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III. EMERGING TRENDS IN ENTREPRENEURSHIP AND BUSINESS TECHNOLOGIES *https://vilniustech.lt/bm*

BRIEF DIGITAL MENTAL HEALTH INTERVENTIONS FOR ADULTS: USER EXPERIENCE, REAL-WORLD UPTAKE, AI PRIORITIES, AND ECONOMIC IMPLICATIONS

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Abstract. Brief digital mental health interventions (DMHIs) represent a promising strategy for addressing the increasing global demand for accessible psychological support. Despite high usability and satisfaction reported in clinical trials, real-world adoption remains limited. This study examines the drivers of this adoption gap by synthesizing evidence from user experience research, digital health competence studies, and health technology assessment literature. The Article introduces the Pharmaco Economic Digital Twin (PEDT) concept as a framework for integrating clinical, behavioral, and economic data streams into adaptive evaluation models. Results indicate that sustained engagement with digital mental health tools depends on maintaining an equilibrium between therapeutic effectiveness and user experience quality while simultaneously strengthening workforce digital competence and establishing sustainable reimbursement pathways.

Keywords: digital mental health, artificial intelligence, user experience, digital competence, digital twins, health economics.

JEL Classification: I12, O33, L86.

1. Introduction

Mental health disorders represent one of the most significant public health challenges globally. International epidemiological research indicates that nearly one quarter of the adult population experiences symptoms associated with anxiety, depression, or related psychological conditions at some point in their lifetime. Traditional healthcare systems are increasingly strained by rising demand for psychological services, limited numbers of trained professionals, and geographic inequalities in service availability.

In response to these structural pressures, digital mental health interventions (DMHIs) have emerged as scalable tools capable of delivering elements of cognitive behavioral therapy, psychoeducation, and behavioral self-management support through mobile or web-based platforms. Clinical trials often report high usability scores and positive user feedback. However, real-world implementation data reveal a persistent discrepancy between trial performance and long-term user engagement.

This phenomenon, commonly described as the "uptake gap", refers to the difference between the technical usability demonstrated in experimental settings and the significantly lower engagement observed once interventions are deployed in everyday environments.

2. Methods

2.1. Research design

This study employs an interpretative synthesis methodology to examine the adoption gap in digital mental health interventions (DMHIs). Interpretative synthesis is particularly suited for emerging interdisciplinary fields where empirical evidence is dispersed across multiple

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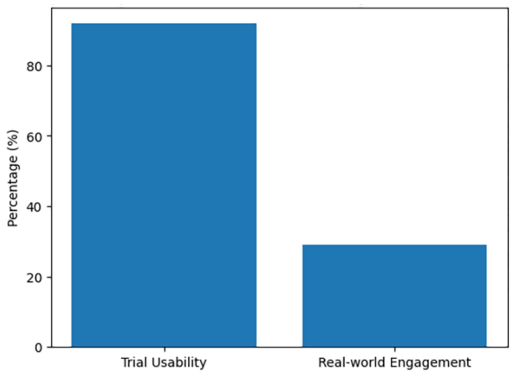


Figure 1. Uptake gap between clinical trial usability and real-word engagement

academic domains and where the goal is theory development rather than aggregative summary (Dixon-Woods et al., 2005). Unlike systematic reviews that seek to combine effect sizes from homogeneous studies, interpretative synthesis enables the integration of diverse evidence types – including quantitative trials, qualitative user studies, economic evaluations, and policy analyses – into coherent conceptual frameworks.

The approach is appropriate for this study for three reasons. First, digital mental health research spans multiple disciplines including clinical psychology, human-computer interaction, health economics, and implementation science, each with distinct methodological traditions and evidence standards. Second, the phenomenon of interest – the gap between clinical trial performance and real-world uptake – requires understanding not only what works but why, how, and under what circumstances. Third, the emerging nature of AI-enabled mental health technologies means that traditional meta-analytic approaches are premature given the heterogeneity of interventions, outcomes, and study designs currently available (Figure 1).

2.2. Research questions

This synthesis was guided by four research questions:

- **RQ1:** What factors contribute to the uptake gap between clinical trial performance and real-world engagement with digital mental health interventions?
- **RQ2:** How does healthcare workforce digital competence influence the adoption and integration of DMHIs into clinical practice?
- **RQ3:** What economic evaluation frameworks are most appropriate for assessing the value of AI-enabled mental health interventions?
- **RQ4:** How can the Pharmaco Economic Digital Twin (PEDT) concept integrate clinical, behavioral, and economic data to support adaptive evaluation of digital health technologies?

2.3. Search strategy and information sources

A systematic literature search was conducted to identify relevant studies across multiple databases, including PubMed, Scopus, Web of Science, PsycINFO, Google Scholar, and EconLit. The search focused on peer-reviewed articles published between 2023 and 2026 to capture the most recent evidence in this rapidly evolving field. Only English-language publications were included.

The search strategy combined keywords related to five core themes: digital mental health interventions (e.g., "DMHI", "e-mental health", "mental health app"), adoption and engagement (e.g., "uptake", "implementation", "real-world"), artificial intelligence (e.g., "AI" , "machine learning", "predictive analytics"), workforce digital competence (e.g., "digital literacy", "healthcare professional training"), and economic evaluation (e.g., "cost-effectiveness", "HTA", "reimbursement", "digital twin"). These terms were combined using Boolean operators and adapted for each database's syntax.

The initial search was conducted in December 2025 and updated in March 2026 to capture recently published articles.

2.4. Inclusion and exclusion criteria

Studies were included if they met the following criteria (Table 1):

Table 1. Criteria, inclusion, exlusion

Criterion	Inclusion	Exclusion
Population	Adults (18+ years) using or delivering DMHIs	Children/adolescents only; non-human studies
Intervention	Digital mental health interventions with technological component	Purely face-to-face interventions; non-mental health digital tools
Outcomes	User experience, engagement, clinical effectivenes, digital competence, economic outcomes	Technical performance only (e.g., algorithm accuracy without implementation context)
Study type	Empirical studies (quantitative, qualitative, mixed methods), systematic reviews, HTA reports	Opinion pieces, editorials, conference abstracts without full text
Context	Healthcare settings or real-world implementation	Laboratory-only studies without implementation focus

2.5. Study selection and screening

The study selection process followed PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021).

Stage 1 – Title and abstract screening: Two reviewers independently screened titles and abstracts of all retrieved records. Disagreements were resolved through discussion or consultation with a third reviewer.

Stage 2 – Full-text review: Full texts of potentially eligible studies were retrieved and assessed against

inclusion criteria. Reasons for exclusion at this stage were documented.

Stage 3 – Forward and backward citation searching: Reference lists of included studies were screened for additional relevant publications (backward citation searching). Web of Science and Google Scholar were used to identify studies citing key included papers (forward citation searching).

Search results: The initial search yielded 847 records. After removing duplicates, 623 records underwent title and abstract screening, with 89 progressing to full-text review. A final set of 47 studies were included in the synthesis.

2.6. Data extraction and synthesis

Data extraction. A standardized data extraction form was developed to capture:

- Bibliographic information (authors, year, journal);
- Study characteristics (design, setting, country, sample);
- Intervention characteristics (type, duration, technological features);
- Key findings related to adoption, user experience, competence, or economics;
- Quality indicators (as relevant to study design).

Synthesis approach: Following interpretative synthesis methodology (Dixon-Woods et al., 2005), the analysis proceeded through three iterative phases:

Phase 1 – Literature mapping: Extracted findings were organized thematically, identifying recurring concepts, theoretical frameworks, and empirical patterns across the included studies. This phase produced preliminary categories including "user experience factors", "competence clusters", "AI integration challenges", and "economic evaluation barriers".

Phase 2 – Cross-sector comparison: Studies were compared across different healthcare systems (e.g., Germany's DiGA pathway, UK's NICE evaluations, emerging economy contexts) to identify how institutional and regulatory factors shape adoption patterns. This comparative lens revealed both context-specific findings and cross-cutting themes.

Phase 3 – Conceptual model development: Through iterative discussion and re-examination of the evidence, individual findings were synthesized into an integrated conceptual framework. This process involved constant comparison between emerging concepts and the source studies to ensure the final model remained grounded in the evidence. The Efficacy Equilibrium model and PEDT framework emerged from this synthesis process (Andrews et al., 2018).

2.7. Quality appraisal

Quality of included studies was assessed using appropriate tools for each study design:

Randomized trials: Cochrane Risk of Bias tool (RoB 2)

Observational studies: ROBINS-I (Risk of Bias in Non-randomized Studies)

Qualitative studies: Critical Appraisal Skills Programme (CASP) Qualitative Checklist

Economic evaluations: Drummond checklist for economic studies

Systematic reviews: AMSTAR 2 (A MeaSurement Tool to Assess systematic Reviews)

Quality appraisal was used to inform interpretation of findings rather than to exclude studies, given the exploratory nature of this synthesis. Studies of lower methodological quality were given less weight in the development of conclusions.

2.8. Limitations of the methodology

This study has several methodological limitations that should be acknowledged. First, as an interpretative synthesis, it does not provide quantitative effect estimates or meta-analytic summary statistics. Second, the rapid evolution of both AI technologies and digital health interventions means that some findings may have limited temporal generalizability; studies published even 12–18 months ago may not reflect current technological capabilities (Antonini et al., 2023). Third, the exclusion of non-English language publications may introduce language bias, potentially missing relevant evidence from non-English speaking healthcare systems. Fourth, the focus on peer-reviewed literature means that valuable implementation insights from grey literature, industry reports, and policy documents may be underrepresented. Finally, the synthesis inevitably reflects the interpretive lens of the authors; while we have attempted to remain faithful to the source studies, alternative interpretations of the evidence are possible.

3. Results

Workforce digital competence

The successful implementation of digital mental health technologies depends not only on technological innovation but also on the competence of healthcare professionals who integrate these tools into clinical workflows (Bennebach et al., 2026). Digital competence refers to the ability to effectively, responsibly, and ethically utilise digital technologies within professional practice (Table 2).

Table 2. Digital competence clusters

Cluster	Share	Profile	Support Need	Supporting Sources
Beginners	5.3%	Minimal use of digital tools	Basic literacy	Mikkonen et al. (2026); Contreras et al. (2025)
Developing Professionals	8.8%	Strong ICT but weak counseling integration	Training	Mikkonen et al. (2026); Sahoo et al. (2025)

End of Table 2

Cluster	Share	Profile	Support Need	Supporting Sources
Emerging Users	14.6%	Balanced but evolving competence	Mentorship	Mikkonen et al. (2026); Geelen et al. (2026)
Proficient Practitioners	42.5%	Routine integration in practice	Peer exchange	Mikkonen et al. (2026); Rixon et al. (2026)
Pioneers	28.9%	Innovation leaders	Advanced design leadership	Mikkonen et al. (2026); Lee et al. (2025)

Artificial intelligence and personalised care

Artificial intelligence technologies are increasingly integrated into digital mental health platforms, offering capabilities that extend far beyond simple content delivery (Cobben et al., 2026). These systems employ natural language processing, predictive analytics, and adaptive recommendation algorithms to create interventions that can respond dynamically to individual user needs, preferences, and clinical presentations.

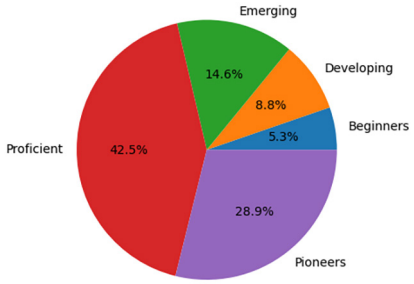


Figure 2. Distribution of digital health competence clusters

AI applications in digital mental health. Natural language processing enables analysis of written interactions between users and digital platforms, detecting linguistic markers associated with depression, anxiety, and suicidal ideation that may escape human observation (Gupta et al., 2025). Large language models can analyze journal entries, chat conversations, or even social media posts to identify emotional patterns and indicators of psychological distress, potentially enabling early intervention before crisis points are reached (Figure 2). Predictive analytics algorithms can identify users at risk of dropout or deterioration, triggering additional support or modified content delivery. Adaptive recommendation systems can personalize intervention content based on user progress, preferences, and engagement patterns, moving beyond one-size-fits-all approaches to truly tailored care (Opie et al., 2026).

The promise of personalisation. The personalisation potential of AI is particularly valuable in mental health, where treatment response varies significantly across individuals. Machine learning algorithms can identify which intervention components are most effective for which user subgroups, enabling dynamic adaptation of treatment pathways (Zhang et al., 2026). Capability aligns with the broader movement toward precision psychiatry, though implementation in digital formats remains nascent (Song et al., 2026).

Ethical challenges and responsible AI frameworks. The integration of artificial intelligence into mental healthcare raises important ethical questions that cannot be overlooked. Sahoo et al. (2025), in their systematic review of health professionals' perspectives on AI, found that clinicians express both optimism about AI's potential to augment clinical capacity and significant concern about transparency, accountability, and the potential erosion of therapeutic relationships.

Transparency and explainability. When AI systems make recommendations or flag concerns, users and clinicians need to understand the basis for these judgments (Haycock et al., 2023). "Black box" algorithms that cannot explain their reasoning are problematic in clinical contexts where decisions have significant consequences.

Bias and fairness. AI systems trained on existing datasets may perpetuate or amplify existing healthcare disparities. If training data underrepresents certain populations, algorithms may perform poorly for those groups, exacerbating rather than reducing inequities in mental healthcare access and outcomes.

Data governance and privacy. Mental health data is among the most sensitive personal information. AI systems that require extensive data collection raise concerns about data security, secondary use, and user control over personal information.

Human oversight and accountability. Artificial intelligence tools were used for language editing, text clarity improvement, and structural refinement of the manuscript. No AI tools were used for data analysis or generation of scientific results (Gomes et al., 2022).

In response to these challenges, responsible AI frameworks emphasize human oversight, algorithmic transparency, and accountability in algorithm-supported decision making (Sahoo et al., 2025; Song et al., 2026). The consensus emerging from the international priority-setting exercise by Song et al. (2026) is that AI governance in global health must balance innovation with protection, ensuring that vulnerable populations are not harmed in the pursuit of technological advancement.

Balancing automation and human connection. A particular concern in mental health is the risk that AI-mediated interventions may diminish the human connection that is central to therapeutic relationships. The challenge for DMHI developers is therefore to deploy AI in ways that augment rather than replace human clinical input, using automation to extend reach while preserving opportunities for meaningful human connection when needed (Opie et al., 2026).

4. The Efficacy Equilibrium model

The concept of Efficacy Equilibrium introduced in this study describes the balance between therapeutic effectiveness and user experience quality. Digital interventions that are clinically effective but difficult to use may experience high dropout rates, while highly engaging applications that lack clinical value may fail to produce meaningful health outcomes (Figure 3).

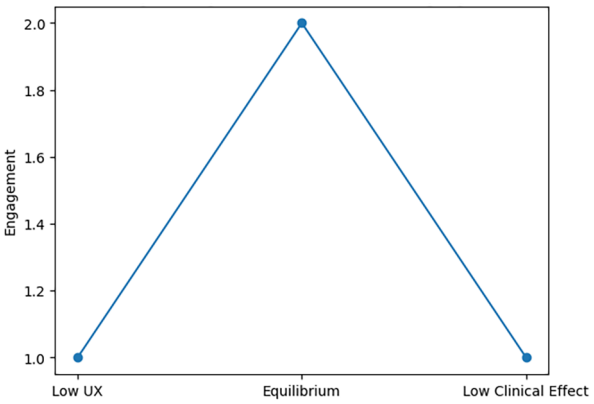


Figure 3. Conceptual representation of the Efficacy Equilibrium model

Economic sustainability and digital twins

Economic sustainability remains one of the major barriers to large-scale deployment of digital health technologies. Traditional health technology assessment (HTA) frameworks, designed for pharmaceutical interventions and medical devices with stable efficacy profiles, struggle to accommodate the dynamic, continuously evolving nature of digital health platforms. Voets et al. (2026) identify several methodological challenges in economic evaluations of AI-based health technologies. These challenges are particularly acute for digital mental health interventions, where outcomes depend on complex interactions between technological features, user behavior, and clinical support (Konttila et al., 2019).

Traditional cost-effectiveness models rely on population-level data and static economic assumptions derived from randomized controlled trials conducted at a single point in time. The fundamental mismatch between static evaluation frameworks and dynamic digital interventions creates a paradox: by the time a traditional HTA concludes, the technology being evaluated may already be obsolete (Gehder & Goeldner, 2025).

The Pharmaco Economic Digital Twin (PEDT) concept. In response to these limitations, the Pharmaco Economic Digital Twin (PEDT) framework has emerged as a conceptual model for integrating clinical data, behavioral indicators, and economic metrics within a dynamic simulation environment (Belančić & Janković, 2026). Drawing on digital twin technology originally developed in engineering, the PEDT approach creates virtual representations of patients, interventions, and healthcare systems that can be continuously updated with real-world data. Unlike static cost-effectiveness models that assume fixed efficacy parameters, PEDT models enable adaptive evaluation, personalized treatment optimization, and iterative refinement as new evidence accumulates.

The PEDT framework offers several potential advantages for digital mental health interventions. First, it can incorporate real-time engagement data from DMHI platforms, allowing researchers to observe not only whether an intervention works but under what conditions and for which users. Second, it enables modeling of long-term outcomes by simulating treatment trajectories beyond the duration of clinical trials. Third, it facilitates value-based reimbursement models where payment is tied to demonstrated real-world effectiveness rather than assumed efficacy (Neubert et al., 2026; Opie et al., 2026).

Early implementation examples. Germany's DiGA (Digitale Gesundheitsanwendungen) pathway represents an early attempt to create a regulatory framework that accommodates the dynamic nature of digital health technologies (Gehder & Goeldner, 2025). Under this model, manufacturers receive provisional reimbursement while gathering real-world evidence, with continued coverage contingent on demonstrated effectiveness. This approach aligns with the PEDT philosophy of iterative evaluation, though it currently lacks the sophisticated simulation capabilities that full digital twin implementation would enable.

Challenges and limitations. Despite its promise, the PEDT framework faces substantial implementation challenges (Riley et al., 2023). Data integration across heterogeneous sources remains technically demanding. Privacy concerns arise when aggregating clinical, behavioral, and economic data at the individual level (Kryzhanivska et al., 2026). Validation of simulation models against real-world outcomes requires extensive testing. Regulatory acceptance of dynamic evaluation frameworks is uncertain, as most HTA bodies remain accustomed to static evidence packages. Finally, the methodological infrastructure for PEDT implementation –including standardised data formats, interoperable platforms, and validated simulation algorithms –remains underdeveloped (Voets et al., 2026).

5. Discussion

This study synthesized evidence across user experience research, digital competence studies, and health technology assessment literature to examine the adoption gap in digital mental health interventions. Four key findings emerge with implications for research, practice, and policy.

Integrating the findings. The results demonstrate that the adoption gap is not attributable to any single factor but emerges from the interaction of technological design, workforce readiness, and economic governance (Reddy et al., 2020). The Efficacy Equilibrium model suggests that interventions achieving optimal balance between clinical effectiveness and user experience are

necessary but not sufficient for sustained real-world engagement. Even well-designed tools fail to achieve population-level impact when healthcare professionals lack the digital competence to recommend and integrate them (Mikkonen et al., 2026), when reimbursement pathways remain uncertain (Gehder & Goeldner, 2025), or when economic evaluation frameworks cannot capture their dynamic value (Voets et al., 2026).

Addressing the research questions. Returning to the four research questions guiding this synthesis: First, factors contributing to the uptake gap include usability barriers, lack of clinical integration, insufficient workforce training, and misaligned economic incentives. Second, healthcare professional competence is a critical determinant, with the five-cluster taxonomy (Mikkonen et al., 2026) providing a roadmap for targeted interventions. Third, appropriate economic evaluation frameworks must move beyond static HTA models toward adaptive approaches such as the PEDT concept. Fourth, integrating clinical, behavioral, and economic data through digital twin methodologies offers promise but requires substantial methodological development before implementation.

Implications for stakeholders. These findings have distinct implications for different groups. For **policymakers**, developing regulatory frameworks that enable iterative evidence generation while maintaining patient safety standards should be prioritized, as exemplified by Germany's DiGA pathway (Gehder & Goeldner, 2025). For **technology developers**, the challenge is designing interventions that maintain therapeutic fidelity while optimizing for user engagement, potentially leveraging AI for personalization while preserving human oversight (Sahoo et al., 2025; Song et al., 2026). For **healthcare educators**, the cluster analysis provides a basis for tailored training programs addressing each competence level. For **health economists**, the PEDT framework offers a direction for dynamic evaluation models capable of accommodating the unique characteristics of digital health technologies.

Comparison with existing frameworks. The Efficacy Equilibrium model complements but extends existing technology acceptance frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) by explicitly incorporating the therapeutic-effectiveness dimension alongside user experience. Similarly, the PEDT concept builds on but advances traditional cost-effectiveness analysis by enabling real-time data integration and adaptive modeling, addressing limitations identified by Voets et al. (2026).

Limitations. This study has several limitations. As an interpretative synthesis, it does not provide quantitative effect estimates. The rapid evolution of AI technologies means that some findings may have limited temporal generalizability. The exclusion of non-English publications may introduce language bias. The focus on peer-reviewed literature means implementation insights from grey literature may be underrepresented. Finally, the synthesis reflects the authors' interpretive lens; alternative interpretations are possible.

Future research directions. Empirical validation of the Efficacy Equilibrium model requires longitudinal studies tracking both engagement patterns and clinical outcomes across diverse interventions. The PEDT framework needs operationalization through prototype development and testing in real-world settings. Cross-national comparative research could identify how different regulatory contexts influence adoption patterns (Seleiro et al., 2025). The research is needed on effective training interventions tailored to each digital competence cluster, moving from descriptive analysis to prescriptive guidance.

6. Conclusions

This study examined the gap between clinical trial performance and real-world adoption of digital mental health interventions (DMHIs), synthesizing evidence across user experience research, digital competence studies, and health technology assessment literature. Three main findings emerge from this synthesis.

First, the uptake gap is a systemic phenomenon requiring coordinated intervention across technological design, workforce development, and economic governance. The Efficacy Equilibrium model introduced in this study provides a framework for understanding the balance between clinical effectiveness and user experience that sustains long-term engagement.

Second, healthcare professional competence is a critical determinant of DMHI adoption. The cluster analysis by Mikkonen et al. (2026) demonstrates that workforce digital competence varies significantly across five profiles, requiring differentiated training strategies rather than one-size-fits-all approaches. Without healthcare professionals capable of integrating digital tools into practice, even well-designed interventions achieve limited reach.

Third, economic evaluation frameworks must evolve to accommodate the unique characteristics of AI-enabled digital health technologies. Traditional HTA models, designed for static interventions, cannot capture the dynamic nature of continuously improving platforms. The Pharmaco Economic Digital Twin (PEDT) concept (Belančić & Janković, 2026) offers a promising direction for adaptive evaluation, though significant methodological work remains before implementation.

Theoretical contributions. The study introduces the Efficacy Equilibrium model and extends the digital twin concept to economic evaluation through the PEDT framework.

Practical implications. Healthcare systems should invest in workforce development alongside technology procurement. Training programs should target specific competence clusters, and reimbursement frameworks should enable iterative evidence generation.

Future research. Empirical validation of the Efficacy Equilibrium model, operationalization of the PEDT

framework, and cross-national comparative research on regulatory contexts are needed.

In conclusion, digital mental health interventions hold genuine promise for expanding access to psychological support, but realizing this potential requires moving beyond technological innovation toward integrated approaches that address workforce readiness and sustainable economic models.

AI declaration

Artificial intelligence tools (*Sonet 4.6*) were used for language editing, text clarity improvement, and structural refinement of the manuscript. No AI tools were used for data analysis or generation of scientific results.

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