigate the mental health and wellbeing impacts of using 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 (Bakker, Kazantzis, Rickwood, & Rickard, 2018b) 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 wellbeing 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, as measured by app feedback questionnaire, would be associated with an increase in mental wellbeing, as measured by the Warwick-Edinburgh Mental Well-being Scale, and a decrease in depression and anxiety symptomatology, as measured by the PHQ-9 and GAD-7. Furthermore, these predicted relationships were hypothesised to be mediated by increases in CSE, as measured by the Coping Self-Efficacy Scale, and MHL, as measured by a self devised questionnaire, that users experienced while using the app, rather than an increase in ESA, as measured by a revised version of the Emotional Self-Awareness Scale. It was hypothesised that participants who scored in the clinical range on the baseline PHQ-9 and GAD-7 would experience stronger mediated effects than those who scored in the nonclinical range.

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). 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. Age ranged from 13 to 70 (Mean = 26.9, *SD* = 10.9, Median = 24, IQR = 19–32), 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).

2.2 | Materials

2.2.1 | App description

MoodMission (MoodMission Pty Ltd, 2018) is an app that was developed to provide users with CBT strategies for managing low moods and anxiety. Bakker et al. (2018b) detailed the development of MoodMission and how it was designed for three primary uses: "(a) to provide self-administered prevention and self-help strategies to reduce the risk of clinically significant mood and anxiety disorders; (b) 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 (c) as an adjunct to psychotherapy or other face-to-face treatments for mood and anxiety disorders" (p. 7). The app was designed for a broad range of individuals to increase accessibility and avoid excluding potential users. This study used a community sample, so aimed to investigate the app's first two primary uses but not the third.

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 using an adaptive learning algorithm based on the user's distress scores obtained from past Missions. 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. These assessments were chosen based on (a) length and suitability for administration via mobile device, (b) psychometric quality, and (c) lack of legal restrictions that would prevent use in a MHapp.

2.3 | Procedure

As detailed in Bakker et al. (2018b), 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. Promotions were targeted across ages and genders, with an aim to appeal to a wide audience of people interested in improving their mental health and wellbeing. With the exception of printed flyers, all promotions were not paid, so this influenced their choice. Examples of promotions, for example, links to social media pages and news articles, can be found at moodmission.com.

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 first, third, seventh, and fourteenth 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

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 $\alpha = 0.89$ (Kroenke, Spitzer, & Williams, 2001)
Generalised 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 $\alpha = 0.92$ (Spitzer, Kroenke, Williams, & Löwe, 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 $\alpha = 0.91$ (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 $\alpha = 0.90$ (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 $\alpha = 0.95$, (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 within the same methodology, Cronbach's $\alpha = 0.84$ (Bakker & Rickard, 2017). Items included "The app was interesting" and "Using it motivated me." See Bakker and Rickard (2017) for the full list of items

addition of the App Engagement Scale. This same procedure was also used in Bakker and Rickard's (2017) study on MoodPrism.

2.4 | 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 direct and indirect mediated effects at $\alpha = 0.05$. 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 5,000 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 wellbeing 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 wellbeing 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 Wellbeing (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 (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

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]	

$^{*}p = 0.05$, $^{**}p = 0.01$.

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 Table S1, Supporting Information), 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 Wellbeing" scores, but all take baseline scores into account and therefore operationalise 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 et al., 2001) and the GAD-7 (Spitzer et al., 2006) both list 10–14 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.

3 | RESULTS

The data were inspected and cleaned to ensure that assumptions for linear regression were met. Participants with missing data and outlying cases on any variables $\pm 3SDs$ from the mean were excluded, as this could indicate errors in data collection, incomplete responding, or non-serious responding. This left 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 >0.9, suggesting an absence of multi-collinearity (Field, 2013). Each outcome variable's residuals were inspected to confirm homoscedasticity and normally distributed errors.

3.1 | Descriptive results

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

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), $r\ (614) = -0.160$, $p < 0.001$, and Anxiety (GAD-7), $r\ (614) = -0.123$, $p = 0.002$, but not Mental Wellbeing (WEMWBS), $r\ (614) = 0.045$, $p = 0.260$. No significant effects were observed for Gender, as it was a non-significant covariate for Depression (PHQ-9), $F\ (1,\ 413) = 0.34$, $p = 0.563$, $\eta_p^2 = 0.001$, Anxiety (GAD-7), $F\ (1,\ 413) = 1.64$, $p = 0.201$, $\eta_p^2 = 0.004$, and Mental Wellbeing (WEMWBS), $F\ (1,\ 413) = 1.92$, $p = 0.167$, $\eta_p^2 = 0.005$. 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 Table S1). A univariate ANOVA revealed no significant differences in App Engagement between the Nonclinical, Moderate-clinical, and Severe-clinical subsamples, $F\ (2,\ 614) = 0.54$, $p = 0.586$, $\eta_p^2 = 0.002$.

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 an increase in Mental Wellbeing scores, $\Delta F\ (1,\ 613) = 16.92$, $p < 0.001$, $\Delta R^2 = 0.017$. However, App Engagement did not significantly predict changes in Depression, $\Delta F\ (1,\ 613) = 0.62$, $p = 0.430$, $\Delta R^2 = 0.001$, or Anxiety, $\Delta F\ (1,\ 613) = 0.11$, $p = 0.742$, $\Delta R^2 < 0.001$. When split into Nonclinical, Moderate-clinical, and Severe-clinical subsamples, the same was found, with App Engagement significantly predicting Wellbeing (Nonclinical: $\Delta F\ (1,\ 140) = 4.49$, $p = 0.036$, $\Delta R^2 = 0.021$, $\Delta F\ (1, 140) = 4.49$, $p = 0.036$, $\Delta R^2 = 0.021$; Moderate: $\Delta F\ (1,\ 119) = 4.75$, $p = 0.031$, $\Delta R^2 = 0.026$; Severe: $\Delta F\ (1, 613) = 7.013$, $p = 0.008$, $\Delta R^2 = 0.014$), but not Depression (Nonclinical: $\Delta F\ (1,\ 140) = 0.08$, $p = 0.782$, $\Delta R^2 < 0.001$; Moderate: $\Delta F\ (1,\ 119) = 0.55$, $p = 0.458$, $\Delta R^2 = 0.004$; Severe: $\Delta F\ (1,\ 346) = 0.54$, $p = 0.464$, $\Delta R^2 = 0.001$), or Anxiety (Nonclinical: $\Delta F\ (1,\ 140) = 0.51$, $p = 0.477$, $\Delta R^2 = 0.003$; Moderate: $\Delta F\ (1,\ 119) = 0.80$, $p = 0.374$, $\Delta R^2 = 0.006$; Severe: $\Delta F\ (1, 346) = 0.27$, $p = 0.602$, $\Delta R^2 = 0.001$).

3.4 | 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, $\beta = -0.063$, 95% CI [−0.100, −0.031] (Figure 1a), Anxiety, $\beta = -0.058$, 95% CI [−0.094, −0.027] (Figure 1b), and Mental Wellbeing,

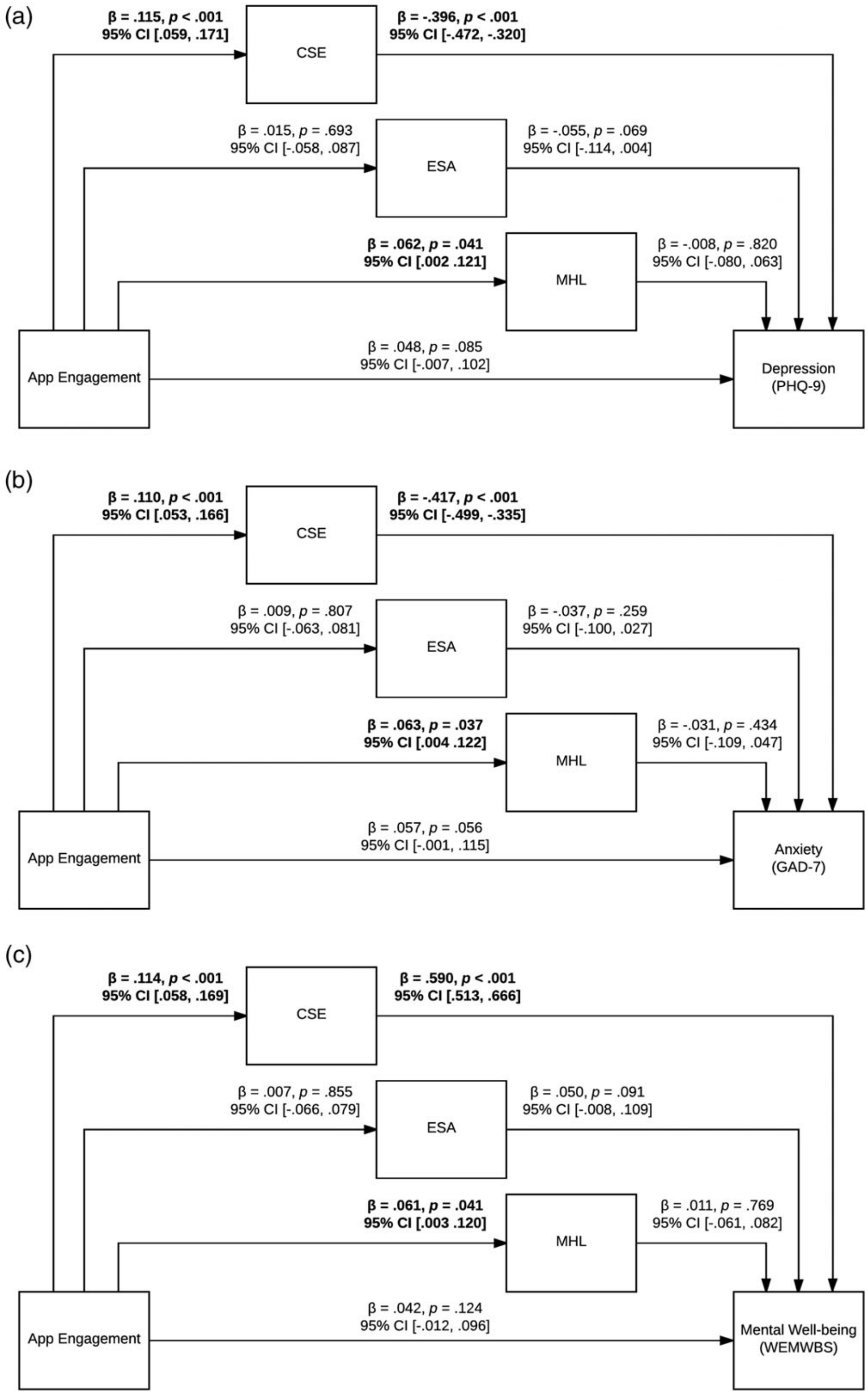

FIGURE 1 Whole sample mediated regression model using app engagement ratings as the predictor and (a) Depression (PHQ-9), (b) Anxiety (GAD-7), and (c) Mental Wellbeing (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < 0.05$

$\beta = 0.085$, 95% CI [0.041, 0.133] (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.

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 Wellbeing (Figure 2c) was found for CSE, with a standardised indirect effect of

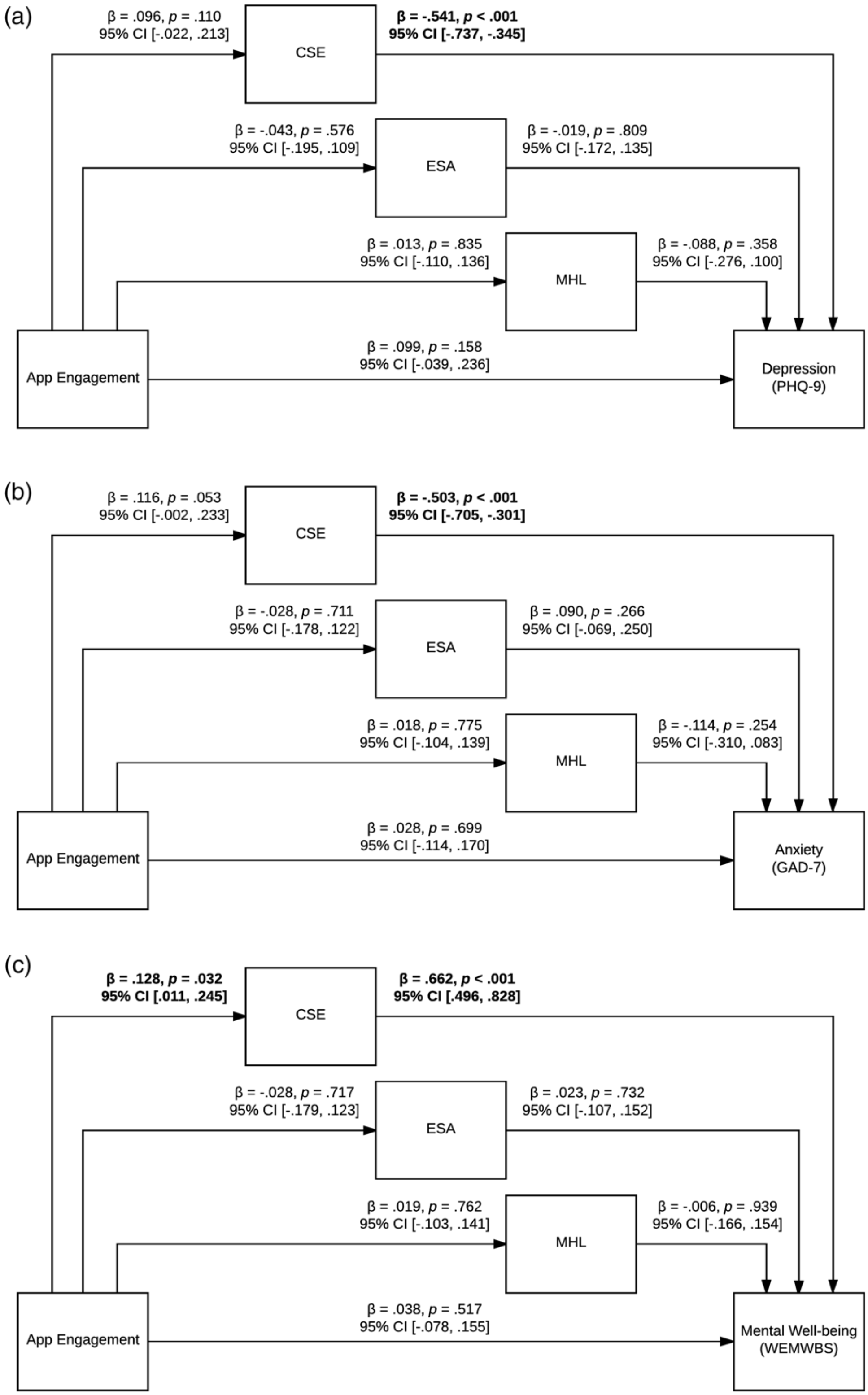

FIGURE 2 Nonclinical subsample mediated regression model using app engagement ratings as the predictor and (a) Depression (PHQ-9), (b) Anxiety (GAD-7), and (c) Mental Wellbeing (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < 0.05$

$\beta = 0.103$, 95% CI [0.002, 0.221]. No other direct or indirect effects were significant for Mental Wellbeing.

In the Moderate-clinical subsample, there were significant mediation effects for CSE in all three regressions, with standardised indirect effects of $\beta = -0.173$, 95% CI [−0.291, −0.080] for Depression (Figure 3a), $\beta = -0.195$, 95% CI [−0.326, −0.094] for Anxiety (Figure 3b), and $\beta = 0.221$, 95% CI [0.114, 0.345] for Mental Wellbeing (Figure 3c). No other direct or indirect effects were found significant.

In the Severe-clinical subsample, there were no significant direct or indirect effects in any of the three regressions (see Figure 4). However, there were significant positive relationships

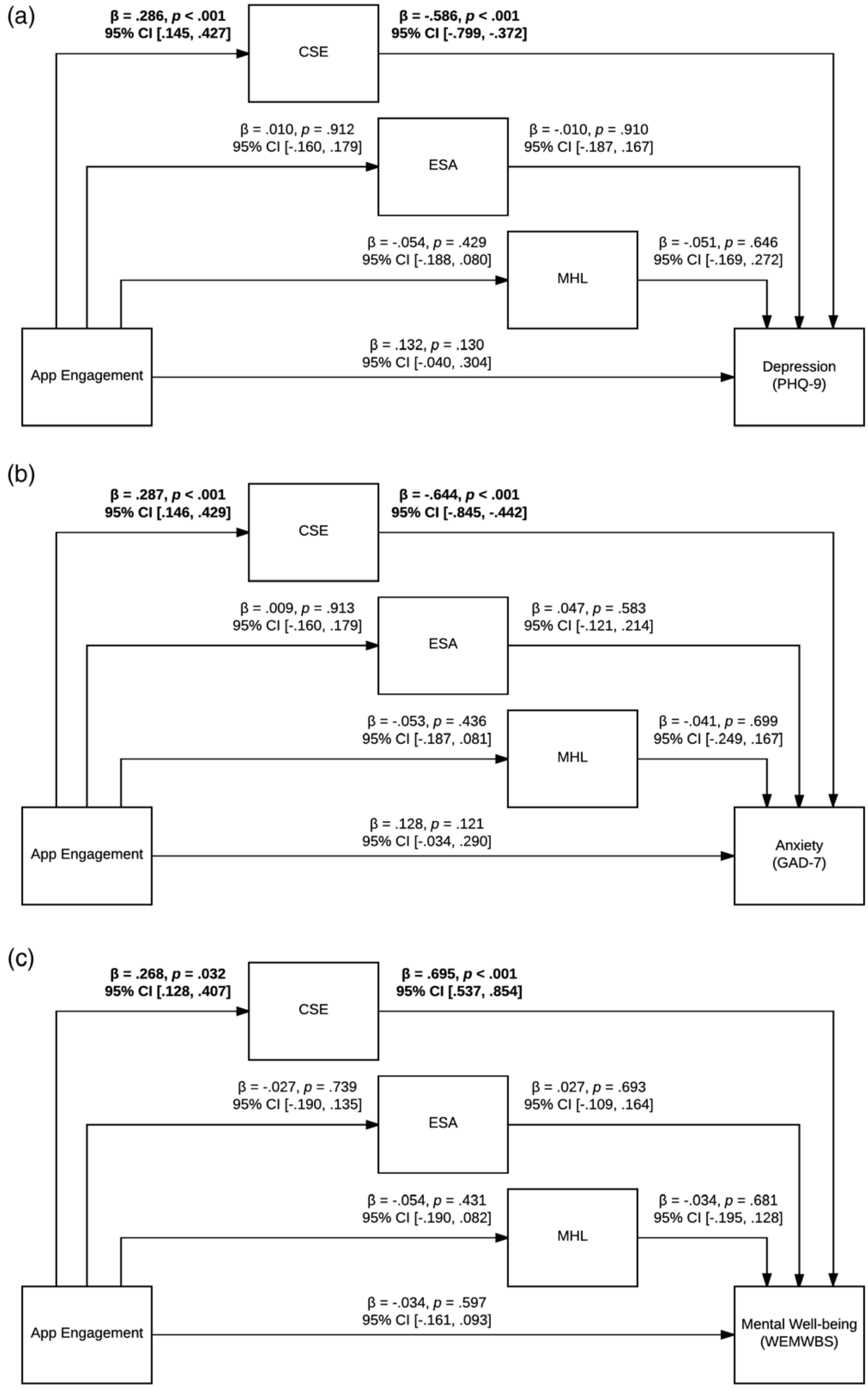

FIGURE 3 Moderate-clinical subsample mediated regression model using app engagement ratings as the predictor and (a) Depression (PHQ-9), (b) Anxiety (GAD-7), and (c) Mental Wellbeing (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < 0.05$

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.

4 | 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 wellbeing. The primary finding was that

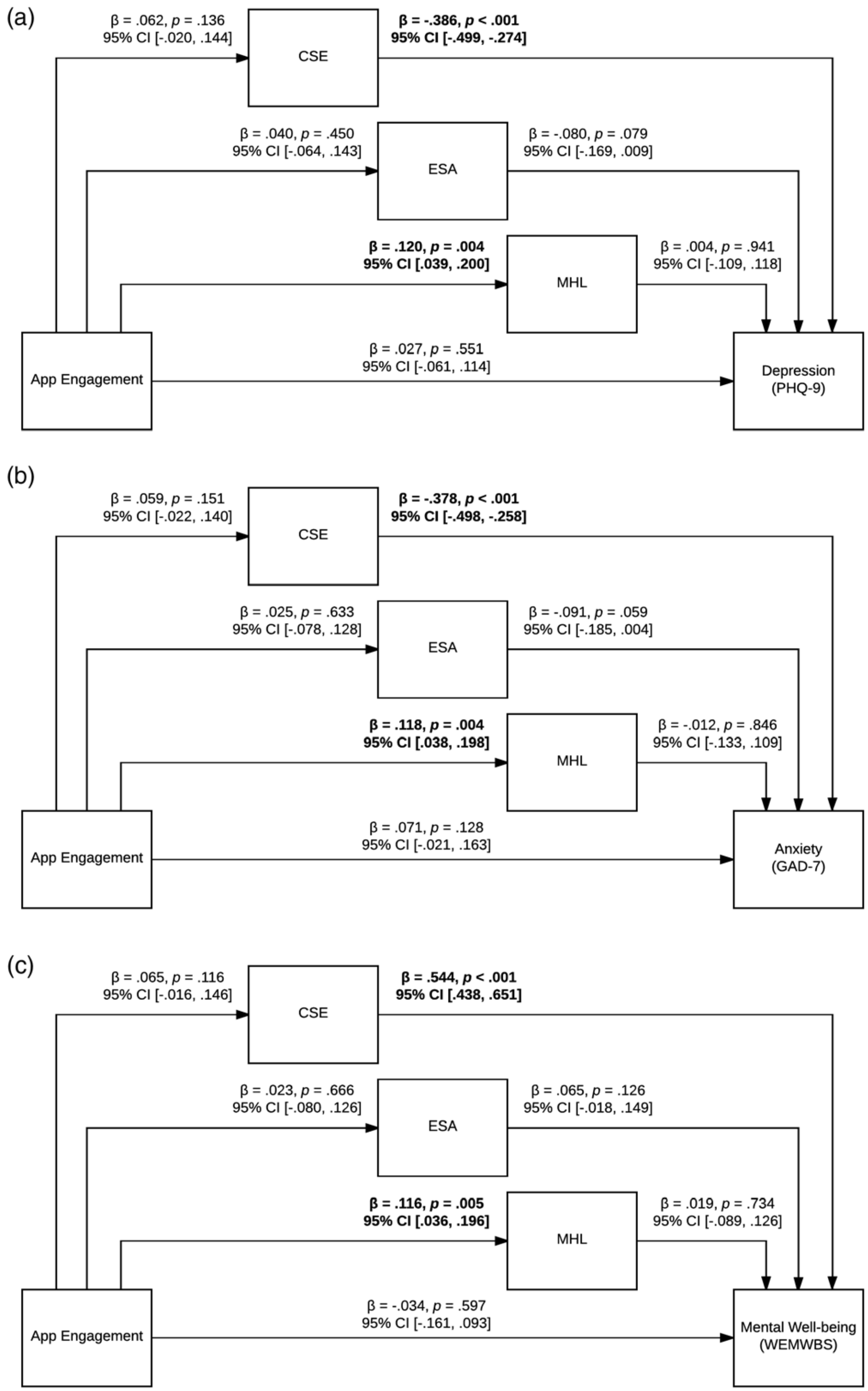

FIGURE 4 Severe-clinical subsample mediated regression model using app engagement ratings as the predictor and (a) Depression (PHQ-9), (b) Anxiety (GAD-7), and (c) Mental Wellbeing (WEMWBS) scores as the outcome. Note: bolded coefficients indicate significance, $p < 0.05$

app engagement predicted improvements in mental well-being, and this relationship was mediated by CSE for all but the severely clinical subsample. These findings are similar to those of Bakker et al.'s (2018a) RCT, but have broader implications of real-world effectiveness due to naturalistic recruitment and comparisons across clinical status.

This study 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. A similar meditation effect was observed in Bakker et al.'s (2018a) RCT for all three MHapps, including

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			Direct effect when mediators added
		ESA	CSE	MHL	
Whole sample					
Depression	X	X	✓	X	#
Anxiety	X	X	✓	X	#
Mental wellbeing	✓	X	✓	X	X
Nonclinical subsample					
Depression	X	X	X	X	X
Anxiety	X	X	X	X	X
Mental wellbeing	✓	X	✓	X	X
Moderate-clinical subsample					
Depression	X	X	✓	X	X
Anxiety	X	X	✓	X	X
Mental Wellbeing	✓	X	✓	X	X
Severe-clinical subsample					
Depression	X	X	X	X	X
Anxiety	X	X	X	X	X
Mental wellbeing	✓	X	X	X	X

X: not significant; ✓: significant ($p < 0.05$); #: approaching significance ($p < 0.10$).

MoodMission. 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.

Participants were included from a wide range of ages, but the median age was 24 and 75% were aged 32 or younger. This is the same age range where the highest rates of global smartphone ownership and use are observed (Nielsen, 2016), so this is a naturalistic reflection of MHapp use in a community sample. The findings should be cautiously generalised to older populations who may engage differently with the intervention, but Firth et al.'s (2017a, 2017b) meta-analyses of a range of MHapp studies using samples of different ages suggest that age did not impact treatment effects.

These findings support the use of MoodMission to improve mental wellbeing, 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, so increasing CSE did not detectably lower them further. On the other end of the spectrum, severely clinical users may have 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. This represents a limitation of this study that future studies could address by collecting a broader range of data for a longer period of time. Such intensive data collection may bias findings away from naturalistic user download scenarios, but could reveal how apps like MoodMission can be best used with nonclinical and severe clinical users.

Although indirect effects via CSE were found for Depression and Anxiety in the moderately-clinical subsample, direct effects were not found. A number of limiting factors could account for this, including the effect of an unmeasured, conflicting mediator nullifying the direct effect (Darlington & Hayes, 2016). For example, anxiety or depression may share a positive relationship with an unmeasured variable like perceived social support, which could be working in opposition to CSE. Both mediators working in opposition may cancel out the overall direct effect (Zhao et al., 2010). Such a mediator going unmeasured represents a limitation of the current study. Bakker and Rickard (2017) conducted a similar study, including the same mediators and methodologies, using the self-monitoring MHapp MoodPrism. 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 wellbeing. Additionally, it was hypothesised that engaging with MoodPrism's reflection-focused features would promote gains in ESA, and so ESA would serve as a mediator between app engagement and mental health and wellbeing 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.

While users experiencing depressive or anxious symptoms may have more motivation to engage with MHapps and other mental health interventions, it was observed that app engagement did not differ based on baseline depression or anxiety severity. There may be several explanations for this. First, MoodMission was not promoted as a treatment for people diagnosed with mental health issues, so users may have been motivated to engage with the app for a wider variety of reasons, including to improve positive mental wellbeing. Second, as depressive and anxious symptomatology increases, overall motivation to engage with anything can decrease, for example, via fatigue and being overwhelmed (Krämer, Helmes, & Bengel, 2014), so this force may have counteracted motivations to engage based on self-perceived symptom severity. The absence of a way to measure and account for these motivations represents another limitation of this study, which future studies could address.

Bakker et al. (2016) suggests three different types of MHapps; goal-focused MHapps are designed to improve CSE by recommending activities and active coping skills, reflection-focused MHapps are designed to improve ESA by using self-monitoring features, and education-focused 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-focused category. While MoodPrism was a reflection-focused MHapp, MoodMission contains features that lends to a goal-focused 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-focused features, such as those used in MoodPrism, may be better suited to users who are severely depressed or anxious, whereas goal-focused 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, as the current study was limited by the current features of MoodMission and an inability to compare the effectiveness of different features within the app.

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 limiting 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 wellbeing 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 wellbeing.

This study suggests that engagement with MoodMission, a goal-focused 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 wellbeing. This is particularly relevant for moderately depressed or anxious users. These findings contrast with those from reflection-focused apps like MoodPrism (Bakker & Rickard, 2017), which work through the mediator of emotional self-awareness. Analysing mediators and considering the mechanisms of different mental health interventions is important to inform directions of development. Creating self-guided interventions that work via multiple mediators because they engage users in several complementary processes may lead to improved effects on outcomes. The addition of reflection-focused features to MoodMission would be an example of this, and one worth pursuing and studying. 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), the findings of this study are important for the development, promotion, and refinement of effective MHapps and other self-guided mental health supports.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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