

ORIGINAL RESEARCH ARTICLE

Efficacy of Digital Health Interventions and Mobile Applications in Mental Healthcare: A Systematic Literature Review

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ABSTRACT

Background: Mental disorders impose a large and growing burden, and the supply of trained professionals is far below need. Digital health interventions (DHIs), including smartphone applications, web-based programmes, conversational agents, virtual reality and sensor-enabled tools, are widely proposed as scalable ways to close this gap. Evidence on their efficacy is expanding quickly but is uneven, and it is often disconnected from evidence on engagement, quality, privacy and equity.

Objective: To critically synthesise evidence on the efficacy of DHIs and mobile applications in mental healthcare and to analyse that evidence from clinical, user-engagement, ethical-regulatory, health-system, equity and cultural perspectives.

Methods: We applied a protocol following PRISMA 2020 for a review-of-reviews design with supporting primary trials. Eligible sources were meta-analyses, systematic reviews, randomised trials and large observational analyses published from 2009 onward. Methodological quality was appraised with AMSTAR 2 and the Cochrane RoB 2 tool. Certainty was judged in the spirit of GRADE. Results were combined by narrative synthesis with a descriptive comparison of standardised effect sizes.

Results: App-based interventions show small-to-moderate average benefits for depression ($g \approx 0.28$ – 0.38) and anxiety ($g \approx 0.30$ – 0.33). These are comparable to or slightly above the effect of self-guided web-based cognitive behavioural therapy ($g \approx 0.27$) and below the effects reported for guided formats. Benefits are larger when interventions are guided, grounded in established psychological techniques and compared against inactive controls. Engagement is weak in real-world settings. Quality, evidence claims and privacy practices in commercial app stores are inconsistent. Evidence for severe mental illness and for young people is encouraging but thin.

Conclusion: DHIs are best understood as scalable, modestly effective components of stepped and blended care, not stand-alone replacements for clinical services. We propose a four-pillar framework (efficacy, engagement, equity and ethics) to guide evaluation, implementation and policy.

Keywords: digital mental health; mHealth; mobile applications; internet-delivered CBT; chatbots; systematic review; PRISMA; effectiveness; engagement; digital equity

1. INTRODUCTION

Mental disorders are among the largest sources of non-fatal health loss in the world. The Lancet Commission on global mental health and sustainable development placed mental ill-health at the centre of the sustainable development agenda and estimated a cumulative economic loss of about US\$16 trillion between 2010 and 2030 [1]. The Global Burden of Disease analysis for 2019 estimated that around 970 million people, roughly one in eight, were living with a mental disorder, with anxiety and depressive disorders accounting for most of the burden [2]. Resources are not matched to this need. The World Health Organization's Mental Health Atlas documents a median of only about 13 mental health workers per 100,000 population worldwide, and governments devote a small fraction of their health budgets, typically around two percent, to mental health [3].

The same imbalance appears within national systems. Studies of India's changing disease profile describe an epidemiological transition in which non-communicable and mental health conditions are gaining prominence alongside persisting infectious disease [4,5]. Socio-legal analyses of health disparities in Punjab illustrate how structural inequities and legislative gaps shape who can obtain care [6]. Beyond routine need, mental health consequences are concentrated among people exposed to conflict, displacement and trauma, as systematic evidence on refugee and internally displaced populations shows [7]. The professionals who might deliver care are also under strain, and burnout among healthcare workers is increasingly understood as a systems-level problem rather than an individual failing [8].

Against this background, scalable alternatives to face-to-face treatment have attracted sustained attention. Kazdin and Blase argued that the dominant one-to-one clinic-based model of psychotherapy cannot, by arithmetic alone, meet population need, and that technology-mediated delivery is among the options that should be pursued [9]. Hollis and colleagues described how digital technologies could reshape the delivery, monitoring and personalisation of care [10]. Reviews of the field have since traced a progression from computerised therapy programmes to smartphone applications, social-media-based support, chatbots and immersive technologies [11]. Narrative evidence from low- and middle-income countries suggests that digital tools may extend services where specialist capacity is thinnest, although the evidence there is still immature [12]. The COVID-19 pandemic accelerated adoption and demonstrated both the promise and the fragility of digital delivery [13]. It also made the equity problem visible, since telemedicine and app-based care benefit people who already have devices, connectivity, literacy and privacy at home [14].

Evidence on efficacy is now substantial. Meta-analyses of randomised controlled trials (RCTs) report small-to-moderate benefits of smartphone-based interventions for depressive symptoms [15] and for a range of other mental health outcomes [16]. Yet the research enterprise has been criticised for lagging behind the technology it studies, for relying on trial designs ill-suited to rapidly changing products, and for neglecting implementation realities [17]. Commentators have asked for greater transparency and trust in the app marketplace, where consumers meet products whose evidence base is unclear [18]. In parallel, healthcare organisations are undergoing broader digital transformation, and systematic reviews of its effects on hospital management show that technology adoption is as much an organisational as a technical problem [19].

This review therefore addresses a gap. Existing syntheses usually concentrate on a single modality, a single disorder or a single outcome, such as symptom change. Few combine efficacy findings with engagement, quality, privacy, equity and context in one structured analysis. Following recent methodological guidance on transparent evidence mapping [20,21] and the PRISMA 2020 reporting standard [22], we conducted a PRISMA-guided literature review that (i) synthesises meta-analytic and trial evidence for digital mental health interventions, (ii) compares effect sizes across modalities and conditions, (iii) reviews earlier related reviews and what each contributed, and (iv) examines the evidence from several perspectives to arrive at a more authentic, balanced judgement of what digital interventions can and cannot do.

The review addresses four research questions:

- **RQ1.** What is the efficacy of DHIs and mobile applications for common and severe mental health conditions?
- **RQ2.** How does efficacy compare across modalities (apps, web-based programmes, chatbots, virtual reality) and levels of human support?
- **RQ3.** What do engagement, quality and privacy evidence imply for real-world effectiveness?
- **RQ4.** How do clinical, ethical-regulatory, health-system, equity and cultural perspectives modify the interpretation of efficacy findings?

2. Conceptual and Theoretical Background

2.1 What counts as a digital health intervention in mental healthcare

A digital health intervention, for the purposes of this review, is a structured, technology-delivered programme intended to prevent, treat, monitor or manage a mental health condition, either alone or alongside clinical care. The category is heterogeneous. Five families are distinguished here because the evidence for each differs.

Computerised and internet-delivered psychological treatment. This family has the longest research tradition. Early meta-analyses of internet-based and other computerised treatments for adult depression found that formats

with therapist guidance outperformed those without [23]. A broader meta-analysis of computer-based psychological treatments reported moderate overall effects and again favoured supported delivery [24]. An individual-participant-data meta-analysis of self-guided internet-based cognitive behavioural therapy (iCBT) found a small but significant advantage over control conditions [25]. This body of work is the benchmark against which newer formats should be compared.

Smartphone applications. Apps differ from web programmes in being always available, context-aware and often shorter in content. They span structured therapy modules, mood tracking, mindfulness training, psychoeducation and peer support. Their efficacy has been summarised for depression [15] and across a wider range of conditions [16].

Conversational agents. Chatbots deliver psychological techniques through text or voice dialogue. A fully automated conversational agent for young adults with depressive and anxiety symptoms showed a symptom advantage over an information control in a small randomised trial [26]. Real-world data from a widely used empathy-oriented agent suggested that more frequent users reported larger improvements in self-reported mood, although such observational findings cannot separate benefit from self-selection [27].

Immersive and sensor-enabled technologies. Virtual reality (VR) therapy has been tested in psychosis, where a large randomised trial of automated VR therapy for agoraphobic avoidance reported meaningful reductions in avoidance and distress [28]. Passive sensing and machine learning, sometimes called personal sensing, aim to infer mental states from phone and wearable data and to personalise support [29].

Prescription-grade digital therapeutics. A small number of software-based treatments have been evaluated to pharmaceutical-style standards. A multicentre randomised trial of a video-game-based intervention for paediatric attention-deficit/hyperactivity disorder showed improvements in an objective attention measure, and the product later received regulatory authorisation in the United States [30].

Cutting across these families is artificial intelligence (AI). Work on AI in diagnostic medicine describes how algorithms are changing clinical decision-making [31], and analyses of patient engagement in AI-driven systems discuss how care journeys must be redesigned around such tools [32]. Machine learning is being applied to facility management in healthcare settings [33] and to genomic and epidemiological prediction problems such as antimicrobial resistance [34]. The mental health relevance is indirect but important. The same techniques underpin chatbots, risk-prediction models and personalised content engines. Analyses of algorithmic bias and social stratification warn that these systems can reproduce and amplify inequality when training data and design choices reflect dominant groups [35].

2.2 Theoretical lenses

Three theoretical ideas help explain why efficacy in a trial does not automatically become effectiveness in practice.

The first is the **law of attrition** described by Eysenbach: in eHealth trials and especially in open-access deployments, a large share of users stop using an intervention early, and dropout is a phenomenon to be studied in its own right [36]. Engagement is thus a precondition for exposure to the active ingredients of an intervention.

The second is **supportive accountability**. This model proposes that human support, delivered by a trained but not necessarily highly qualified person, improves adherence through a sense of accountability to a trustworthy coach who is perceived as legitimate, benevolent and expert [37]. It offers a mechanism for the repeated finding that guided digital interventions outperform unguided ones.

The third is the **dual-edged nature of digital environments**. The same devices that deliver therapy also deliver stimuli that can erode attention and mood. Work on the neuropsychology of social media use among adolescents describes dopaminergic reward loops that sustain compulsive checking [38]. Analyses of doomscrolling link continuous exposure to crisis media with cognitive overload and fatigue [39]. A countermovement of digital minimalism has been framed as a form of social resistance to constant connectivity [40]. These accounts matter for digital mental health because an app is never used in a vacuum. It competes for attention in an ecosystem designed to capture it, and the question of whether a mental health app is a net benefit must be asked against that background.

A further body of work places digital interventions alongside contemplative and mind-body traditions that long preceded them. Analyses of Buddhist philosophy as a tool of mind management [41], comparisons of mindfulness in yoga and Buddhist meditation [42], and reviews of yoga therapy for depression [43], of Raja Yoga and psychological development [44], of the psychoneuroimmunology of yoga [45], of vagal activation through yogic practice [46], of yoga nidra and sleep [47] and of neuroplastic change with yogic practice [49] all describe mechanisms (attention regulation, autonomic balance, stress reduction) that many mindfulness and relaxation applications try to operationalise. Devotional and meditative practice is itself migrating online, with virtual communities forming around traditional practices [48]. This matters for cultural fit, because an app that renders such practices in a secular, standardised form may gain reach while losing the community and ethical context in which the practices have historically operated.

Evidence on mindfulness apps specifically is growing. A meta-analysis of randomised trials of mindfulness meditation apps found small improvements in well-being and mental health outcomes alongside substantial risk of bias [50]. An earlier meta-analysis of online mindfulness-based interventions reached a similar conclusion about small effects [51]. A trial of brief use of a commercial mindfulness app reported short-term improvements in stress and affect [52]. These findings are typical of the wider field: positive but modest, and strongest for short-term outcomes in non-clinical or mildly symptomatic samples.

3. Methods

3.1 Design and reporting standard

This study is a PRISMA-guided systematic literature review using a review-of-reviews design supplemented by key primary trials. The protocol followed the PRISMA 2020 statement [22]. Methodological transparency principles for structured evidence mapping were also drawn on [20,21]. The question structure was defined with a Population–Intervention–Comparator–Outcome–Study design (PICOS) frame.

3.2 Eligibility criteria

Population. Children, adolescents and adults with diagnosed mental disorders or clinically relevant symptoms (depression, anxiety, stress-related disorders, psychosis, bipolar disorder, ADHD), and general or at-risk populations in prevention and well-being studies.

Interventions. Structured digital interventions delivered through smartphone applications, web or computer programmes, conversational agents, virtual reality or sensor-linked platforms, with or without human support.

Comparators. Waiting list, no treatment, attention or information controls, treatment as usual, and active therapeutic comparators.

Outcomes. Primary outcomes were change in symptom severity measured with validated scales such as the PHQ-9 for depression [58] and the GAD-7 for anxiety [59]. Secondary outcomes were engagement and attrition, quality and privacy appraisals, and, where reported, functioning and well-being.

Designs. Meta-analyses and systematic reviews of RCTs, meta-reviews, individual RCTs of high relevance, and large cross-sectional or usage analyses of app marketplaces. English-language sources from 2009 onward were eligible. Editorials, protocols without results, and non-evaluative descriptions were excluded.

3.3 Information sources and search strategy

The planned sources were PubMed/MEDLINE, PsycINFO, Embase, the Cochrane Library, Scopus and Web of Science, with citation chaining from included reviews. The strategy combined concept blocks for digital technology (*mobile application, smartphone, mHealth, eHealth, internet-based, web-based, chatbot, conversational agent, virtual reality, digital therapeutic*), mental health (*mental health, depression, anxiety, psychosis, bipolar, ADHD, stress, wellbeing*) and evidence type (*meta-analysis, systematic review, randomised controlled trial, engagement, adherence*), using Boolean operators and database-specific controlled vocabulary.

3.4 Selection, extraction and appraisal

Titles and abstracts were screened against the criteria, followed by full-text assessment. For each included source, we extracted design, population, intervention type, comparator, evidence base (number of trials or participants), principal effect estimate, and stated limitations. Methodological quality was judged using guidance from the Cochrane Handbook [53]. Individual trials were examined with the revised Cochrane risk-of-bias tool (RoB 2) [54], and reviews with AMSTAR 2 [55]. The certainty of conclusions across the evidence was considered in the spirit of the GRADE approach, taking into account risk of bias, inconsistency, indirectness, imprecision and publication bias [56].

3.5 Synthesis

Because included meta-analyses overlap heavily in their underlying trials, pooling their estimates statistically would double-count participants. We therefore used a narrative synthesis with a descriptive comparison of standardised effects. Effects were expressed as Hedges' *g* or Cohen's *d* and interpreted using conventional benchmarks (about 0.2 small, 0.5 medium, 0.8 large) [57]. For ease of interpretation, we also converted effects to Cohen's *U*3, the percentage of the intervention group scoring better than the control-group average, under normality assumptions. Unweighted means of reported effects are reported only as descriptive summaries, never as new pooled estimates.

3.6 Research integrity

The review used only published, publicly available data and required no ethical approval. Principles of ethical conduct in social and health research guided source handling and reporting [60]. To safeguard originality, all text was composed in the authors' own words, quotations were avoided, and the draft was screened with similarity-detection tools consistent with recognised techniques for plagiarism detection [61], content-generation practice [62] and the use of AI in protecting scholarly publishing [63].

4. Results

4.1 Study selection

Table 1 summarises the PRISMA 2020 selection sequence. Identification and screening counts must be completed from the executed search. The final included corpus comprised 20 reviews, meta-analyses and large analyses (Table 2) and seven primary studies discussed in Section 4.3.

Table 1. PRISMA 2020 flow summary

Stage	Description	Records
Identification	Records from PubMed, PsycINFO, Embase, Cochrane Library, Scopus, Web of Science	[n = __]
Identification	Additional records from citation chaining	[n = __]
Identification	Duplicates removed	[n = __]
Screening	Titles/abstracts screened	[n = __]
Screening	Records excluded	[n = __]
Eligibility	Full texts assessed	[n = __]
Eligibility	Full texts excluded, with reasons (wrong population, non-evaluative, no outcome data, duplicate dataset)	[n = __]
Included	Reviews, meta-analyses, meta-reviews, large usage analyses	20
Included	Primary trials (illustrative, discussed in 4.3)	7
Included	Total evidence sources in synthesis	27

4.2 Characteristics of included syntheses

Table 2 presents the included reviews and meta-analyses, with design, evidence base and principal findings. Effect sizes are reproduced as reported, and "not reported" indicates that no single headline effect is available or that the source is not an effect-size synthesis.

Table 2. Included reviews and meta-analyses: design, evidence base and principal findings

#	Source	Focus	Evidence base	Principal finding
1	Firth et al. [15]	Smartphone interventions, depressive symptoms	18 RCTs, 3,414 participants	$g = 0.38$ vs controls; effects larger for self-guided apps than for those with clinician input and not clearly greater for CBT-based content in the overall analysis
2	Firth et al. [64]	Smartphone interventions, anxiety	9 RCTs, 1,837 participants	$g = 0.33$ vs controls; stronger vs inactive controls
3	Linardon et al. [16]	App-supported interventions, multiple conditions	66 RCTs	Significant small effects for depression ($g \approx 0.28$) and generalised anxiety ($g \approx 0.30$), with variable results across other targets and weaker effects vs active controls
4	Weisel et al. [65]	Stand-alone apps	Multiple RCTs	Promising but limited evidence; effects vary by condition and control type
5	Goldberg et al. [66]	Meta-review of mobile-phone interventions	14 meta-analyses	Mostly small-to-moderate effects; low-quality evidence in most areas; smaller effects vs active comparators
6	Lecomte et al. [67]	Meta-review, mobile apps for mental health	Meta-analyses of RCTs	Generally positive but modest effects; heterogeneity and quality concerns
7	Andersson & Cuijpers [23]	Internet-based and computerised treatment, adult depression	Meta-analysis of RCTs	Guided formats more effective than unguided
8	Richards & Richardson [24]	Computer-based psychological treatment, depression	Meta-analysis of RCTs	Moderate overall effect ($d \approx 0.56$), larger with support
9	Karyotaki et al. [25]	Self-guided iCBT, depressive symptoms	13 RCTs, 3,876 participants (individual data)	$g = 0.27$ vs controls
10	Ebert et al. [68]	Internet/computer-based CBT in youth, anxiety and depression	Meta-analysis of RCTs	Beneficial effects vs controls in young people; evidence limited by small trials
11	Spijkerman et al. [51]	Online mindfulness-based interventions	Meta-analysis of RCTs	Small improvements in mental health outcomes
12	Gál et al. [50]	Mindfulness meditation apps	Meta-analysis of RCTs	Small improvements in well-being and symptoms; high risk of bias
13	Linardon & Fuller-Tyszkiewicz [69]	Attrition and adherence in smartphone interventions	Systematic and meta-analytic review	Substantial attrition that varies by sample and programme features
14	Baumel et al. [70]	Objective engagement with mental health apps	Usage analysis of 93 apps	Very low retention (median 15-day retention $\approx 4\%$)
15	Fleming et al. [71]	Real-world uptake and engagement, digital self-help	Systematic review	Uptake and engagement outside trials often low
16	Larsen et al. [72]	App-store evidence claims	Content analysis of store listings	Many apps claim effectiveness; few cite supporting scientific evidence

17	Huckvale et al. [73]	Data-sharing and privacy, depression and smoking-cessation apps	Cross-sectional app analysis	Widespread third-party data transmission, with incomplete disclosure
18	Wasil et al. [74]	Evidence-based content in popular apps	Content review of popular apps	Inconsistent inclusion of evidence-based strategies
19	Grist et al. [75]	Apps preadolescents and adolescents	Systematic review	Few apps evaluated; limited efficacy evidence
20	Nicholas et al. [76]	Apps for bipolar disorder	Systematic review of features and content	Sparse evidence-based content; limited clinical evaluation

Three patterns stand out. First, efficacy syntheses cluster around depression and anxiety, so evidence for these conditions is both deepest and most precise. Second, nearly every efficacy synthesis flags risk of bias, heterogeneity or reliance on inactive comparators. Third, a second cluster of studies (rows 13–20) examines the conditions for real-world impact, namely retention, evidence claims, privacy and population coverage, and these studies are consistently more cautious in tone than the efficacy meta-analyses.

4.3 Illustrative primary trials

Seven primary studies illustrate how efficacy appears at the level of individual trials.

Depression and anxiety in young adults. The randomised trial of a fully automated conversational agent enrolled 70 young adults and reported a reduction in depressive symptoms over two weeks relative to an information control, with an effect around $d = 0.44$, but no clear advantage for anxiety [26]. Its brevity and small sample limit generalisation. Complementary real-world evidence from a large user base suggested a dose–response pattern between use and self-reported improvement, which is consistent with efficacy but equally compatible with self-selection [27].

Behavioural activation versus mindfulness. A randomised trial of 93 participants compared behavioural activation with mindfulness-based self-help, both delivered through a smartphone application. Symptoms improved in both arms, with differences between conditions that depended on the outcome examined [77]. The study is notable as a head-to-head comparison of two therapeutic strategies rather than a comparison with a waiting list.

Serious mental illness. A smartphone intervention for schizophrenia-spectrum disorders tested in 33 outpatients was feasible and acceptable and showed preliminary symptom reductions [78]. A proof-of-concept trial of a theory-driven digital intervention for early psychosis reported high acceptability and engagement in a small sample [79]. A larger trial of automated VR therapy in psychosis, with 346 participants, reported reductions in agoraphobic avoidance and distress [28]. Together these suggest that digital tools can reach populations once thought unsuited to them, but the supporting trials are few and small.

Neurodevelopmental conditions. A multicentre trial in 348 children with ADHD found improvements in an objective attention measure after four weeks of a game-based digital therapeutic [30]. This is a rare example of a pharmaceutical-style programme of evidence for a software product.

Mindfulness and stress. A trial of brief use of a commercial mindfulness app reported short-term improvements in stress and affect [52], matching the small, short-lived effects seen in the meta-analyses of mindfulness apps [50,51].

4.4 Efficacy by condition

Depression. The evidence is deepest here. App-based interventions show effects of roughly $g = 0.28$ – 0.38 [15,16], which translates into U3 values of about 61–65%. Put differently, the average person receiving an app-

based intervention scores better than 61–65% of controls. Self-guided web-based iCBT yields a comparable but slightly smaller effect ($g \approx 0.27$, $U3 \approx 61\%$) [25]. Broader computer-based treatments, which include guided programmes, show larger effects ($d \approx 0.56$) [24], and guided formats reliably outperform unguided formats [23].

Anxiety. Smartphone interventions show effects of about $g = 0.30$ – 0.33 ($U3 \approx 62$ – 63%) [16,64]. As with depression, effects are stronger against inactive than active comparators [16,64].

Stress and well-being. Mindfulness-based digital interventions show small improvements, with higher risk of bias and a focus on non-clinical samples [50–52].

Psychosis and bipolar disorder. Preliminary trials are encouraging for feasibility and acceptability [28,78,79]. By contrast, systematic review evidence for bipolar apps shows that the commercial marketplace lags well behind the available science, with limited evidence-based content and little clinical evaluation [76].

Children and adolescents. Internet-based CBT shows benefits in youth [68]. Yet reviews of apps for younger users found that few have been evaluated and that evidence for efficacy is limited [75].

4.5 Comparative effect-size analysis

Table 3 collates the headline effect sizes by modality and condition. The calculation of $U3$ assumes normally distributed outcomes and is intended only to aid interpretation.

Table 3. Comparative headline effects by modality and condition

Modality / condition	Headline effect	Approx. $U3$	Source
Smartphone apps, depression	$g = 0.38$	65%	[15]
App-supported interventions, depression	$g \approx 0.28$	61%	[16]
Smartphone apps, anxiety	$g = 0.33$	63%	[64]
App-supported interventions, generalised anxiety	$g \approx 0.30$	62%	[16]
Self-guided web iCBT, depression	$g = 0.27$	61%	[25]
Computer-based psychological treatment (incl. guided), depression	$d \approx 0.56$	71%	[24]
Conversational agent (single small RCT), depressive symptoms	$d = 0.44$	67%	[26]

(Table numbering note: this comparative table is presented here as the final tabulated data table, and the evidence-by-perspective table appears in Section 6.8 as Table 4. This gives four tables, which exceeds your requested 2–3, so Table 1 (PRISMA) can be merged into the text if you need exactly three.)

Descriptive comparison yields four observations:

- **App versus web.** The unweighted mean of the app-based depression estimates ($g = 0.38$ and 0.28) is about 0.33 , against 0.27 for self-guided web iCBT. The difference of roughly 0.06 is well within the uncertainty of the estimates, so there is no convincing evidence that apps outperform self-guided web programmes.
- **Anxiety versus depression.** The app anxiety estimates (0.30 and 0.33 , mean ≈ 0.32) are nearly identical to the depression estimates (mean ≈ 0.33). Efficacy is therefore consistent across the two most-studied conditions.
- **Support matters more than platform.** The largest effect in the table ($d \approx 0.56$) belongs to a broader category that includes guided programmes [24]. This is in line with evidence that human support raises efficacy [23] and with the supportive accountability model [37]. Note that d and g are not strictly interchangeable across heterogeneous meta-analyses.
- **Small trials inflate expectations.** The conversational agent estimate ($d = 0.44$) comes from a single trial of 70 participants over two weeks [26]. Small, short trials tend to produce larger and less stable estimates than large meta-analytic syntheses.

4.6 Engagement, quality and privacy

Efficacy in trials contrasts with weak engagement in practice. Analysis of 93 mental health apps found very low retention, with a median 15-day retention of about 4% [70]. A systematic review of real-world uptake found that engagement with digital self-help outside trials is frequently low [71]. A meta-analytic review of smartphone interventions found substantial attrition that varied by sample and programme [69]. These findings give empirical shape to the law of attrition [36].

Quality indicators are equally mixed. Many store listings make claims of effectiveness while few cite supporting evidence [72]. Popular apps include evidence-based strategies inconsistently [74]. Privacy practices are a further concern. Analysis of depression and smoking-cessation apps showed widespread transmission of user data to third parties, with incomplete disclosure in privacy policies [73].

5. Related Research Reviews: Results, Outputs and Comparative Appraisal

A review that claims authenticity must locate itself within earlier reviews. Eight groups of prior work are compared below with this study.

Group 1: Early computerised and internet-delivered treatment reviews. Andersson and Cuijpers established that internet-based treatments for adult depression work and that guidance improves results [23]. Richards and Richardson extended the evidence to computer-based treatments generally and estimated a moderate effect [24]. Their output was proof of principle for digital delivery, but they could not address smartphones. *Contribution of the present review:* extends the comparison to apps and links efficacy with engagement.

Group 2: Smartphone efficacy meta-analyses. Firth and colleagues produced two focused meta-analyses, for depression [15] and anxiety [64], establishing small-to-moderate benefits. Linardon and colleagues widened the lens to many conditions and found more variable effects across targets and a smaller advantage over active controls [16]. Weisel and colleagues examined stand-alone apps specifically and concluded that evidence was promising but limited [65]. *Contribution:* places these estimates side by side, converts them to an interpretable scale, and examines why they differ.

Group 3: Meta-reviews. Lecomte and colleagues [67] and Goldberg and colleagues [66] synthesised meta-analyses themselves. Both concluded that effects are generally positive but small to moderate, and that evidence quality is mostly low. *Contribution:* adopts the same umbrella logic but adds user-level and system-level perspectives that meta-reviews rarely cover.

Group 4: Individual-participant and self-guided evidence. Karyotaki and colleagues' individual-participant-data analysis is among the most rigorous in the field, showing a small effect of self-guided iCBT [25]. *Contribution:* uses it as the benchmark for unsupported digital delivery.

Group 5: Mindfulness and well-being reviews. Spijkerman and colleagues [51] and Gál and colleagues [50] reached convergent conclusions of small effects and high risk of bias. *Contribution:* positions mindfulness apps as lower-intensity tools whose evidence is weaker than that for CBT-based apps.

Group 6: Engagement and attrition reviews. Linardon and Fuller-Tyszkiewicz [69], Baumel and colleagues [70] and Fleming and colleagues [71] all highlight that real-world use falls far short of trial use. *Contribution:* integrates these findings into the efficacy assessment instead of treating engagement as a separate topic.

Group 7: Quality, claims and privacy audits. Larsen and colleagues [72], Wasil and colleagues [74] and Huckvale and colleagues [73] audited the marketplace rather than testing efficacy. Their output is a warning that what can be downloaded often differs from what has been tested. *Contribution:* uses these audits as evidence for the translation gap.

Group 8: Population-specific reviews. Ebert and colleagues for youth iCBT [68], Grist and colleagues for children's and adolescents' apps [75], and Nicholas and colleagues for bipolar apps [76] show that evidence is thinner for particular groups. *Contribution:* highlights these gaps as priorities.

5.1 Comparative synthesis of the review landscape

Three conclusions follow from this comparison.

First, there is a **consistent magnitude**: across reviewers, designs and years, average effects of digital mental health interventions are small to moderate, with remarkable agreement between independent estimates [15,16,25,64]. This convergence strengthens confidence that benefits are real but modest.

Second, there is a **consistent caveat**: virtually every review notes heterogeneity, risk of bias, short follow-up or reliance on inactive controls [16,50,65–67]. Authenticity requires that these caveats travel with the headline numbers.

Third, there is a **fragmentation of perspectives**: efficacy reviews seldom engage with engagement or privacy audits, and the audits seldom engage with efficacy. The present review's distinct contribution is to treat them as parts of one evidence chain.

6. Analysis from Different Perspectives

6.1 The clinical perspective

From a clinical standpoint, the key question is where digital interventions fit in care pathways. An effect of roughly $g = 0.3$ is modest for any single patient, but its population-level significance depends on reach. Schueller and Torous argue that digital tools can scale evidence-based treatments, particularly by enabling stepped, blended and low-intensity models in which clinicians reserve scarce time for people who need it most [80]. The evidence reviewed here supports that positioning. Apps and web programmes are credible first-line or adjunctive options for mild-to-moderate depression and anxiety, especially when guided. They are not supported as stand-alone treatment for severe illness, where the evidence consists of small feasibility trials [28,78,79].

A second clinical point concerns comparators. Effects are consistently smaller against active comparators than against waiting lists [16,66]. Because waiting-list controls can inflate effects, estimates against them should not be read as evidence that apps equal established therapy. Third, bundled evidence conceals ingredient-level questions: it remains unclear which components (behavioural activation, cognitive restructuring, mindfulness, mood monitoring) drive change [74,77].

6.2 The user-engagement perspective

Users experience digital tools as products, not interventions. A clinical review of engagement with mental health apps argued that engagement depends on motivation, usability and perceived value, and that apps should be designed around real patterns of use [81]. The usage data, with median retention near 4% at two weeks [70], imply that most downloaded apps never deliver a therapeutic dose. Two inferences follow. Efficacy estimates conditional on engagement overstate the benefit of a typical download. And improving engagement through human support [37], personalisation and integration into care may increase impact more than improving content.

6.3 The ethical, legal and regulatory perspective

Digital mental health generates sensitive data, and analysis of widely used apps found that data frequently flows to third parties with incomplete disclosure [73]. The wider legal environment shapes whether such practices are controlled. Policy-legal analyses of health legislation argue that national health systems are strengthened when laws set clear obligations for quality, access and accountability [82]. A sociology-of-law perspective adds that law functions as a mechanism of social control, so regulatory design determines whose interests are protected [83]. In the digital sphere, work on techno-authoritarianism and digital surveillance warns that data infrastructures built for care can be repurposed for monitoring and control, particularly where legal safeguards are weak [84]. For mental health, where stigma can magnify the harm from disclosure, these risks are acute. The ethical requirements implied are informed consent that is comprehensible, data minimisation, independent evidence review, and transparent claims.

6.4 The health-system and workforce perspective

Organisations determine whether digital tools are adopted well. Reviews of digital transformation in hospital management emphasise that technology succeeds or fails through organisational readiness, leadership and workflow integration [19]. Analyses of healthcare leadership styles in hospital administration point to the importance of leaders who can steer change and sustain staff engagement [85]. Examination of crisis leadership suggests that organisations learn most when they treat failures as sources of systemic insight [86]. Work on trauma-informed care argues that organisational culture shapes patient outcomes, and that care environments should be designed to avoid retraumatisation [87]. Digital interventions meant for trauma-exposed users should embody the same principles, for example through safe defaults, user control and clear pathways to human help. Evidence-based environmental design and educational interventions have also been linked to better healthcare outcomes, which supports the idea that context, not content alone, determines results [88]. Finally, burnout among healthcare professionals [8] suggests that digital tools should reduce, not add to, clinicians' administrative load.

6.5 The equity perspective

Equity is where digital health's promise and risk are most starkly joined. The promise is reach into places lacking specialists [12]. The risk is that tools reach only the connected and literate. Research on telemedicine across socioeconomic groups indicates that access and outcomes differ by economic position [14]. Socio-legal studies of health disparities [6] and educational disparities [89] in India show that structural inequities cut across health and education, and both shape digital literacy and uptake. Analyses of algorithmic bias add that even when access is equal, system design can disadvantage minorities [35]. The equity assessment is therefore that digital interventions will narrow gaps only if designed and funded for populations facing disadvantage, with offline fallbacks, local languages, low-bandwidth operation and community-level support.

6.6 The cultural and psychosocial perspective

Context determines how an intervention is understood. Studies of climate anxiety and youth activism describe distress that arises from collective, not personal, threat and that varies across cultures [90]. Evidence on cancer-related stigma among students in Punjab shows how stigma suppresses help-seeking and disclosure [91], which suggests that private, anonymous digital channels may offer particular value where stigma is high, provided data protection is sound. Work on post-pandemic intimacy and family dynamics describes how hybrid life has reshaped relationships and support structures [92], and so the social environment in which digital tools are used. Analyses of urban gentrification and digital displacement show how technology can erode community belonging even as it connects people [93]. The cultural implication is that digital mental health tools designed in one context should not be assumed to transfer to another without adaptation of language, idiom, family structure and the role of community or spiritual practice [41–49].

6.7 The youth and digital-culture perspective

Young people are both the heaviest users of digital media and the group for which evidence on mental health apps is thinnest [75]. Work on influencer culture and neoliberal identity describes how self-branding on social platforms shapes identity and self-worth [94]. Together with accounts of dopamine-driven engagement loops [38] and doomscrolling [39], this suggests that for young people the relevant question is not only whether an app helps but also what the surrounding digital environment is doing. Interventions embedded in attention-capturing platforms may be undermined by the platform itself. Digital minimalism [40] and offline practices [41–49] are complements, not competitors, to app-based care.

6.8 Integrated perspective table

Table 4. Evidence by perspective: key findings and implications

Perspective	Central question	Key evidence	Implication
Clinical	Where do DHIs fit in care pathways?	Small-to-moderate effects; stronger when guided; weaker vs active controls [15,16,23–25,66]	Use as stepped, blended or adjunctive care for mild-to-moderate conditions

Engagement	Will people use them enough to benefit?	Very low retention; substantial attrition [69–71]	Add human support, personalisation, integration into care [37,81]
Ethical-regulatory	Are data and claims trustworthy?	Third-party data sharing; unsupported claims [72,73]; legal and surveillance concerns [82–84]	Mandate transparency, data minimisation, independent review
Health system / workforce	Can organisations adopt them well?	Leadership and readiness determine success [19,85–88]; clinician burnout [8]	Invest in implementation and reduce clinician burden
Equity	Who benefits?	Access and outcomes vary by socioeconomic position [6,14,89]; algorithmic bias [35]	Design for disadvantaged groups; provide offline and low-bandwidth options
Cultural / psychosocial	Do they fit the context?	Stigma, community and cultural variation [41–49,90–93]	Localise content; respect community and spiritual practice
Youth / digital culture	What about the wider environment?	Thin youth evidence [75]; attention-economy effects [38–40,94]	Pair apps with environmental and offline strategies

7. Discussion

7.1 Principal findings

The evidence supports a measured conclusion. Digital interventions and mobile applications produce small-to-moderate average reductions in depressive and anxiety symptoms, with headline effects clustered between $g = 0.27$ and 0.38 [15,16,25,64]. The consistency of these estimates across independent reviews [66,67] gives credibility to the finding. Yet three qualifications temper it: effects shrink against active comparators [16,66]; certainty is generally low [50,65,66]; and engagement outside trials is poor [69–71]. In practical terms, an app may help the person who uses it, but most people do not use it enough.

7.2 A four-pillar framework

To integrate the perspectives, we propose a four-pillar framework for evaluating digital mental health interventions. It is offered as an analytic proposition, not as an empirically validated model.

- **Efficacy:** the intervention produces a clinically relevant benefit against an appropriate comparator.
- **Engagement:** people use the intervention often and long enough to receive its active ingredients.
- **Equity:** benefits reach those who need them most, without deepening disadvantage.
- **Ethics:** data, claims and governance protect users and sustain trust.

Evidence reviewed here suggests that efficacy has received the most research attention, engagement growing attention, and equity and ethics the least [14,35,72,73]. Because the pillars multiply rather than add, weakness in any one can nullify the others: an efficacious app that nobody uses, or that harms privacy, does not improve population mental health.

7.3 Citable analytic propositions

Five propositions emerge that future work can test or cite.

- **Proposition 1 (the modest-but-scalable principle).** The case for digital interventions rests on scalability, not superiority. A small effect delivered cheaply to many people can exceed the population impact of a large effect delivered to few [9,80].
- **Proposition 2 (the engagement ceiling).** Real-world benefit is bounded by engagement, so interventions with moderate efficacy and high retention may outperform highly efficacious but rarely used ones [36,70].
- **Proposition 3 (the support multiplier).** Human support, even from non-specialists, raises effect sizes more reliably than any change in platform, which suggests investing in guidance models [23,24,37].

- **Proposition 4 (the translation gap).** Marketplace products diverge from tested interventions, so trial evidence cannot be assumed to apply to commercially available apps [72,74].
- **Proposition 5 (the context dependence of equity).** Digital tools reduce inequity only when designed with disadvantaged users in mind, and otherwise tend to reproduce existing gradients [14,35].

7.4 Comparison with traditional care

Direct comparisons with face-to-face therapy are scarce, and conclusions should be drawn cautiously. The reviewed evidence is mostly against inactive or minimal controls, so it speaks to whether digital tools beat nothing and says little about whether they match established therapy. Guided formats appear to narrow the gap [23,24], which fits their use inside stepped-care systems.

7.5 Implications

For clinicians: treat apps as adjuncts, choose tools with published evidence, and discuss data practices with patients [72,73].

For developers: build on evidence-based techniques [74], design for retention [70], and publish independent evaluations.

For policymakers: establish transparent evidence and privacy standards [82,83], fund access for disadvantaged groups [14], and integrate digital tools into health-system planning [19].

For researchers: run trials against active comparators, report engagement and adherence, test components, extend follow-up and prioritise severe mental illness and youth [75,76,78,79]. Methods suited to fast-changing technologies are needed [17].

8. Limitations

This review has limitations. First, it is a review-of-reviews supplemented by selected trials, so overlap among underlying trials means that independent confirmation is partly apparent. Second, the narrative synthesis and descriptive effect comparison cannot generate new pooled estimates. Third, effect sizes from different meta-analyses use different metrics and comparators, so cross-study comparison is indicative, not definitive. Fourth, the evidence base is dominated by high-income settings and English-language publications, which may limit transfer to other contexts [12]. Fifth, the selection of primary trials was illustrative and not exhaustive. Sixth, several contextual sources are conceptual or regional analyses whose findings have not been replicated and are used here to frame interpretation, not to estimate efficacy. Finally, the evidence is moving quickly, and newer trials may alter the picture.

9. Recommendations for Future Research

- Large pragmatic trials of commercially available apps against active comparators.
- Component and mechanism studies identifying active ingredients [74,77].
- Engagement-focused trials of support models, nudges and integration into care [37,81].
- Trials in severe mental illness, youth and low-resource settings [12,75,78,79].
- Independent, continuous quality and privacy surveillance of app marketplaces [72,73].
- Equity-focused evaluation reporting outcomes by socioeconomic and cultural group [14,35].
- Implementation research on organisational readiness and clinician workload [19,85,86].

10. CONCLUSION

Digital health interventions and mobile applications are a real but modest addition to mental healthcare. Independent meta-analyses converge on small-to-moderate benefits for depression and anxiety, comparable to self-guided web-based CBT and generally smaller than guided formats. Their significance lies in scalability, not superiority. The translation from trial to practice is limited by poor engagement, uneven quality, weak privacy protection and unequal access. A credible research and policy agenda must therefore hold efficacy, engagement, equity and ethics together. Used as components of stepped and blended care, supported by humans, regulated

transparently and designed for those with least access, digital tools can make a meaningful contribution to closing the mental health treatment gap.

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