Remote measurement-based care (RMBC) interventions for mental health - systematic review and meta-analysis

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Abstract

Background: Poor management of mental health conditions leads to reduced adherence to treatment, prolonged illness, unnecessary rehospitalisation and significant financial burden to the health care system. Recognizing this, ecological momentary assessment (EMA) and remote measurement-based care (RMBC) interventions have emerged as promising strategies to address gaps in current care systems. They provide convenient means to continuously monitor patient-reported outcomes, thereby informing clinical decision-making and potentially improving outcomes such as psychopathology, relapse, and quality of life.

Objective: This systematic review and meta-analysis aims to comprehensively appraise and analyse the existing evidence on the use of EMA and RMBC for people living with mental illness.

Methods: The study was conducted according to PRISMA-P guidelines and pre-registered with PROSPERO. A comprehensive search was conducted in four online databases using MeSH terms related to mental disorders and digital technologies. Studies were included if they included adults with a formally diagnosed mental disorder and measured symptoms using ecological momentary assessment or remote measurement-based care. Studies were independently reviewed by subgroups of authors and data were extracted focusing on symptom-focused or disease-specific outcomes, relapse, recovery-focused outcomes, global functioning, quality of life and acceptability of the intervention. We performed a descriptive analysis of demographic variables and a meta-analysis of randomised controlled trials. Risk of bias was assessed using the Cochrane risk-of-bias tool for randomised trials version 2.

Results: The systematic review included K = 89 studies, of which k=13 used remote measurement-based care (RMBC). Of these, k = 8 were randomised controlled trials that were meta-analyzed. RMBC interventions varied in effectiveness, generally showing small but significant effects on symptom-specific outcomes, with notable effects on mania symptoms and empowerment. Adherence to all tracking items was 75.5% (k = 31). More prompts per day, but not more items per prompt, was associated with lower adherence. Adverse effects were infrequently reported and included technical problems and psychological distress. Concerns about bias were raised, particularly regarding participants' awareness of the interventions and potential deviations from the intended protocols.

Conclusions: Although RMBC shows growing potential in improving and tailoring psychiatric care to individual needs, the evidence of its clinical effectiveness is still limited. However, we found potential effects on mania symptoms and on empowerment. Overall, there were only a few RCTs with formal psychiatric diagnoses to be included in our analyses, and these had moderate risks of bias. Future studies assessing RMBCs effectiveness and long-term efficacy with larger populations are needed. Clinical Trial: PROSPERO CRD42022356176

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Trial Registration: PROSPERO CRD42022356176

Keywords: measurement-based care; mobile health; mHealth; mental health; patient-reported outcome measures; ecological momentary assessment

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Introduction

Mental health disorders have some of the highest global burdens of disease [1] and are difficult to manage. Hurdles include subjective symptom reporting [2,3], memory biases [4], complex treatment dynamics, and suboptimal coordination during transitions between inpatient and outpatient care settings [5] Additionally, short and infrequent outpatient appointments contribute to the loss of essential information about symptom progression and treatment side-effects [6]. This increases the risk of reduced treatment adherence, worsening conditions, preventable readmissions and higher healthcare costs [7,8].

In response to these challenges, there has been a notable increase in the development of diagnostic and therapeutic mobile mental health (MMH) technologies [9–12]. One prominent application of MMH is remote measurement-based care (RMBC), which involves the asynchronous assessment of patient-reported outcomes (PROs) outside of clinical visits. These assessments can then be utilized for clinical decision-making and triage purposes [13,14]. Apart from traditional retrospective PRO assessment methods, such as validated self-report questionnaires, there is growing interest in ambulatory and diary approaches. These methods, collectively known as ecological momentary assessment (EMA) capture real-time, in-situ data on patients' symptoms and well-being [15]. With advancements in technology, EMA has evolved to allow self-reporting of symptoms via internet or mobile platforms, including web/online, text messaging, or phone call-based systems [16]. Passive or sensor data integration further enhances the richness of this approach by capturing objective behavioural and physiological indicators in real-world settings, complementing the subjective self-reports provided by patients [13,14]. While RMBC and EMA share similarities in leveraging technology to enhance the understanding and treatment of mental health issues, the literature does not always make a clear distinction between the two, often seeing them as part of a continuum in advancing personalized health monitoring and intervention.

Research has consistently demonstrated the benefits of RMBC, in that it may improve clinical outcomes and improve treatment adherence [17–19]. For example, a study involving 6,424 participants diagnosed with various psychiatric conditions revealed that providing continuous feedback to therapists on symptom progression was associated with a twofold increase in therapeutic effects related to individual functioning, symptom load, interpersonal relationships, and social role performance [20]. Additionally, RMBC has been associated with faster remission rates than standard treatment approaches [21,22] and reduced missed outpatient appointments [21,22]. Moreover, RMBC enables clinicians to make timely and effective adjustments to treatment plans. Patients have reported finding RMBC valuable [23]. RMBC also showed potential to enhance doctor-patient communication and increase treatment motivation [24,25].

Despite the potential benefits, the integration of asynchronous MBC using digital solutions remains limited in clinical practice [26]. While MMH technology companies develop extensive solutions, their scientific evaluation often lacks the depth seen in university settings, presenting a significant dissemination barrier for healthcare providers and insurers. Conversely, the proliferation of MMH technologies has led to numerous pilot and feasibility studies on RMBC systems by clinical research teams, which typically suffer from academic research limitations such as insufficient power and bias reduction strategies, resulting in incoherent and scattered evidence. This variability in available data underscores the need for regular systematic evaluations to identify overarching trends and effects, facilitating the wider adoption of MBC and MMH in clinical practice.

A 2018 systematic review by Goldberg et al. synthesized existing evidence on RMBC, including 36 unique samples of which 13 were RCTs [27]. While generally promising, only three studies isolated the effects of RMBC experimentally, with one showing greater symptom improvement in the RMBC group and two finding no significant differences between intervention and control groups. The feasibility and acceptability of RMBC varied across studies, with promising adherence rates reported but concerns raised regarding decreased responsiveness over time. The review identified the need for more robust evaluations to better understand the isolated clinical impact of RMBC interventions, especially when implemented as part of multicomponent interventions, highlighting the need for further research to clarify its role and potential benefits.

This systematic review and meta-analysis presents a comprehensive overview of current evidence on RMBC in psychiatric care, building upon the findings of Goldberg and colleagues [27]. In contrast to Goldberg et al., our study focused on patients who underwent a manualised psychiatric diagnostic assessment and actively engaged with digital tools to report their individual experiences. Specifically, we concentrate on interventions targeting disorder-specific symptoms, relapse reduction, and improvement in recovery-oriented outcomes, global functioning, and quality of life. Additionally, we provide a quantitative estimate of effects via a meta-analysis.

Methods

Search strategy and study selection
The study adhered to PRISMA-P (preferred reporting items for systematic review and explanation meta-analysis protocols) guidelines [28] and was pre-registered with PROSPERO, University of York (CRD42022356176). The detailed protocol was published elsewhere [29]. On August 24th 2022 we conducted a comprehensive search across four online databases (PubMed, Medline, Embase, and PsychINFO) using terms related to mental disorders, psychological distress, measurement-based care, and digital technologies (Multimedia Appendix 1).
We included studies targeting adults (≥18 years) with mental health disorders as defined by the International Statistical Classification of Diseases and Related Health Problems (ICD) or the Diagnostic and Statistical Manual (DSM) [30,31]. Central to the selected interventions was the assessment of self-reported symptoms of mental illness and other well-being factors to guide clinical decision-making and/or treatment planning. Studies were required to provide quantitative data reflecting symptom-related, recovery-oriented, functional, or quality of life outcomes and had to be published in either English or German. To maximize the scope of research, there was no restriction on the comparator condition (Multimedia Appendix 2). While the systematic review included randomized and non-randomized studies, the meta-analysis was restricted to randomized controlled trials (RCTs) only.

Data extraction
The systematic extraction process was described in the study protocol [29]. Subgroups of authors (TwM&LS, FM&LH, JK&CW&ToM) independently reviewed the abstracts and full texts, resolving any discrepancies through group consensus. A comprehensive data set, encompassing study identification (author, year of publication, doi, URL), population (e.g. the number of cases and controls, diagnosis, age, gender, years pre-university education), tracking- (e.g. mode, number and content of items, frequency) and study characteristics (e.g. design, hypotheses, study site, duration, randomization, post-assessment period, follow-up, outcomes, response rate) was extracted. Outcomes were systematically grouped into six predefined categories: symptom-focused or disease-specific outcomes, relapse, recovery-focused outcomes (in particular empowerment), (global) functioning, quality of life and acceptability.

Data synthesis and statistical analysis
RStudio statistical software [32] was used for statistical analysis. Demographic variables were descriptively analyzed by calculating means and standard deviations. A linear regression model examined the effects of daily prompt frequency and the number of tracking items on participant response rate. An exploratory approach using a linear regression model investigated how variations in the frequency of daily prompts and the number of tracking items might impact the response rates of participants.

Frequentist meta-analysis. Random-effects analyses were performed using the metafor package (version 4.6-0) [33]. When $k > 2$ studies reported the same outcome, they were meta-analytically pooled. Only instruments with evidence of construct validity or correlation with other instruments were included. In cases where different instruments within a study measured the same construct, the outcome most commonly reported in other studies was included. For our analyses, we included all measures of psychopathology, even if they were not disease-specific, e.g. measure of depression in a sample of patients with psychosis. This approach recognizes the transdiagnostic nature of many symptoms and prioritizes symptoms over diagnoses. The full list of constructs and outcomes can be found in Multimedia Appendix 3. Intention-to-treat data were used for analyses where available. Where outcomes were reported as medians and interquartile ranges, means and standard deviations were estimated using median-based imputation [34]. If only standard errors were reported, standard deviations were calculated [35]. For trials that reported outcome data at multiple follow-up points, data from the time point immediately after the end of the intervention were used. Effect sizes for continuous measures were expressed as standardized mean differences (SMDs), calculated by using the pooled standard deviation of the interventions. SMDs are presented as values of Hedges' g, along with their 95% confidence intervals (95 % CI). Heterogeneity was assessed using the I^2 statistic and by visual inspection of the forest plots. Heterogeneity was defined as very low, low, medium, and high heterogeneity when I^2 values were < 25%, 25% to < 50%, 50% to < 75%, and ≥ 75%, respectively [36].

Bayesian meta-analysis. In addition to the frequentist approach, a random-effects Bayesian meta-analysis explored the results in a probabilistic manner to account for the small sample size and incorporate the uncertainty of estimates of heterogeneity and effect sizes [37–39]. In the statistical software R, the bayesmeta package (version 2.21) generated posterior distributions for both the overall effect and heterogeneity parameters using Markov Chain Monte Carlo (MCMC) simulations [40]. Given the paucity of literature on RMBC interventions and the lack of prior knowledge, weakly informative priors $\mu = 0$ and $\sigma = 4$ were used for the analysis [41,42]. The prior for between-study heterogeneity $\tau = 0.5$ was set using a half-normal distribution [43]. Funnel plots checked for potential publication bias and visualized the distribution of effect sizes against their standard errors. Marginal posterior density plots for the overall effect and heterogeneity illustrated the uncertainty and variability in these estimates.

Risk of bias

The risk of bias was examined by two researchers (FM&TwM), employing the Cochrane risk-of-bias tool for randomised trials version 2 (RoB 2) [36]. They assessed potential biases across five domains: randomization process, effect of assignment to intervention, missing outcome data, measurement of outcome, and selection of reported results, utilizing the RoB 2 tool [44]. An overall low risk was assigned when all domains were deemed low risk. A study was considered to have some concern if any of the domains raised concerns. The overall risk was designated as high if at least one domain was rated as high risk. In cases of disagreement, the researchers engaged in discussions to achieve consensus.

Results

Studies selection

The database search (k = 2.898) yielded 2.314 records after deduplication (Multimedia Appendix 1), which were screened by title and abstract. Of the k = 304 records that qualified for full-text analysis, k = 215 records were excluded for not meeting the inclusion criteria (Figure 1). The most common reason for exclusion (k = 103) was the lack of a formal psychiatric diagnosis, by either ICD or DSM. The systematic review includes a final sample of k = 89 studies representing 91 unique samples.

The systematic review revealed that k = 13 studies examined technologies as defined more narrowly by RMBC of which the k = 8 RCT studies were used for meta-analysis, i.e. in terms of using data to support clinical decision-making or treatment planning (e.g. scheduling). The other studies (k = 86) matched the definition of EMA, whereby technologies were also used to collect mental health data remotely in real-time, but the data did not have a significant impact on treatment.

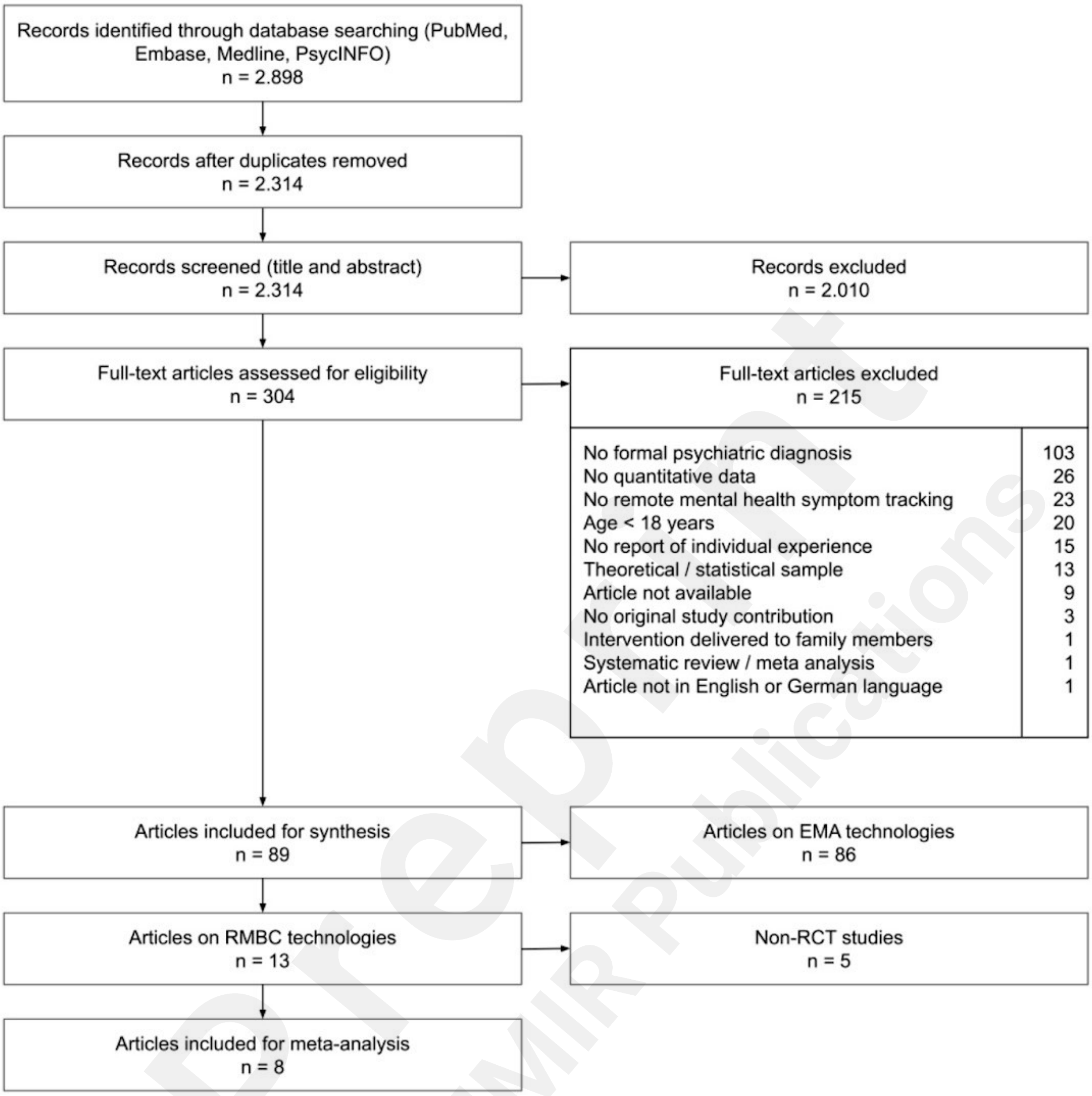

Figure 1. Flow chart of the search and selection process

Study characteristics

Of the 89 studies that were systematically analyzed, 41 contained healthy or diagnosis-matched control groups. Individual samples (k = 89) varied due to overlapping or related datasets (Multimedia Appendix 4). Across the studies, the mean sample size was 75.92 cases (SD = 93.54), with an average participant age of 40.86 years (SD = 7.86) and a gender distribution of 53.7% female participants. For the studies including control groups, the average sample size was 65.05 controls (SD = 21.99) with an average age of 42.42 years (SD = 6.61) and a 53.5% representation of women. Educational attainment was reported through various metrics, the most frequent being total years of education, which averaged at 13.62 (SD = 1.22) for cases and 13.52 (SD = 1.25) for control samples. The most common population were participants with schizophreniform disorders (23%) (i.e., F2x diagnoses), followed by bipolar disorder (19.5%). Most studies (k = 61) employed digital prompts formulated by the study team, while k = 14 studies used validated questionnaires. Six studies used a combination of both methods and seven studies incorporated prompts that were individually generated by the participants themselves. The predominant mode of remote data collection involved smart- or mobile phones owned by the participants themselves. Adherence to data entries was mainly measured by the percentage of total measurements entered by the participants.

Remote measurement-based care studies

Table 1 and Multimedia Appendices 5 and 6 report information extracted from the RMBC studies. Across the k=8 unique samples of studies examining RMBC, the intervention groups had M = 66 (SD = 58.98) cases with a mean age of 38.53 years (SD = 7.14), and 54.58% females. Comparably, the control groups (k = 8) had M = 58.63 (SD = 60.38) participants with a mean age of 39.93 (SD = 7.08) years, and 52.89% females. Most of the studies (k = 5) did not report on education, and the remaining studies used varying measures. Three studies included patients with schizophreniform disorders [45–47]; others included patients with bipolar disorder (k=2), borderline personality disorder (k = 1) and a range of different diagnoses or transdiagnostic symptoms (k = 2). On the patient side, the majority of RMBC systems (k = 6) were mobile- or smartphone-based. All interventions (consisted of self-administered symptom tracking along with additional formalized (e.g., psychotherapy) or informal psychiatric/ psychotherapeutic support.

While half the studies found the RMBC interventions to be effective, the others found no effects (k = 3) or mixed results. Faurholt-Jepsen et al. (2019) found no benefit of a 9-month self-administered symptom assessment that provided patients with automated predictions of future mood states. In an exploratory subgroup analysis, patients in the intervention group were more likely to experience a relapse of depressive symptoms than patients receiving usual outpatient care.

Adverse effects

Three RMBC studies reported adverse or potential negative effects of the interventions. These included technical malfunctioning, psychological distress attributed to prompts [48], hospitalization within the trial period (notably considered an outcome parameter, not an adverse effect, by several other studies; [49] and changes to patient-therapist interactions due to the new technology [35].

Table 1. Characteristics of RMBC studies included in meta-analysis

Study	*N*	*Psychiatric disorder*	*Setting*	*Treatment*	*Control*	*RMBC device*	*Isolated RMBC*	*Response rate (%)*	*ITT*	*Clinical effectiveness / efficacy*
Cullen et al. 2020	Tx n = 28; cont n = 13	Schizophrenia, schizoaffective disorder	Hospital-based community psychiatry program	self-administered assessment and automated intervention with additional support by healthcare providers.	TAU	Mobile phone	Yes	NA	No	Positive
Ebert et al. 2013	Tx n = 21; cont n = NA	Affective disorders; neurotic, stress-related and somatoform disorders; behavioural	Psychiatric inpatient and outpatient treatment	In-person psychotherapy; internet-based maintenance therapy with additional coaching support	In-person psychotherapy	Not specified (web-based)	No	NA	Yes	Positive

		syndromes associated with physiological disturbances and physical factors; disorders of adult personality and behaviour								
Faurholt-Jepsen et al. 2019	Tx n = 85; cont n = 44	Bipolar disorder	Psychiatric outpatient clinics	Self-administered symptom assessment with additional support from healthcare professionals	TAU	Smartphone	No	72.6	Yes	No significant difference
Faurholt-Jepsen et al. 2020	Tx n = 47; cont n = 51	Bipolar disorder	Psychiatric outpatient clinics	Self-administered symptom assessment with additional support from healthcare professionals	TAU	Smartphone	No	80.6	Yes	No significant difference
Gallinat et al. 2021	Tx n = 12; cont n = 13	Schizophrenia spectrum disorder	Research clinic	Collaborative care; self-administered symptom assessment with additional support from healthcare professionals	TAU	Smart- or mobile phone	No	70.7	NA	Positive
Laursen et al. 2021	Tx n = 42; cont n = 36	Borderline personality disorder	Psychiatric outpatient clinics	In-person psychotherapy (DBT); collaborative care; self-administered symptom assessment and psychoeducation	In-person psychotherapy (DBT); paper-based diary cards	Smartphone	No	NA	Yes	Positive and Negative
Lewis et al. 2020	Tx n = 40; cont n = 41	Schizophrenia spectrum disorder	Outpatient mental health facility	Self-administered symptom assessment with additional support from healthcare professionals	TAU	Smartphone	no	NA	Yes	Positive
Spaniel et al. 2015	Tx n = 74; cont n = 72	Schizophrenia, schizoaffective disorder	Psychiatric outpatient clinic	Self-administered symptom assessment with additional support from psychiatrists	TAU	Mobile phone to computer SMS interface	no	NA	Yes	No significant difference

Abbreviations: N = number, Tx = treatment group, cont = control group, NA = not applicable, TAU = treatment as usual, ITT = Intention to treat

Frequentist random effects meta-analysis

Data related to relapse and readmission rates was inconsistent between the study with differing time spans of observation. Thus no meta-analysis of the data was possible.

Symptom-focused outcomes

Regarding psychotic symptoms (Figure 2), data from three studies (n = 143) showed a small non-significant effect (SMD = -0.20, 95% CI -0.53 - 0.14, *P* = .2). For depressive symptoms (Figure 3), a larger sample of five trials (n = 423) showed a non-significant overall effect (SMD -0.00, 95% CI: -0.37 - 0.36, *P* = 1). For manic symptoms (Figure 4), data from four studies (n = 264) revealed a moderate to large significant effect of RMBC interventions (SMD -0.80, 95% CI: -1.28 to -0.32, *P* = 0.001). Data from one large transdiagnostic study (Figure 5, n = 400) suggested a moderate and significant effect size with an SMD of -0.29 (95% CI: -0.40 to -0.17, *P* = 0.0001). Between-study heterogeneity was low for psychotic symptoms (I^2 = 0%), moderate for depressive symptoms (I^2 = 72%), and moderate for manic symptoms (I^2 = 68%), suggesting varying degrees of similarity between the studies within each construct.

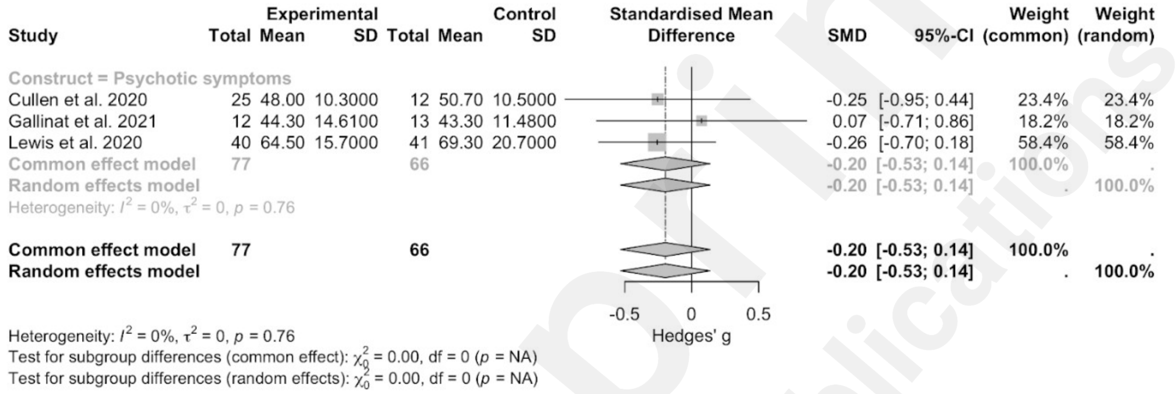

Figure 2. Forest plot of pooled effect on psychotic symptoms

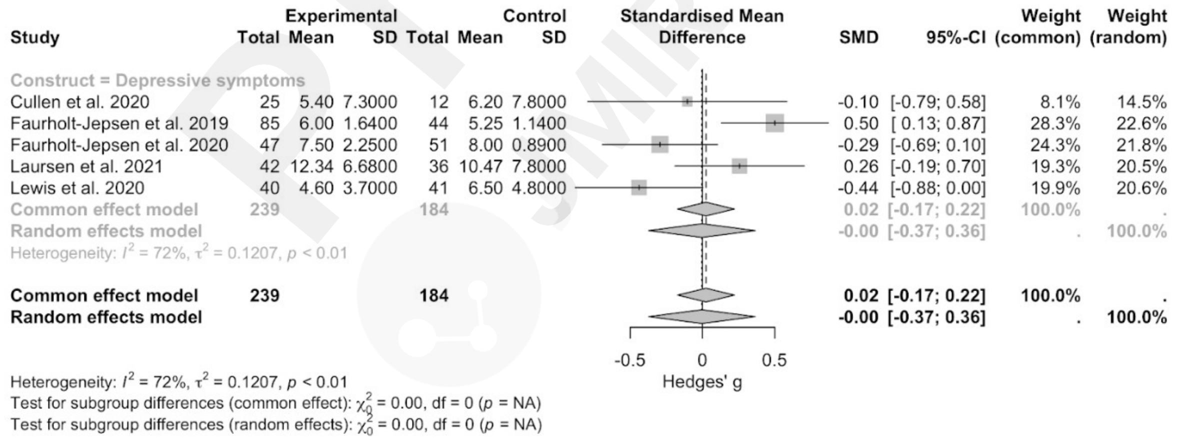

Figure 3. Forest plot of pooled effect on depressive symptoms

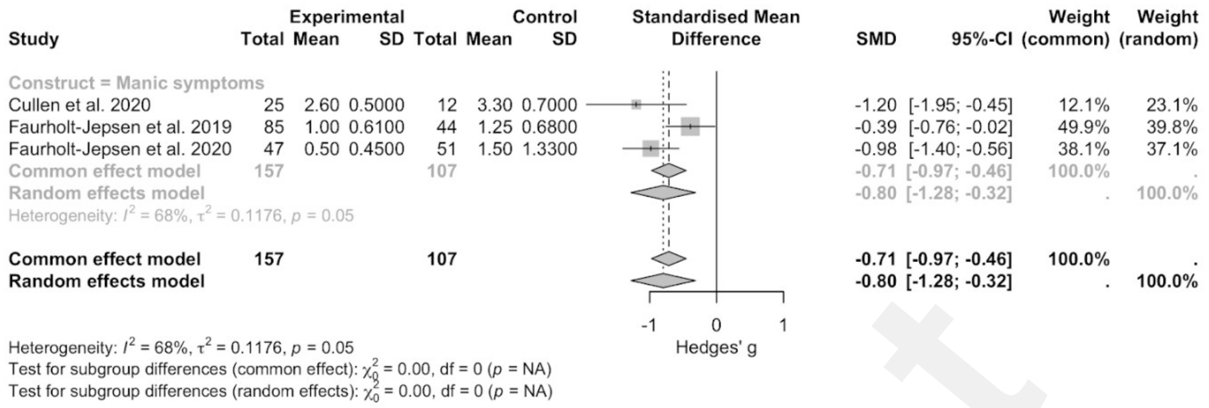

Figure 4. Forest plot of pooled effect on manic symptoms

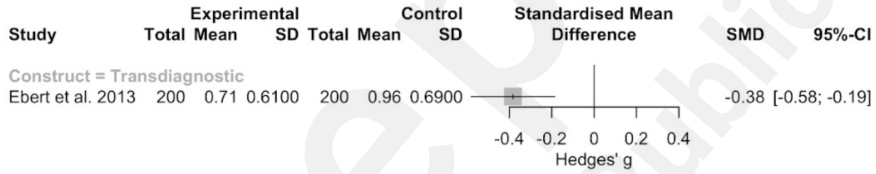

Figure 5. Forest plot of effect on transdiagnostic symptoms

Empowerment, quality of life and functioning

For the construct of empowerment and self-efficacy (Figure 6), pooled data from three studies (n = 518) demonstrated a small to moderate positive effect (SMD 0.39, 95% CI: 0.21 - 0.56, $P < 0.0001$). Regarding quality of life (Figure 7), combined results from three studies (n = 559) showed a non-significant effect (SMD -0.01, 95% CI: -0.51 - 0.49, $P = 1$). For functioning (Figure 7), the analysis included two studies (n = 179) and reported a non-significant effect (SMD = -0.16, 95% CI: -0.45 - 0.14, $P = 1$). Heterogeneity between the studies was zero for empowerment and functioning (I^2 = 0%), and high for quality of life (I^2 = 85%).

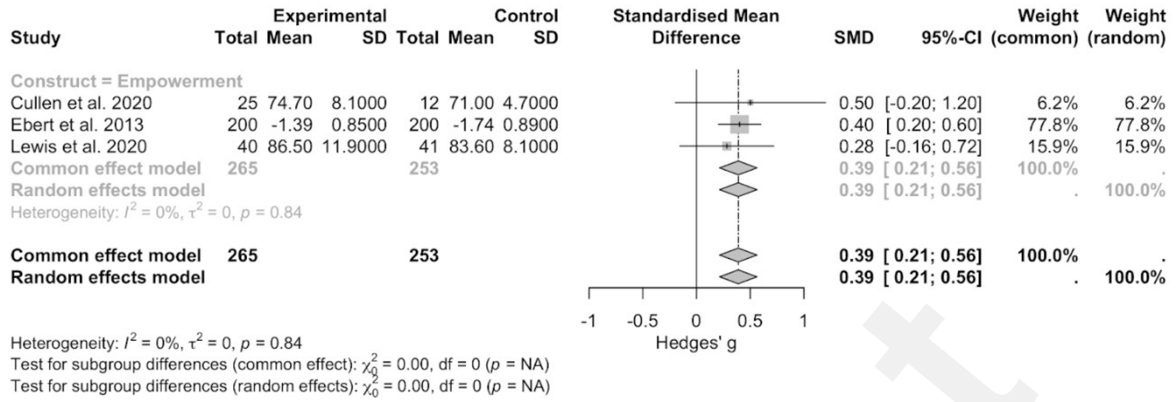

Figure 6. Forest plot of pooled effect on empowerment and self-efficacy

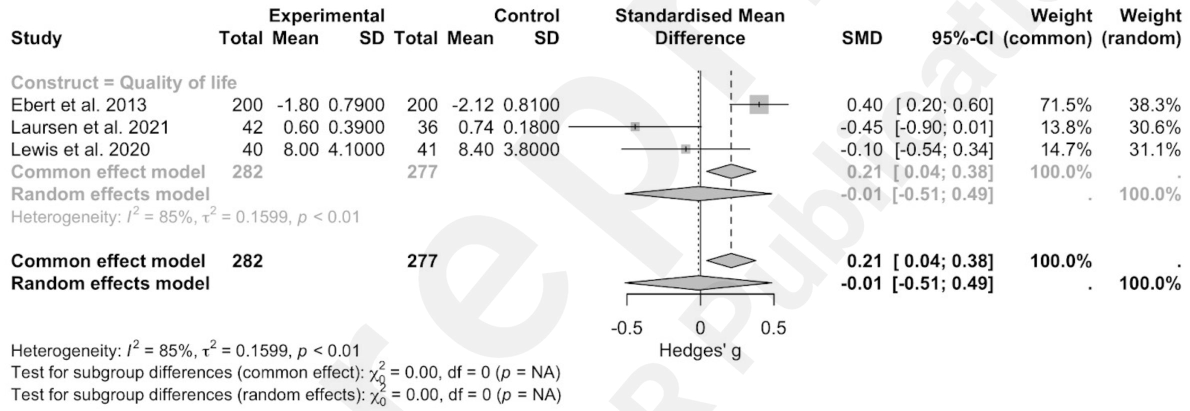

Figure 7. Forest plot of pooled effect on quality of life

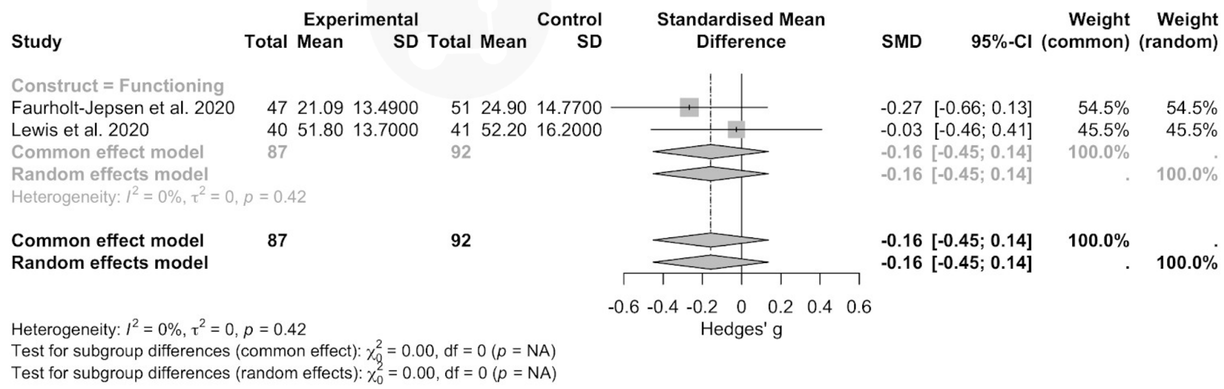

Figure 8. Forest plot of pooled effect on functioning

Bayesian meta-analysis

In general, the Bayesian meta-analysis yielded similar results to the frequentist meta-analysis, but there was only one significant result: the weighted pooled effect size with a mean estimate of -0.79 (95% CI: -1.44 to -0.20), for the reduction in manic symptoms associated with RMBC interventions. There was moderate heterogeneity τ = 0.36 (0.00 to 0.84). The prediction interval of -1.99 to 0.34 reflected moderate uncertainty in predicting new effects based on current data (Multimedia Appendix 7c). The effect on empowerment that was present in the frequentist analysis showed an effect size of 0.39 and the CI crossed the zero (95% CI: -0.02 to -0.79). Other analyses showed nonsignificant effects on the outcomes assessed (Multimedia Appendix 7 a, b, d-f and Multimedia Appendix 8 a, b, d-f).

Risk of bias

The overall risk of bias indicates that the majority of outcomes were of concern to the reviewers (Figure 9). This was largely due to participants, caregivers, or assessors having been aware of the assigned digital interventions, which made it difficult to assess the outcomes, particularly since many relied on participant-reported data. Further, the effect of assignment to the intervention raised concerns about deviations from the intended interventions. Specifically, the outcomes of the Boston University Empowerment Scale in Cullen et al. 2020 were rated as having a high risk of bias because missing data were replaced by scale means from follow-up data [45]. A full assessment of each outcome is provided in Multimedia Appendix 10.

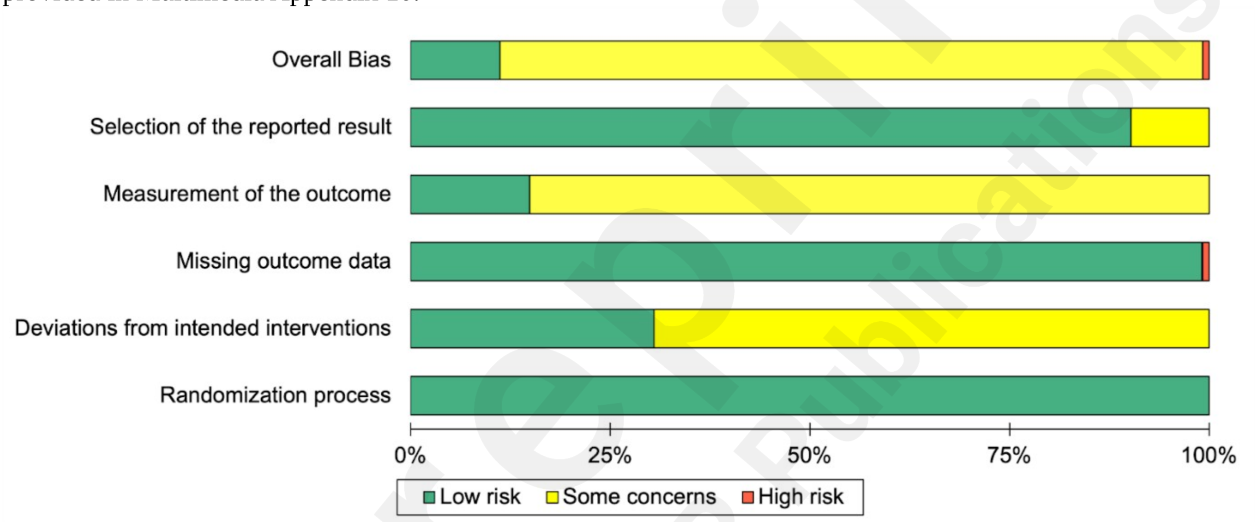

Figure 9. Cochrane Risk of Bias Summary. Authors' judgments about each risk of bias item across all assessment time points.

Tracking and adherence

Typically, participants were prompted to complete questionnaires > 1x / day, followed by daily EMA, with the number of items ranging between 1 and 43 (M = 10.94, SD = 9.15) per session (k = 56; for k = 12 the number of items was unclear, and for k = 5 studies varied. The most granular tracking data was collected by Freedman et al. with 128-136 tracking items per day, amounting to a minimum of 896 individual data points per week [50]. K = 10 studies included additional passive data sensing such as GPS, phone usage, speech activity, ambient noise and light, and sleep activity. K = 39 studies provided a metric of EMA or RMBC adherence, of which k = 31 studies indicated the average overall response rate for the intervention group (75.5%).

A linear regression model investigated the effect of the number of prompts per day and the number of tracking items per day on response rate (Figure 10). The model results (Table 2) showed a significant negative effect of the logarithm of the number of prompts per day (P = .03) and no effect of the number of tracking items on the response rate. Diagnostic plots showed no obvious violations of the key assumptions (Multimedia Appendix 9). There was no multicollinearity between the independent variables as all variance inflation factor (VIF) values were < 5. The model's overall fit was sufficiently good given the residual plots (adjusted R^2 = 0.124), but other variables may have affected the response rate. Due to omitted variable bias, the model may overestimate the effect of predictors.

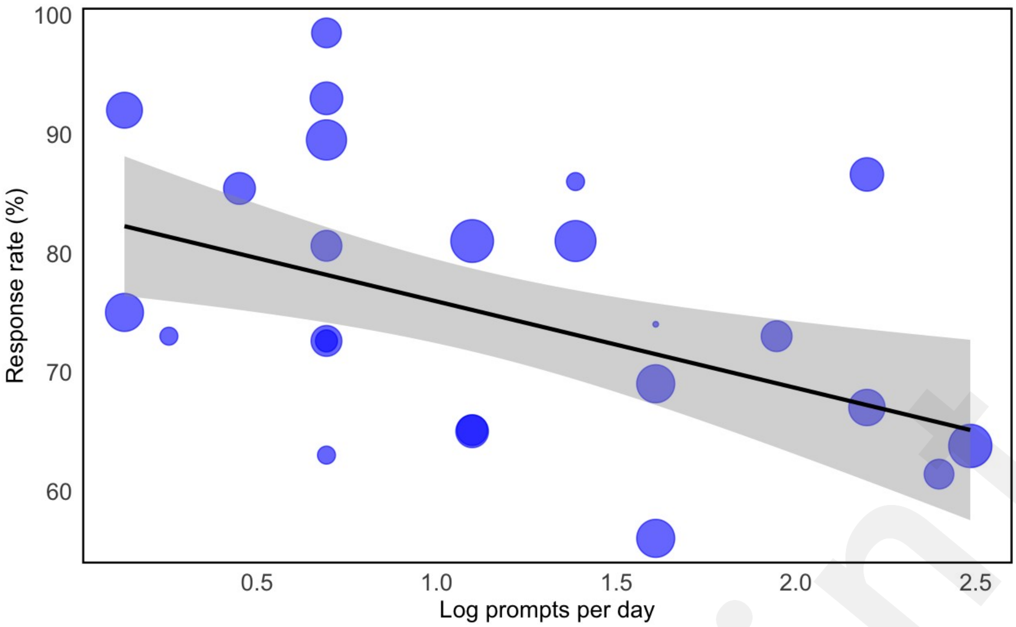

Figure 10. Bubble plot visualisation with the predicted probability line with 95% CI (grey area) for the response rate (%) as a function of the log-transformed number of daily prompts on the x-axis (est = -7.221, t = -2.286, *P* = .03) and the number of tracking items per prompt, represented as the bubble size (est = 1.706, t = 0.567, *P* = .58).

Table 2: Summary table of the linear regression model results

Linear model: Response rate ~ log prompts per day + log number of tracking items per prompt

Coefficients	Est	St. Error	t	*P*	VIF
(Intercept)	80.165	7.959	10.072	1.71e-09	
Log prompts per day	-7.221	3.159	-2.286	.033 *	1.08
Log tracking items	1.706	3.008	0.567	.58	1.08

Abbreviations: Est = estimate, St. Error = standard error, t = t-statistic, *P* = p-value, VIF = variance inflation factor

Discussion

Principal Results

Given the widespread access to smartphone technology, the steadily advancing EMA and RMBC research, and the limited evidence through randomized controlled trials and systematic studies on interventions in mental health care, we aimed to review and evaluate the diverse literature in the field. This systematic review targeted the study design features and procedures of EMA and RMBC across psychiatric disorders. Concurrently, the meta-analysis aggregated and examined the effects of RCTs implementing RMBC interventions, focusing on outcomes pertinent to clinical efficacy and recovery-oriented outcomes.

Overall, we found compliance and retention rates for RMBC and EMA technologies to be encouraging, aligning with previous findings in broad EMA research [51,52]. We found that more prompts, but not tracking items, negatively affected the response rate. This observation corroborates the meta-analytic evidence by Vachon et al. who noted a positive correlation between compliance and fewer daily prompts as well as longer intervals between prompts in severe mental illnesses [50]. It also confirms findings from a systematic review by Williams et al. showing that higher numbers of tracking items per prompt were not associated with reduced compliance in clinical samples; in healthy individuals however, more items were indeed associated with lower compliance [53]. Up to five random EMA prompts per day have been deemed optimal for longitudinal studies [54]. However, in the context of substance use disorders, Jones et al. reported that compliance was not significantly impacted by the number of prompts per day or the duration of the assessment period [55]. Our results support the evidence for severe mental illness and are in favour of longer intervals between successive evaluations to maximize, potentially influenced by the low representation of substance use disorders within our sample due to a lack of formal diagnosis.

Methodology
During the systematic review of the literature, a prominent distinction was identified between RMBC and EMA. Despite their shared aim of collecting subjective, real-time data from remote settings, they serve distinct purposes from a clinical perspective. While RMBC encompasses elements of EMA, it is directed towards informing healthcare decisions and interventions, e.g., supporting real-time and asynchronous treatment adjustments or scheduling of visits [14,27]. For patients, both EMA and RMBC interfaces facilitate reflection on symptoms, with many offering data summaries on symptom trajectories. As the primary difference between RMBC and EMA, RMBC focuses on enabling clinicians to formulate recommendations and implement treatment adjustments based on real-time data. As a result, patients may perceive RMBC as involving closer monitoring, which in turn is subject to individual preference. Some patients may interpret RMBC as an invasion of their autonomy and privacy, while others may find comfort in the increased level of monitoring, viewing it as an additional safety measure.

In our meta-analysis of RMBC interventions, we investigated the transdiagnostic benefits of the technologies often emphasized in the literature. Therefore, the analysis considered psychopathological, cross-diagnostic constructs rather than individual diagnostic groups of participants. In addition to the well-known challenges of different design features and procedures when integrating and aggregating data from EMA and RMBC studies [13,51], this aspect may have increased heterogeneity. Overall, we did not observe clear effects of RMBC interventions for most of the constructs we analyzed, i.e. depressive, psychotic symptoms, quality of life and (daily) functioning. This is consistent with the results of Goldberg et al., who assumed a general effect of RMBC interventions but did not draw any conclusions about specific effects due to the small number of RCTs [13].
There was no overlap between the studies we included in our review and those by Goldberg et al. This is because we only included studies with manualized psychiatric diagnostic procedures and applied a narrower definition of RMBC, emphasizing self-monitoring for decision-making and therapy planning. Goldberg et al. did not set a formal psychiatric diagnosis as an inclusion criterion and used a wider definition of RMBC, in particular regarding its direct effects on treatment trajectories.

Both frequentist and Bayesian meta-analyses demonstrated a significant effect on the reduction of manic symptoms when pooling data from three studies [45–47]. In both RCTs by Fauerholt Jepsen et al. [46,47], which found no significant effect on emotional (depressive and manic) symptoms, medians and standard errors were converted to means and standard deviations. In this respect, it is generally known that the standardization of results can introduce flaws in meta-analysis [56]. Although there is scarce systematic evidence on the effects of RMBC on (hypo)manic symptoms, there appears to be a benefit from clinical practice due to the dynamic and fluctuating nature of the symptoms. The exploratory analysis by Faurholt-Jepsen et al. underlined that smartphone-based monitoring may reduce the risk of relapse of manic episodes but increase the risk of relapse of depressive episodes [46]. This finding is underscored by a systematic review by Hennemann and colleagues (2018), who examined internet- and mobile-based tools for psychiatric aftercare and relapse prevention.They found small to moderate positive effects on symptom severity, with the best evidence for depression and anxiety [57].

In the frequentist meta-analysis we found an effect of RMBC interventions on empowerment and self efficacy. Of note, the largest study (n = 200) by Ebert et al. [58] contributed the largest weight to this result. Although validated, the instrument used includes a limited set of five items as a subscale of the HEALTH-49 questionnaire and has no proven correlation with the BUES [59]. These results should also be evaluated with caution in light of the results of the Bayesian meta-analysis where the effect was also detectable but the confidence interval includes zero. Overall, self-efficacy seems a promising target for RMBC tools.

Quality of evidence
A keyword search of the manuscripts in this systematic review and meta-analysis showed that unfortunately, none of the publications mentions the CONSORT Checklist or its EHEALTH extension. Additionally, some essential outcome measures were missing from the vast majority of studies.
For one, adverse events were reported by only a fraction of studies. This is particularly frustrating seeing as adverse events pertaining to the technologies and treatment modalities may be easily transferable, constituting an efficient knowledge transfer and reducing potential harm to study and clinical populations. Direct adverse psychological effects of symptom tracking include anxiety or obsessiveness about choosing the "wrong" answer and an increased awareness of symptoms mentioned in questions/ prompts [e.g., 59] which may increase disease burden. Symptom tracking has also been found to potentially amplify symptoms, or create the illusion of symptom amplification for patients and/or clinicians through overreporting [61].
Indirect negative effects include feelings of guilt when tracking is missed, cognitive dissonance due to continuous confrontation with mental illness and boredom or fatigue (e.g., Eisner et al., 2019). Symptom-tracking apps may also

promote individualist models of illness that negate social determinants of health and make patients indirectly responsible for their illness if they refuse or fail to track symptoms [62].

Incomplete or absent adverse event reporting may be linked to the circumstance that many EMA/RMBC studies are conducted by the application developers/owners. In this case, funding for further product development may be dependent upon its evaluation, constituting a potential conflict of interest. This scenario presents a significant challenge to the objectivity and credibility of the research findings. When developers or product owners have a vested interest in the success of their apps, there may be a bias towards reporting positive outcomes and downplaying negative findings. This conflict of interest could potentially also lead to selective reporting, inflated claims of efficacy and inadequate scrutiny of potential harms. Consequently, it undermines the integrity of the research and raises concerns about the reliability of the evidence base supporting the effectiveness of mobile mental health apps.

A further concern identified within the analyzed studies is the limited reporting of adherence and response rates. This deficiency poses significant methodological and interpretive challenges. Adherence and response rates are critical indicators of the feasibility and acceptability of interventions among participants. Limited or absent reporting of these metrics hinders a full understanding of intervention effectiveness and the factors influencing user engagement. Without clear insights into adherence and response rates, it becomes difficult to determine the reliability and generalizability of study findings. A further obstacle here is the multitude of metrics used, e.g., the percentage of total assessments completed [63], the percentage of days within the observation period on which assessments were completed [64], or a binary definition of compliance / non-compliance based on a cutoff of completed assessments [65]. We therefore strongly emphasize the importance of standardized adherence reporting. Minimally, authors should report the total share of assessments completed within the study population, the average percent of assessments completed per person, and factors associated with non-adherence (i.e., demographics or time-varying factors; [66,67]).

A common barrier to evidence synthesis that affected this research is the heterogeneity of study populations, specifically the lack of a formal psychiatric diagnosis in many study samples. About a third of the full-text articles were excluded for primarily this reason. Seeing as many of these were clinical populations that most likely fulfilled DSM-5 or ICD10 diagnostic criteria, this issue underscores the importance of standardized diagnostic criteria and rigorous documentation of participant characteristics in clinical research.

Strengths and limitations

On the one hand, our inclusion criteria required a formal psychiatric diagnosis, which led to the exclusion of many studies that used EMA and RMBC technology. On the other hand, this criterion also strengthens the methodology by ensuring a higher standard of diagnostic rigour within the included studies. In addition, our focus on RCTs increases the reliability of our findings by selecting evidence from studies with robust experimental designs. In addition, the heterogeneity of terminology in studies exploring similar concepts, such as EMA or RMBC, may have led to the inadvertent omission of relevant research. To meta-analyze constructs, outcome constructs were pooled, reducing their discriminatory power, possibly leading to an underestimation or non-detection of effects [68].

Recommendations

From studying the existing evidence on EMA and RMBC for mental health care, we recommend adherence to standardized reporting guidelines such as CONSORT-MHEALTH. To effectively analyse acceptability and adherence, we suggest the establishment of standards for response-rate measurement. To gain feedback on the user experience as well as the perspective of healthcare providers with RMBC products, mixed methods designs can provide valuable insights for challenges in implementations of such measures.

Conclusions

In conclusion, our systematic review and meta-analysis underscore the potential of remote measurement-based care (RMBC) interventions in enhancing the management of mental health conditions, particularly in reducing symptom severity in mania and increasing empowerment. While demonstrating promising effects on adherence and symptom-specific outcomes, the variability in intervention effectiveness and concerns about bias highlight the need for further research and refinement to optimize the implementation of RMBC within mental health care systems.

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Competing interests

Jakob Kaminski is a shareholder and managing director of Recovery Cat GmbH. Toni Muffel is an employee at Recovery Cat GmbH, Caspar Wiegmann received remuneration from Recovery Cat for consulting.

Abbreviations

CI	Confidence interval
DSM	Diagnostic and Statistical Manual
EMA	Ecological momentary assessment
ICD	International Statistical Classification of Diseases and Related Health Problems
MBC	Measurement-based care
MCMC	Markov Chain Monte Carlo
MMH	Mobile mental health
PRISMA-P	Preferred reporting items for systematic review and explanation meta-analysis protocols
PRO	Patient reported outcome
RCT	Randomized controlled trial
RMBC	Remote measurement-based care
RoB 2	Cochrane risk-of-bias tool for randomised trials version 2
SD	Standard deviation
SMD	Standardized mean difference
VIF	Variance inflation factor

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Supplementary Files

Multimedia Appendixes

Untitled.
URL: http://asset.jmir.pub/assets/dbf32f9e5cc4c3e7e407324e8567b625.docx