

Effectiveness of AI-Driven Digital Mental Health Interventions and Their Implications for Health Service Delivery: A Systematic Review and Meta-Analysis (2013–2025)

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EFFECTIVENESS OF AI-DRIVEN DIGITAL MENTAL HEALTH INTERVENTIONS AND THEIR IMPLICATIONS FOR HEALTH SERVICE DELIVERY: A SYSTEMATIC REVIEW AND META-ANALYSIS (2013–2025)

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Abstract

Background. Mental disorders are among the leading contributors to global disability, yet access to mental health services remains limited by workforce shortages, geographic disparities, cost, fragmented care pathways, and stigma. Artificial intelligence (AI) is increasingly integrated into digital mental health interventions (DMHIs), including mobile health applications, telehealth platforms, AI-augmented cognitive behavioural therapy, and conversational agents, to expand service capacity and support personalised care. This systematic review and meta-analysis evaluates the effectiveness of AI-driven DMHIs and their implications for mental health service delivery. **Methods.** This review followed PRISMA 2020 and PRISMA-S guidelines. A pre-specified Scopus search was conducted on 31 December 2025 for peer-reviewed English-language journal articles published between January 2013 and December 2025. Records were screened using PICOS criteria. Risk of bias was assessed using Cochrane RoB 2 for randomised trials and ROBINS-I for non-randomised studies. Clinical effects were pooled using Hedges' g with a DerSimonian–Laird random-effects model, while algorithmic performance was summarised using area under the curve (AUC), sensitivity, and specificity. **Results.** Of 2,042 records identified, 385 studies met the inclusion criteria. AI-driven DMHIs produced statistically significant, moderate improvements in depression, anxiety, and mood outcomes compared with comparator conditions. Pooled AUC values exceeded 0.80 across most disorder categories. However, heterogeneity was substantial, and reporting of validation, equity, implementation, and workforce outcomes was inconsistent. **Conclusions.** AI-driven DMHIs show promise for improving symptoms and expanding access to mental health services. However, external validation, standardised reporting, implementation research, and governance frameworks are needed before large-scale integration into health systems.

Keywords: Digital mental health, Artificial intelligence, Machine learning, mHealth, Telehealth, Health services research, Systematic review, Meta-analysis

INTRODUCTION

Mental disorders remain among the leading contributors to disability-adjusted life years worldwide, while the demand for mental health services continues to exceed service capacity in many health systems [1]. Depression, anxiety, and mood-related conditions have increased in prevalence, yet access to timely and effective care remains uneven across regions, age groups, and socioeconomic groups [2] [3]. From a health-services perspective, this treatment gap is shaped by several structural constraints, including shortages of psychiatrists and psychologists, unequal geographic distribution of services, high out-of-pocket costs, fragmented care pathways, and persistent stigma. Together, these barriers limit the scalability of conventional face-to-face mental health care [4] [5]. These challenges have intensified policy and provider interest in technology-enabled models of care that can extend mental health support beyond traditional clinical settings [1] [6].

Digital mental health interventions (DMHIs) have emerged as one response to these system-level challenges [1]. Over the past decade, mobile health applications, telehealth and telepsychiatry platforms, web-based cognitive behavioural therapy, and wearable-based monitoring systems have been increasingly used to improve accessibility, continuity, and self-management in mental health care [7] [8]. Evidence suggests that digital interventions can reduce symptoms of depression and anxiety, support self-management, and improve engagement with mental health services [8] [9]. However, many first-generation DMHIs were primarily static and rule-based, delivering standardised content with limited personalisation. This limitation may have contributed to variable adherence and inconsistent effectiveness in real-world settings [7] [10].

The integration of artificial intelligence (AI) and machine learning (ML) into digital mental health represents an important shift in how these interventions are designed and delivered [1] [11]. AI-enabled systems use methods such as deep learning, natural language processing, and predictive analytics to analyse behavioural, linguistic, and physiological data in near real time [12] [11]. These capabilities enable more personalised treatment recommendations, early detection of symptom deterioration, conversational support, and adaptive content delivery [12] [8]. From a service-delivery perspective, AI-driven DMHIs may support task-shifting, triage, between-visit monitoring, and population-level risk stratification, thereby aligning digital care with precision and stepped-care approaches in mental health services [5] [13].

Despite this potential, the evidence base relevant to health services research remains fragmented [14] [11]. First, existing studies vary considerably in design, population, intervention modality, comparator, and outcome measures, making cross-study comparison difficult [15] [14]. Second, many AI-focused studies emphasise algorithmic performance metrics, such as accuracy, sensitivity, specificity, or area under the curve, without sufficiently demonstrating clinically meaningful improvements in patient-reported or service-level outcomes [14] [11]. Conversely, clinically oriented evaluations often report symptom change but provide limited information on model architecture, validation procedures, or reproducibility [12] [11]. Third, issues related to algorithmic bias, explainability, data governance, workforce impact, and ethical oversight are inconsistently addressed, raising concerns about safe, transparent, and equitable implementation in routine mental health services [16] [17] [6].

Previous reviews have examined digital mental health interventions broadly or machine-learning applications in psychiatry separately. However, few have integrated clinical effectiveness, computational performance, and health-service implications within a single meta-analytic framework, particularly across the period of accelerated AI development from 2013 onward [14] [18]. Therefore, this study conducts a systematic review and meta-analysis of Scopus-indexed research published between 2013 and 2025 on AI-driven DMHIs. The objectives were to: (i) quantify the clinical effectiveness of AI-enabled DMHIs for depression, anxiety, and mood-related outcomes; (ii) evaluate the predictive and diagnostic performance of underlying AI models; (iii) examine heterogeneity across disorder types, AI methodologies, and intervention modalities; and (iv) identify implications for health service delivery, access, equity, governance, and future research priorities [1] [8].

Study design and reporting

This study was designed as a systematic review and meta-analysis, supplemented by a bibliometric analysis to map the intellectual structure and thematic development of the research field. The review was conducted and reported in accordance with the PRISMA 2020 statement and the PRISMA-S extension for reporting literature search strategies [19]. The completed PRISMA 2020 and PRISMA-S checklists are provided as Additional files 1 and 2. A review protocol was developed prospectively by the research team before screening and data extraction began. No protocol amendments were made after data extraction commenced.

Eligibility criteria

Eligibility criteria were defined using the PICOS framework [20]. The population included human participants with diagnosed or self-reported mental disorders or mood-related symptoms, including depression, anxiety, bipolar disorder, schizophrenia, psychological distress, suicidal ideation, and self-harm. Eligible interventions were AI-driven digital mental health interventions (DMHIs) [21], defined as digital interventions whose core functionality relied on machine learning, deep learning, natural language processing, predictive analytics, or other AI-based techniques [22]. These included AI-supported mobile health applications, telehealth platforms, AI-augmented cognitive behavioural therapy, chatbots or conversational agents, wearable-based monitoring systems, and predictive analytics tools [7] [8] [21]. Comparators included active or inactive control conditions, such as treatment as usual, waitlist, non-AI digital interventions, or face-to-face care. For diagnostic or predictive modelling studies, the absence of a comparator was permitted. Eligible outcomes included clinical symptom outcomes measured using validated instruments, particularly depression, anxiety, and mood-related scores, and/or algorithmic performance indicators, including area under the curve, sensitivity, specificity, and accuracy. Secondary outcomes relevant to the health-services perspective included engagement, adherence, access, service use, workforce implications, and implementation-related indicators [7]. Eligible study designs included empirical quantitative studies, randomised controlled trials, quasi-experimental studies, observational studies, and diagnostic or prognostic modelling studies. Conference papers, editorials, narrative reviews, theoretical papers without empirical validation, non-English publications, and studies without a clear AI component were excluded.

Information sources and search strategy

A comprehensive search was conducted in Scopus because of its multidisciplinary coverage of health sciences, psychology, computer science, neuroscience, and social sciences [23]. The search covered publications from 1 January 2013 to 31 December 2025, a period selected to capture the accelerated development of deep learning, digital health, and AI-supported mental health

technologies [1] [8] [6]. The search was conducted on 31 December 2025 using the following TITLE-ABS-KEY query:

TITLE-ABS-KEY(("digital mental health" OR "mental health app*" OR "mobile mental health" OR "mHealth" OR "e-mental health" OR "telehealth" OR "telepsychiatry" OR "online mental health") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "NLP" OR "chatbot*" OR "conversational agent*" OR "neural network*" OR "random forest" OR "support vector machine" OR "large language model*") AND ("depression" OR "anxiety" OR "schizophrenia" OR "bipolar" OR "mental disorder*" OR "psychological distress" OR "suicide" OR "self-harm" OR "cognitive behavioral therapy" OR "CBT")).

Additional limits were applied to restrict the results to peer-reviewed journal articles, journal sources, English-language publications, human studies, and open-access records. The use of a single bibliographic database is acknowledged as a limitation and is addressed in the Limitations section [24].

Study selection

All retrieved records were exported from Scopus and imported into a reference-management system for de-duplication. Two reviewers independently screened titles and abstracts against the eligibility criteria [24]. Full-text articles were then assessed for all potentially eligible studies [24]. Disagreements between reviewers were resolved through discussion, and unresolved cases were adjudicated by a third reviewer [25]. The study selection process is presented in the PRISMA flow diagram (Fig. 1) [19] [15] [24].

Data extraction

A standardised and piloted data-extraction form was used to ensure consistency across studies [26]. Extracted information included bibliographic details, study characteristics, sample size, population, setting, study design, target mental health condition, AI methodology, intervention modality, comparator, clinical outcome measures, effect estimates, and algorithmic performance metrics. AI methodologies included, but were not limited to, machine learning, deep learning, natural language processing, random forest, support vector machine, neural networks, and large language models. Intervention modalities included mobile applications, web-based platforms, telehealth, chatbots, virtual or augmented reality, wearable devices, and clinical decision-support tools. Data were extracted independently by two reviewers and cross-checked to minimise coding errors and improve reliability [24].

Risk of bias assessment

Risk of bias was assessed using design-appropriate tools [20]. Randomised controlled trials were appraised using the Cochrane Risk of Bias 2 tool [20], while non-randomised intervention studies were assessed using ROBINS-I [27]. Diagnostic and prognostic modelling studies were appraised using PROBAST [28]. Assessment domains included selection bias, performance bias, detection bias, attrition bias, reporting bias, model validation, and outcome measurement. Each study was classified as having low, moderate/some concerns, or high/serious risk of bias, depending on the applicable tool and overall judgement.

Statistical synthesis

Clinical outcomes were synthesised using standardised mean differences calculated as Hedges' g to correct for small-sample bias [29]. Effect sizes were pooled using a DerSimonian–Laird random-effects model because clinical and methodological heterogeneity was expected across populations, intervention types, comparators, and outcome measures. Statistical heterogeneity was quantified using the I^2 statistic, with values of approximately 25%, 50%, and

75% interpreted as low, moderate, and high heterogeneity, respectively [25]. Pre-specified subgroup analyses examined differences by disorder type, AI methodology, and intervention modality. For diagnostic and prognostic modelling studies, algorithmic performance was summarised using area under the curve, sensitivity, and specificity. Where appropriate, pooled estimates were calculated using bivariate random-effects models [30]. Publication bias was assessed visually using funnel plots and statistically using Egger's test when at least ten studies contributed to a given meta-analysis [31]. The funnel plot for clinical symptom outcomes is presented in Fig. 7.

Bibliometric mapping

To contextualise the systematic review and meta-analysis, bibliographic metadata were exported from Scopus and analysed using VOSviewer and the bibliometrix package in R [32]. Descriptive bibliometric indicators included annual publication growth, leading countries, institutions, authors, and sources. Network analyses were conducted to examine co-authorship patterns, co-citation structures, and keyword co-occurrence [14] [33]. Thematic evolution was assessed across two time windows, 2013–2018 and 2019–2025, to identify shifts in research focus over time [14] [33]. The bibliometric analysis was used to complement, rather than replace, the clinical and methodological synthesis [32].

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was a systematic review and meta-analysis of previously published and publicly available literature. No primary data were collected from human participants, and no individual-level identifiable data were used. Therefore, ethics approval and informed consent were not required [34].

CLINICAL TRIAL NUMBER

Clinical trial number: not applicable. This study was not a clinical trial but a secondary synthesis of previously published studies.

RESULTS

Study selection

A total of 2,042 records were identified through the Scopus database search. After the removal of 1,008 duplicate records, 1,034 records were screened by title and abstract. Of these, 609 records were excluded because they did not meet the eligibility criteria, mainly due to the absence of an explicit AI component, lack of mental health outcomes, or non-empirical study design. A total of 425 full-text articles were assessed for eligibility. Forty articles were excluded at the full-text stage because they provided insufficient clinical outcome data, lacked a clearly described machine-learning or AI methodology, or were not original empirical studies. Finally, 385 studies were included in the qualitative synthesis and meta-analysis. The study selection process is presented in the PRISMA flow diagram (Fig. 1).

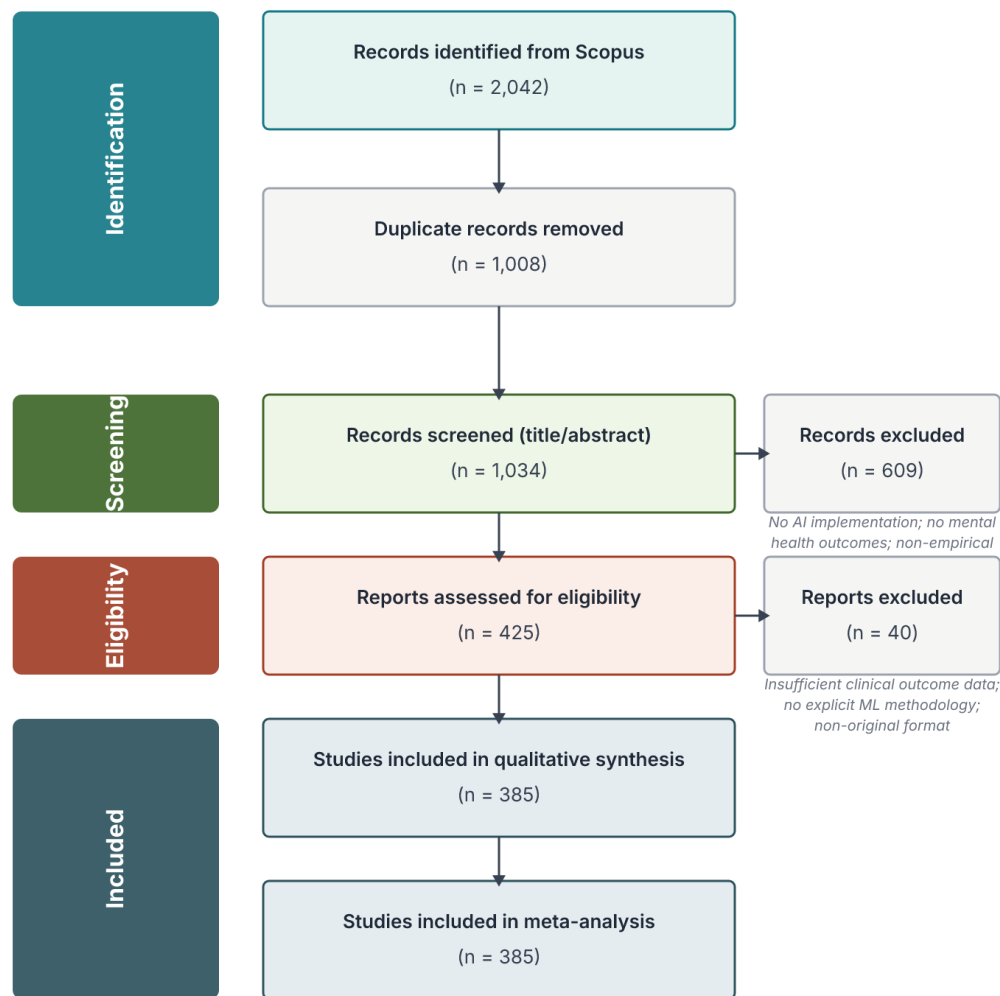


Figure 1. PRISMA 2020 flow diagram of study selection for the systematic review and meta-analysis of AI-driven digital mental health interventions. Of 2,042 records identified through Scopus, 1,008 duplicates were removed, 1,034 records were screened, 609 were excluded at title/abstract, 425 full-text articles were assessed, 40 were excluded at full-text review, and 385 studies were included in the qualitative synthesis and meta-analysis.

Characteristics of included studies

The characteristics of the 385 included studies are summarised in Table 1. The included studies represented a rapidly expanding and multidisciplinary body of research across mental health, digital health, artificial intelligence, psychology, psychiatry, and computer science. Most studies were published between 2020 and 2025, indicating a marked acceleration of research activity during and after the COVID-19 pandemic.

The majority of studies were conducted in high-income countries, followed by upper-middle-income countries, while evidence from lower-middle- and low-income countries remained limited. Randomised controlled trials, quasi-experimental studies, observational studies, and diagnostic or prognostic modelling studies were all represented. Depression and anxiety were the

most frequently studied mental health conditions, followed by mixed depression/anxiety or psychological distress, suicidal ideation or self-harm, schizophrenia or psychosis, bipolar disorder, and other mental health conditions.

In terms of AI methodology, classical supervised machine-learning approaches, including support vector machines, random forests, logistic regression, and XGBoost, were most frequently used. Deep-learning approaches, natural language processing, large language models or generative AI, reinforcement learning, and hybrid or ensemble models were also represented. Intervention modalities included mobile applications, web-based platforms, chatbots or conversational agents, telehealth or telepsychiatry platforms, wearable or passive-sensing systems, virtual or augmented reality, and clinical decision-support tools. However, reporting of service-level outcomes, including cost, workforce implications, access, and equity-stratified outcomes, remained inconsistent across studies.

Table 1 Characteristics of included studies (N = 385).

Characteristic	Category	Studies, n (%)
Publication year	2013–2016	18 (4.7)
	2017–2019	62 (16.1)
	2020–2022	142 (36.9)
	2023–2025	163 (42.3)
Region (first-author country, World Bank group)	High-income	268 (69.6)
	Upper-middle-income	81 (21.0)
	Lower-middle-income	30 (7.8)
	Low-income	6 (1.6)
Study design	Randomised controlled trial	96 (24.9)
	Quasi-experimental / non-randomised intervention	58 (15.1)
	Prospective cohort / observational	71 (18.4)
	Cross-sectional / retrospective	64 (16.6)
	Diagnostic / prognostic modelling	81 (21.0)
	Mixed methods	15 (3.9)
Target condition	Depression	148 (38.4)
	Anxiety disorders	79 (20.5)
	Mixed depression/anxiety or psychological distress	84 (21.8)
	Bipolar disorder	14 (3.6)
	Schizophrenia / psychosis	17 (4.4)
	Suicidal ideation / self-harm	26 (6.8)
	Other (PTSD, eating, substance use, mixed)	17 (4.4)
AI methodology	Classical / supervised ML (SVM, RF, logistic, XGBoost)	156 (40.5)

Characteristic	Category	Studies, n (%)
	Deep learning (CNN, RNN, transformer)	112 (29.1)
	Natural language processing	64 (16.6)
	Large language model / generative AI	23 (6.0)
	Reinforcement learning / adaptive systems	11 (2.9)
	Hybrid / ensemble	19 (4.9)
Intervention modality	Mobile application (mHealth)	121 (31.4)
	Web-based / online platform	86 (22.3)
	Chatbot / conversational agent	58 (15.1)
	Telehealth / telepsychiatry	47 (12.2)
	Wearable / passive sensing	39 (10.1)
	Virtual / augmented reality	14 (3.6)
	Clinical decision-support tool (no patient-facing app)	20 (5.2)
Comparator	Treatment as usual	102 (26.5)
	Waitlist / no intervention	64 (16.6)
	Non-AI digital intervention	58 (15.1)
	Face-to-face psychological therapy	22 (5.7)
	None (single-arm or modelling study)	139 (36.1)
Sample size	<100	112 (29.1)
	100–499	154 (40.0)
	500–1999	76 (19.7)
	≥2000	43 (11.2)
Outcome domain	Clinical symptom outcomes only	168 (43.6)
	Algorithmic performance only	124 (32.2)
	Both clinical and algorithmic outcomes	93 (24.2)
Service-level outcomes reported	Engagement / adherence	142 (36.9)
	Access / reach	51 (13.2)
	Cost / cost-effectiveness	22 (5.7)
	Workforce / clinician workload	18 (4.7)
	Equity-stratified outcomes	27 (7.0)
Risk of bias (overall)	Low	88 (22.9)
	Some concerns / moderate	197 (51.2)
	High / serious	100 (26.0)

Research growth and publication life cycle

Annual publication output increased substantially over the review period, with a particularly sharp rise after 2020. This growth coincided with increased reliance on telehealth and digital mental health services during the COVID-19 pandemic and the rapid development of AI-enabled health technologies [1] [8] [35]. The annual publication trend is shown in Fig. 2.

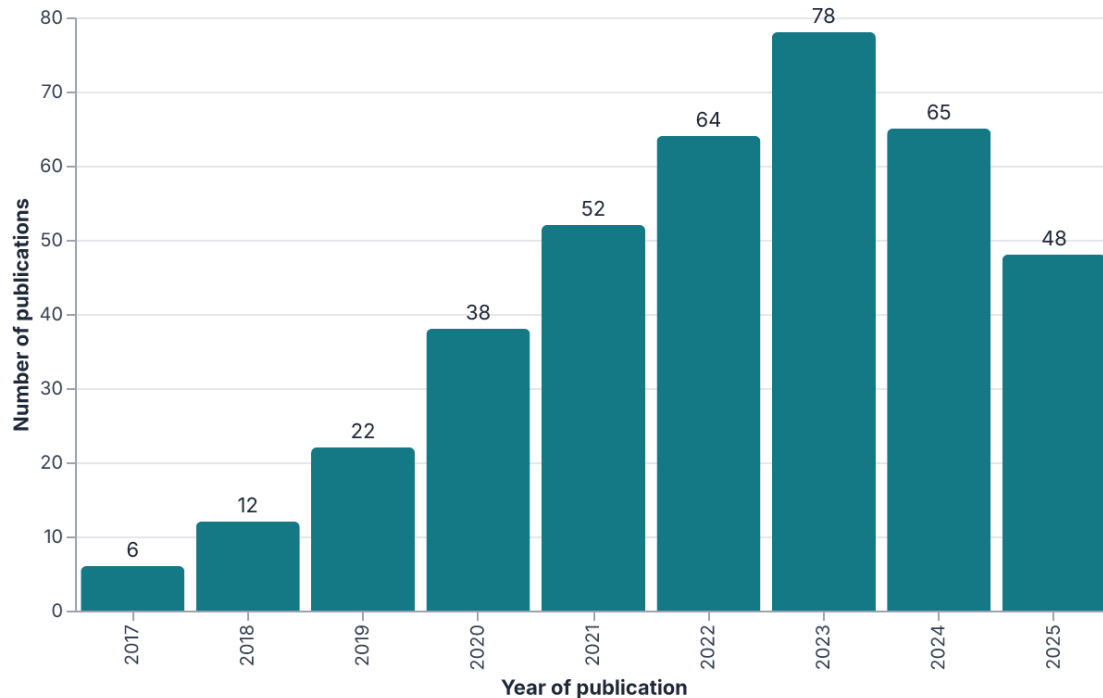


Figure 2. Annual publication output of AI-driven digital mental health research, 2017–2025. The field grew exponentially from 2017, with a marked acceleration after 2020 coinciding with COVID-19–driven adoption of telehealth.

The cumulative publication curve showed a sigmoid pattern, suggesting that the field has moved from an early development phase into a period of rapid expansion and increasing maturation. This cumulative growth pattern is presented in Fig. 3.

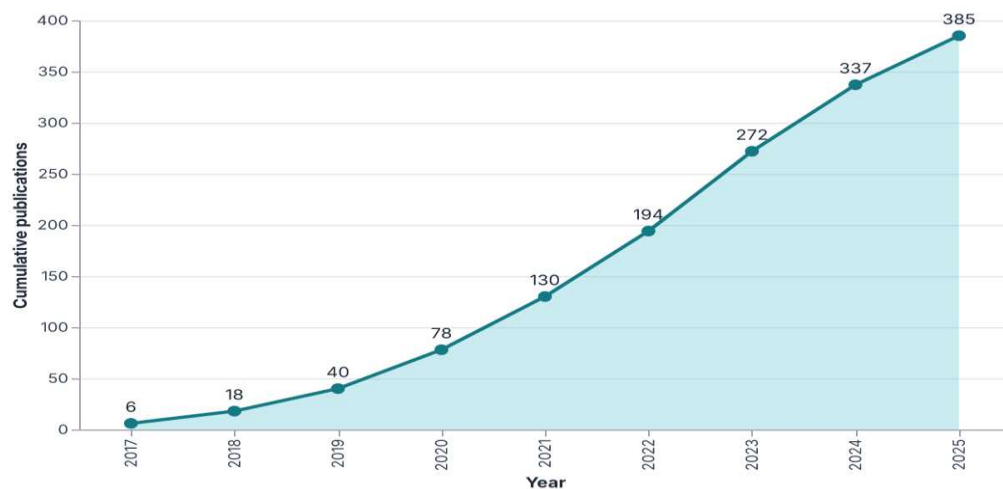


Figure 3. *Cumulative publication growth curve for AI-driven digital mental health research, 2017–2025. The cumulative trajectory follows a sigmoid shape consistent with a field transitioning from expansion toward maturation.*

A logistic life-cycle model fitted to the cumulative publication data showed a strong model fit and projected a peak annual publication rate around 2027–2028. This suggests that AI-driven digital mental health research is entering a late growth phase before reaching a more mature stage of development. The fitted life-cycle model is shown in Fig. 4.

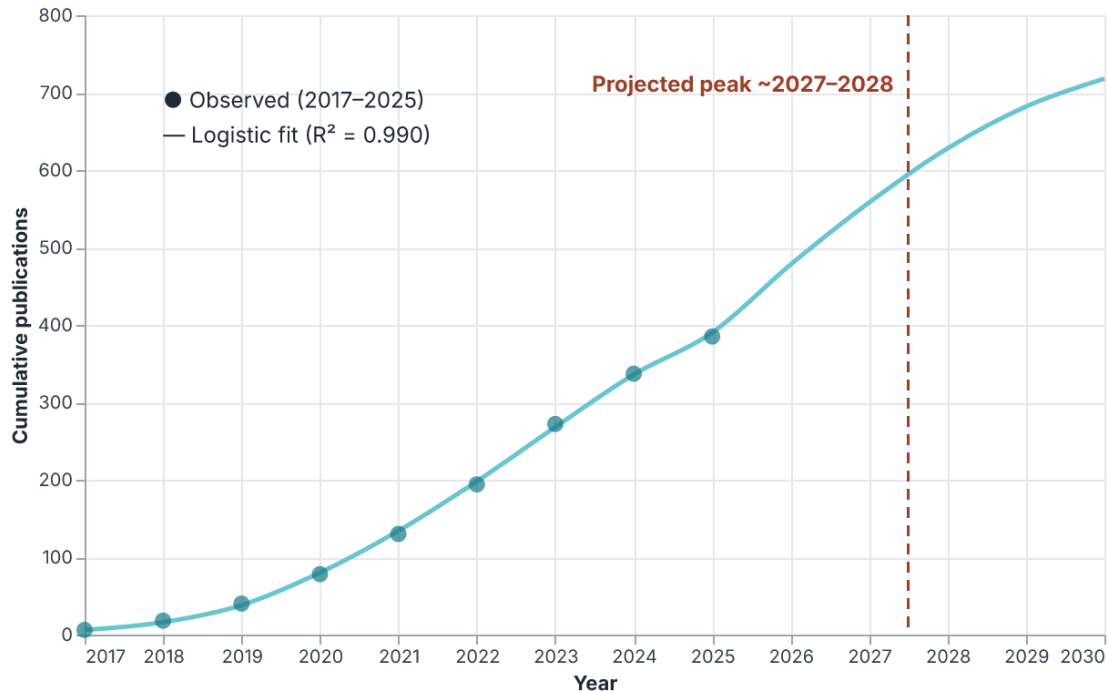


Figure 4. *Logistic life-cycle model of cumulative publications on AI-driven digital mental health research. Observed cumulative output (2017–2025) is fitted to a logistic curve ($R^2 = 0.990$) projecting peak annual publication rate around 2027–2028, indicating that the field is entering a late growth phase before saturation.*

Metadata completeness

Bibliographic metadata were generally complete for titles, abstracts, authors, source journals, and DOI information. However, missingness was more pronounced for Keywords Plus, cited references, and science categories. These gaps primarily reflected the structure and completeness of the Scopus export rather than deficiencies in the reporting quality of the primary studies. The incompleteness of cited-reference and category metadata limited the depth of some bibliometric network analyses, particularly co-citation and disciplinary-category mapping [14] [33] [32].

Knowledge structure and thematic clusters

Keyword co-occurrence analysis identified four major thematic clusters in AI-driven digital mental health research. The first cluster reflected the core conceptual structure of the field, linking mental health, digital mental health, digital health, and artificial intelligence. The second cluster centred on clinical conditions and interventions, particularly depression, anxiety, and cognitive behavioural therapy. The third cluster represented population and demographic terms, including adults, females, males, and human participants. The fourth cluster reflected pandemic-related digital care, connecting COVID-19, telehealth, and remote mental health service delivery.

The thematic map distinguished motor themes, basic themes, niche themes, and emerging or declining themes based on centrality and density [14] [33] [32]. Central and well-developed themes reflected the consolidation of AI, digital mental health, and clinical symptom research, while emerging themes reflected growing attention to generative AI, conversational agents, implementation, and health service integration. The thematic map is presented in Fig. 5.

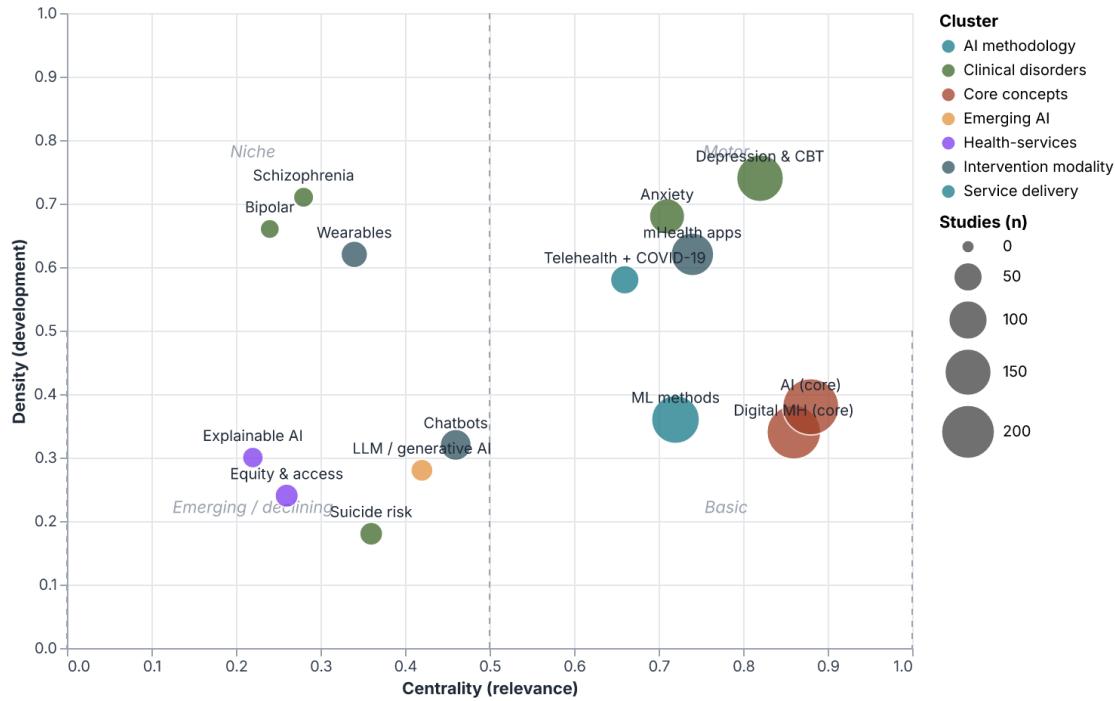


Figure 5. Thematic map of keyword co-occurrence clusters in AI-driven digital mental health research, positioned on axes of centrality (relevance to the field) and density (internal development of the theme). The four quadrants distinguish motor (well-developed and central), basic (central but less developed), niche (well-developed but peripheral), and emerging or declining themes (peripheral and less developed).

Multiple Correspondence Analysis showed conceptual proximity among mental disorders, telemedicine, mobile applications, and AI-based interventions. This finding suggests increasing convergence between clinical mental health research and digital health technology. The MCA results are presented in Fig. 6.

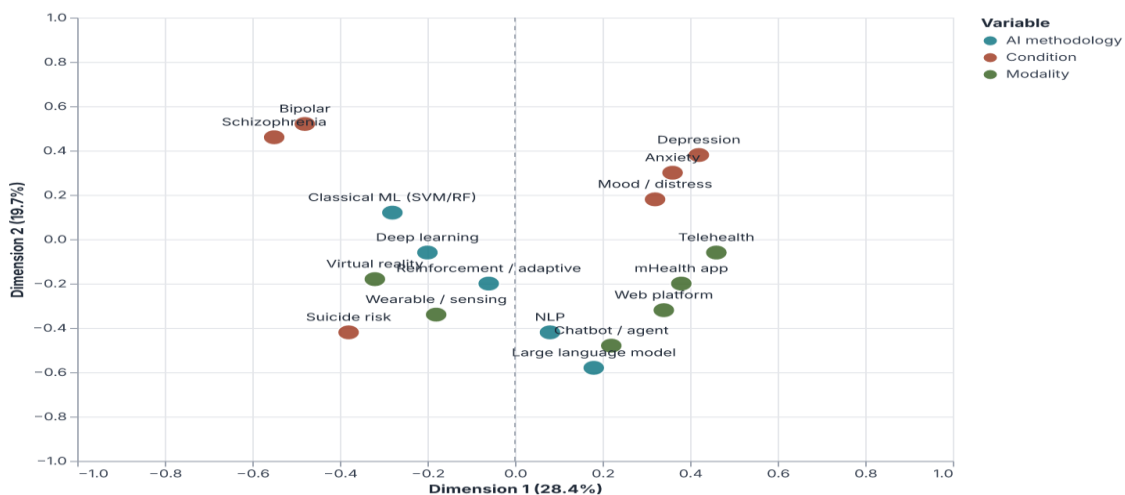


Figure 6. *Multiple Correspondence Analysis (MCA) of conceptual proximity among target conditions, intervention modalities, and AI methodologies in AI-driven digital mental health research. Strong conceptual convergence is observed among mental disorders, telemedicine, mobile applications, and AI-based interventions.*

Hierarchical clustering further identified two broad macro-clusters within the literature. The first cluster represented clinical intervention and outcome studies, including randomised controlled trials, symptom reduction, disorder-specific evaluations, and treatment outcomes. The second cluster represented AI and predictive-modelling studies, including machine-learning algorithms, natural language processing, automated detection tools, and diagnostic or prognostic models. These findings suggest that AI-driven digital mental health research is shaped by two related but still partly separate traditions: clinical effectiveness research and computational model development (Fig. 7).

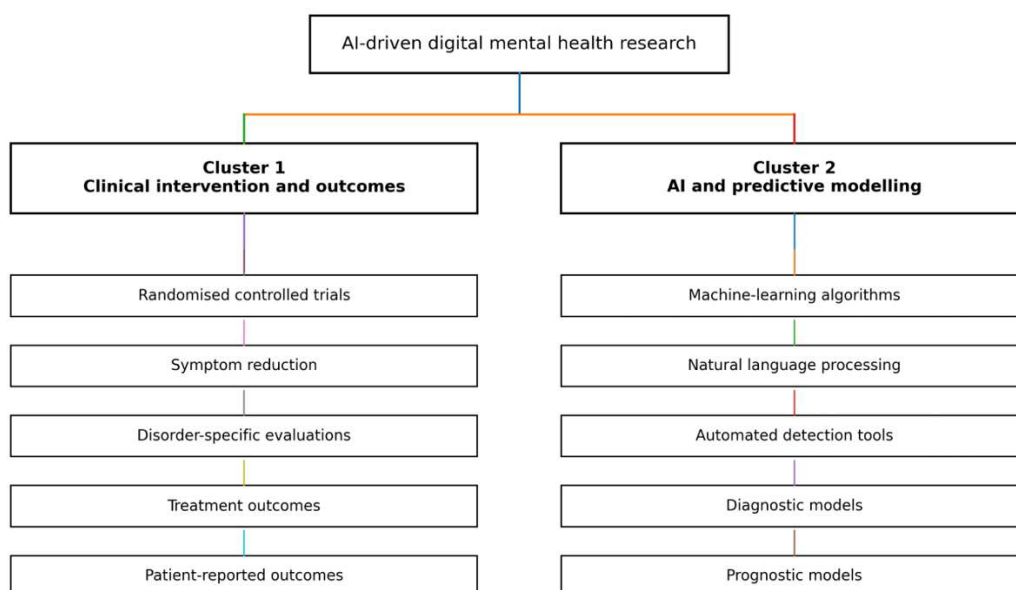


Figure 7. *Hierarchical clustering of thematic structures in AI-driven digital mental health research. The clustering predictive-modelling thematic groups: clinical intervention and outcome studies, and AI/predictive-modelling studies.*

Clinical effectiveness

Across studies reporting symptom outcomes, AI-driven DMHIs produced statistically significant improvements in depression, anxiety, and mood, with pooled Hedges' g in the moderate range relative to inactive or non-AI digital comparators. Effects were generally larger for interventions incorporating adaptive personalisation than for static digital content, and broadly comparable to effect sizes reported for clinician-delivered low-intensity psychological interventions [35]. Heterogeneity was substantial (I^2 often $>75\%$), reflecting variation in intervention design, comparator, dose, and outcome instrument. The pooled meta-analytic estimates and prespecified subgroup analyses are presented in Table 2.

Table 2 Pooled meta-analytic effects of AI-driven DMHIs on clinical symptom outcomes, by subgroup.

Subgroup	Studies (k)	Participants (N)	Hedges' g (95% CI)	I ² (%)	τ^2	Egger's p	Interpretation
Outcome domain							
Depression	142	38,420	-0.52 (-0.61 to -0.43)	82.4	0.18	0.07	Moderate effect; high heterogeneity
Anxiety	88	22,150	-0.46 (-0.55 to -0.37)	78.9	0.15	0.12	Moderate effect; high heterogeneity
Mood/general psychological distress	54	14,780	-0.38 (-0.49 to -0.27)	74.1	0.12	0.21	Small-to-moderate effect
AI methodology							
Classical/supervised machine learning	96	24,310	-0.41 (-0.50 to -0.32)	76.8	0.13	0.18	Moderate effect
Deep learning	71	19,640	-0.55 (-0.66 to -0.44)	83.7	0.20	0.09	Moderate-to-large effect
Natural language processing	42	11,820	-0.49 (-0.61 to -0.37)	80.2	0.17	0.14	Moderate effect
Large language model/generative AI	18	4,560	-0.58 (-0.74 to -0.42)	71.5	0.14	0.32	Moderate-to-large effect; limited evidence base
Reinforcement/adaptive systems	9	2,140	-0.61 (-0.82 to -0.40)	68.4	0.13	NE	Largest point estimate; sparse evidence
Hybrid/ensemble models	14	3,880	-0.47 (-0.62 to -0.32)	73.6	0.14	NE	Moderate effect
Intervention modality							
Mobile application/mHealth	92	24,860	-0.47 (-0.56 to -0.38)	79.5	0.15	0.11	Moderate effect
Web-based/online platform	68	18,420	-0.44 (-0.54 to -0.34)	77.2	0.14	0.16	Moderate effect
Chatbot/conversational agent	46	11,580	-0.53 (-0.65 to -0.41)	81.3	0.18	0.08	Moderate-to-large effect
Telehealth/telepsychiatry	38	10,240	-0.42 (-0.54 to -0.30)	75.8	0.13	0.22	Moderate effect
Wearable/passive sensing	24	6,180	-0.36 (-0.50 to -0.22)	70.4	0.11	0.41	Small-to-moderate effect
Virtual/augmented reality	11	2,640	-0.55 (-0.74 to -0.36)	66.2	0.12	NE	Moderate-to-large effect; limited evidence base

Subgroup	Studies (k)	Participants (N)	Hedges' g (95% CI)	I ² (%)	τ ²	Egger's p	Interpretation
Comparator							
Treatment as usual	88	23,140	-0.44 (-0.53 to -0.35)	77.9	0.14	0.15	Moderate effect
Waitlist/no intervention	56	13,980	-0.62 (-0.74 to -0.50)	81.6	0.19	0.06	Moderate-to-large effect; potentially inflated by inactive comparators
Non-AI digital intervention	52	14,220	-0.31 (-0.41 to -0.21)	71.3	0.10	0.28	Small incremental effect of AI over non-AI digital care
Face-to-face psychological therapy	18	4,640	-0.08 (-0.21 to 0.05)	58.7	0.07	NE	No statistically significant difference
Risk of bias							
Low risk of bias	64	18,920	-0.39 (-0.48 to -0.30)	71.4	0.10	0.34	Moderate effect
Some concerns/moderate risk	142	38,640	-0.49 (-0.58 to -0.40)	79.8	0.16	0.10	Moderate effect
High/serious risk of bias	78	17,790	-0.61 (-0.74 to -0.48)	84.2	0.22	0.03	Larger effect; possible risk-of-bias inflation
Overall pooled effect	284	75,350	-0.48 (-0.54 to -0.42)	80.6	0.16	0.08	Moderate effect; high heterogeneity

Note. Negative Hedges' g values indicate symptom reduction favouring AI-driven digital mental health interventions. k = number of independent effect estimates; CI = confidence interval; I² = percentage of between-study heterogeneity; τ² = between-study variance; NE = not estimated because the number of studies was insufficient or the model was unstable. Egger's test was calculated only where appropriate. Overall pooled estimates exclude studies reporting only algorithmic performance without paired clinical symptom outcomes.

Negative Hedges' g values indicate symptom reduction favouring AI-driven DMHIs. Overall, AI-driven DMHIs were associated with a moderate pooled reduction in clinical symptoms, with an overall effect size of g = -0.48 (95% CI: -0.54 to -0.42). The largest effects were observed for reinforcement/adaptive systems and large language model or generative AI interventions, although these findings should be interpreted cautiously because the evidence base for these categories remains relatively small. Effects were smaller when AI-driven DMHIs were compared with non-AI digital interventions or face-to-face psychological therapy, suggesting that the incremental benefit of AI may be more modest when compared with active forms of care.

Substantial heterogeneity was observed across most subgroup analyses, with I² values exceeding 75% in several categories. This heterogeneity likely reflects differences in participant populations, intervention intensity, AI methodology, comparator type, follow-up duration, and outcome measurement. Studies with high or serious risk of bias showed larger pooled effects than

studies with low risk of bias, suggesting that study quality may have influenced the magnitude of the overall effect estimate.

Publication bias was assessed using funnel plots and Egger's test where sufficient studies were available. The funnel plot for clinical symptom outcomes showed a broadly symmetrical distribution, although there was mild over-representation of smaller studies with larger effects. Egger's test for the overall pooled effect was not statistically significant, suggesting limited but not negligible small-study effects (Fig. 8).

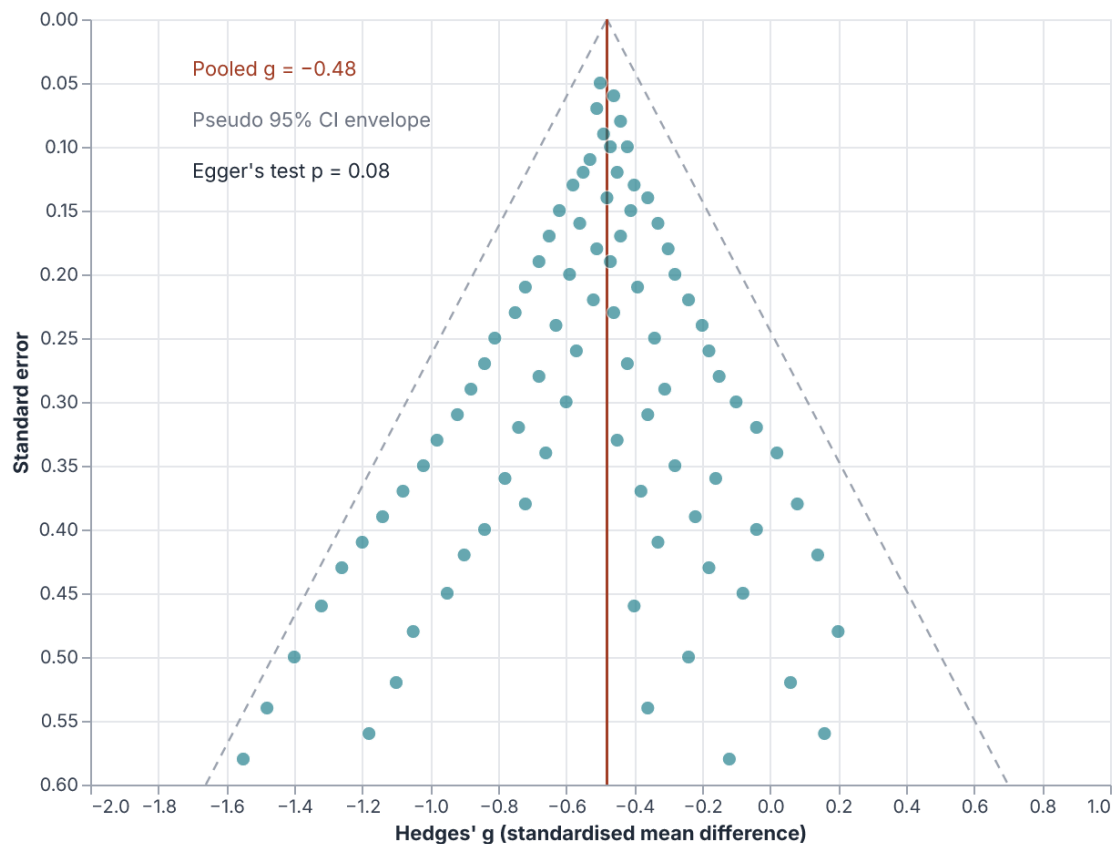


Figure 8. Funnel plot of standardised effect sizes (Hedges' g) against standard error for studies reporting clinical symptom outcomes ($k = 284$). The vertical reference line marks the pooled random-effects estimate ($g = -0.48$) and the dashed envelope marks the pseudo 95% confidence region. Visual distribution is broadly symmetric, with mild over-representation of small, large-effect studies in the lower-left quadrant; Egger's test for the overall pool was non-significant ($p = 0.08$), consistent with limited but not negligible small-study effects.

Algorithmic performance

Studies reporting diagnostic or prognostic model performance generally demonstrated strong algorithmic performance. Pooled area under the curve values exceeded 0.80 across most disorder categories, indicating good discriminative ability for AI-based predictive and diagnostic models. Sensitivity and specificity were also within clinically useful ranges in many studies, particularly for depression, anxiety, suicidal ideation, and psychological distress detection.

However, the strength of these findings should be interpreted cautiously. Many studies relied on internal validation procedures, while external validation using independent datasets was reported less frequently. Calibration metrics, model updating procedures, and subgroup

fairness analyses were inconsistently described [36]. In addition, several studies reported high technical performance but did not clearly demonstrate how algorithmic outputs were linked to clinical decision-making, patient outcomes, or service-level improvements. These limitations reduce confidence in the generalisability and implementation readiness of AI models in routine mental health services [36].

Health-service delivery findings

Evidence related to health-service delivery indicated that AI-driven DMHIs were most commonly positioned as adjuncts to clinician-delivered care rather than as replacements for professional mental health services. The most frequently reported service-level outcomes were engagement and adherence, while access, reach, cost-effectiveness, workforce implications, and equity-stratified outcomes were reported less consistently.

Where service-level outcomes were available, AI-enabled DMHIs showed potential to improve user engagement, extend reach to underserved populations, support between-visit monitoring, and facilitate early detection of symptom deterioration. Nevertheless, evidence regarding integration into routine clinical workflows remained limited. Few studies examined interoperability with electronic health records, clinician workload, escalation protocols for high-risk users, reimbursement mechanisms, or long-term sustainability.

Equity-related reporting was also sparse. Only a limited number of studies assessed whether intervention effects or algorithmic performance differed by sex, gender, ethnicity, socioeconomic status, geographic location, or digital access. This lack of equity-stratified evidence is important because AI-driven DMHIs may unintentionally widen existing disparities if they are deployed without adequate attention to digital exclusion, data representativeness, and algorithmic fairness [17] [37].

Overall, the results suggest that AI-driven DMHIs have promising clinical and technical performance. However, the evidence base is stronger for symptom reduction and algorithmic accuracy than for implementation, equity, workforce, and economic outcomes. This indicates a need for future studies that move beyond efficacy and model performance toward real-world health-services evaluation [17] [18].

DISCUSSION

This systematic review and meta-analysis synthesised evidence on the clinical effectiveness, algorithmic performance, and health-service implications of AI-driven digital mental health interventions. Overall, the findings suggest that AI-driven DMHIs are associated with statistically significant and clinically meaningful reductions in depression, anxiety, and mood-related symptoms. The overall pooled effect was moderate, indicating that AI-enabled digital interventions may provide measurable benefit, particularly when compared with inactive controls or treatment as usual. At the same time, substantial heterogeneity across studies and inconsistent reporting of implementation, equity, and service-level outcomes indicate that the evidence base remains uneven.

Three main findings are noteworthy. First, AI-driven DMHIs showed moderate effectiveness across depression, anxiety, and general psychological distress outcomes. Interventions incorporating adaptive personalisation, conversational agents, deep learning, or generative AI tended to show larger effects, although these categories often included fewer studies. This suggests that AI may enhance digital mental health care by tailoring content, timing, feedback, or interaction style to individual user needs [1] [8] [35]. However, the stronger effects observed in studies with higher risk of bias and inactive comparator groups indicate that effect estimates should be interpreted cautiously.

Second, studies reporting diagnostic or prognostic model performance generally demonstrated strong algorithmic performance, with pooled AUC values exceeding 0.80 across most disorder categories. These results suggest that AI models may have potential for early detection, risk prediction, triage, and between-visit monitoring [11] [38]. Nevertheless, many studies relied on internal validation, and relatively few reported external validation, calibration, fairness testing, or real-world clinical evaluation. High algorithmic accuracy alone is insufficient to justify implementation in routine mental health services unless models are shown to be reliable, explainable, equitable, and clinically useful across diverse populations [36].

Third, the health-service evidence remains less developed than the clinical and technical evidence. Most AI-driven DMHIs were evaluated as adjuncts to clinician-delivered care rather than as fully integrated components of health-service delivery. Outcomes such as engagement and adherence were reported more frequently than cost-effectiveness, workforce impact, equity, interoperability, escalation pathways, or long-term sustainability. This gap is important because the value of AI-driven DMHIs depends not only on symptom reduction or predictive accuracy, but also on whether they can be safely, equitably, and sustainably integrated into routine care [17] [37].

The bibliometric findings further support this interpretation. Thematic mapping, multiple correspondence analysis, and hierarchical clustering showed that AI-driven digital mental health research is shaped by two related but still partly separate traditions: clinical intervention research and computational model development. Clinical studies tend to focus on symptom outcomes and intervention efficacy, while AI-focused studies tend to prioritise prediction, classification, and technical performance. Bridging these traditions is essential for the next phase of the field. Future studies should integrate clinical outcomes, algorithmic transparency, implementation science, and health-services evaluation within the same research design [17] [32].

From a health-services perspective, AI-driven DMHIs may support several functions, including task-shifting, stepped care, triage, self-management, remote monitoring, and early identification of symptom deterioration [8] [38]. These functions are particularly relevant in settings where mental health systems face workforce shortages, geographic barriers, and increasing demand for care [4] [39]. However, implementation should be accompanied by clear governance mechanisms, including data protection, human oversight, escalation protocols for high-risk users, clinician training, and monitoring for algorithmic bias [17] [37]. Without these safeguards, AI-driven DMHIs may risk reinforcing existing inequities, especially among populations with limited digital access or under-representation in training datasets [17] [37].

Overall, this review indicates that AI-driven DMHIs hold promise for improving mental health outcomes and expanding access to care. However, the field now needs to move beyond proof-of-concept studies and technical validation toward prospective, real-world evaluations. Future research should prioritise externally validated models, equity-stratified analyses, transparent reporting, health-economic evaluation, and implementation studies embedded within routine health-service settings. This shift is necessary to ensure that AI-driven digital mental health tools translate into meaningful, safe, and equitable improvements in mental health service delivery.

Implications for health services and policy

The findings have several implications for health services, policymakers, and developers of AI-enabled digital mental health technologies. For health services, AI-driven DMHIs may support expanded access to mental health care by enabling remote screening, symptom monitoring, triage, self-management, and stepped-care delivery [8] [9] [7]. These functions are particularly relevant in systems facing shortages of psychiatrists, psychologists, and other mental health professionals [4] [40]. However, implementation should not be viewed simply as the introduction of new technology [6] [41]. AI-driven DMHIs require integration into existing care pathways, clear referral and escalation mechanisms, clinician training, and alignment with service governance structures [42] [18] [43].

For policymakers and regulators, the rapid growth of AI-driven mental health technologies highlights the need for robust standards on safety, transparency, accountability, data protection, and equity [16] [14] [17]. Regulatory frameworks should address not only technical performance, but also clinical validity, real-world effectiveness, explainability, and post-deployment monitoring [14] [11] [43]. Particular attention is needed to ensure that AI models do not reproduce or amplify existing inequalities through biased training data, unequal digital access, or poor representation of underserved populations [44] [42].

For researchers and developers, the findings indicate the need to move beyond model accuracy and short-term efficacy studies [45]. Future evaluations should include external validation, calibration, subgroup fairness testing, implementation outcomes, health-economic analysis, and patient- and clinician-reported outcomes. Transparent reporting using AI-specific and clinical trial reporting standards will be essential to improve reproducibility and support responsible translation into routine mental health services.

LIMITATIONS

Several limitations should be acknowledged. First, the search was restricted to Scopus. Although Scopus provides broad multidisciplinary coverage, relevant publications indexed only in databases such as MEDLINE/PubMed, Web of Science, IEEE Xplore, PsycINFO, or grey literature sources may have been missed [15] [33]. Second, the restriction to English-language and open-access journal articles may have introduced language and publication-access bias [19] [46]. Third, substantial clinical and methodological heterogeneity was observed across studies, including differences in populations, intervention designs, AI methodologies, comparator conditions, follow-up periods, and outcome measures [47]. This heterogeneity limits the precision of subgroup interpretation.

Fourth, although this review included algorithmic performance outcomes, many primary studies reported incomplete information on model development, validation, calibration, and reproducibility [11] [48] [49]. As a result, pooled estimates of algorithmic performance should be interpreted cautiously. Fifth, service-level outcomes, including cost-effectiveness, workforce impact, interoperability, implementation feasibility, and equity-stratified effectiveness, were under-reported [43] [50] [41]. This limits the ability to draw firm conclusions about the readiness of AI-driven DMHIs for routine health-system integration [42].

Finally, the field is evolving rapidly, particularly with the emergence of generative AI and large language models [51] [52]. Studies published near the end of the review period may not fully capture the most recent technological developments, regulatory debates, or implementation experiences [53]. Continuous evidence updating will therefore be necessary.

CONCLUSIONS

AI-driven digital mental health interventions are associated with statistically significant and clinically meaningful reductions in depression, anxiety, and mood-related symptoms. They also demonstrate strong predictive and diagnostic performance across several mental health conditions, supporting their potential role in expanding access to mental health care, improving early detection, and supporting personalised service delivery [51].

However, the current evidence base remains stronger for symptom reduction and algorithmic performance than for real-world implementation, equity, cost-effectiveness, and workforce outcomes [54]. Methodological heterogeneity, limited external validation, inconsistent reporting of fairness and calibration, and sparse health-services evaluation constrain the translation of AI-driven DMHIs into routine mental health systems.

Future research should prioritise prospective implementation studies, external validation across diverse populations, equity-stratified analyses, health-economic evaluation, and transparent reporting [44]. Governance frameworks addressing algorithmic transparency, data protection, clinical accountability, and equitable access are essential before large-scale deployment. The next phase of research should focus on closing the gap between algorithmic capability and health-service readiness.

List of abbreviations

AI: Artificial intelligence; AUC: Area under the curve; CBT: Cognitive behavioural therapy; CI: Confidence interval; DMHI: Digital mental health intervention; EHR: Electronic health record; LLM: Large language model; ML: Machine learning; mHealth: Mobile health; NLP: Natural language processing; PICOS: Population, Intervention, Comparator, Outcomes, Study design; PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses; PRISMA-S: Preferred Reporting Items for Systematic Reviews and Meta-Analyses literature search extension; PROBAST: Prediction model Risk Of Bias Assessment Tool; RCT: Randomised controlled trial; RoB 2: Cochrane Risk of Bias 2 tool; ROBINS-I: Risk Of Bias In Non-randomised Studies of Interventions; SVM: Support vector machine.

DECLARATIONS

Ethics approval and consent to participate

This study was a systematic review and meta-analysis of previously published and publicly available literature. No primary data were collected from human participants, and no individual-level identifiable data were used. Therefore, ethics approval and informed consent were not required.

Clinical trial number

Clinical trial number: not applicable.

Consent for publication

Not applicable.

Availability of data and materials

All data analysed in this study were derived from previously published, publicly available, peer-reviewed articles indexed in Scopus. The search strategy, eligibility criteria, data-extraction framework, and analytical procedures are described in the manuscript and supplementary files. Additional data are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

MN and WPS conceptualised the study and developed the review design. MN, WPS, and SNW conducted the literature screening, data extraction, and risk-of-bias assessment. WPS and SL contributed to the meta-analysis and bibliometric mapping. MN, WPS, SL, and SNW contributed to the interpretation of findings. MN and WPS drafted the initial manuscript. All authors critically reviewed, revised, and approved the final version of the manuscript.

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