International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

Operating Publisher
SciFormat Publishing Inc.
ISNI: 0000 0005 1449 8214

2734 17 Avenue SW,
Calgary, Alberta, T3E0A7,
Canada
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ARTICLE TITLE	MOBILE HEALTH APPLICATIONS FOR MEDICATION ADHERENCE IN CHRONIC DISEASE MANAGEMENT: A REVIEW OF EFFECTIVENESS, BEHAVIOURAL MECHANISMS, AND SOCIOECONOMIC BARRIERS
DOI	https://doi.org/10.31435/ijitss.3(51).2026.6023
RECEIVED	20 April 2026
ACCEPTED	29 June 2026
PUBLISHED	06 July 2026
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MOBILE HEALTH APPLICATIONS FOR MEDICATION ADHERENCE IN CHRONIC DISEASE MANAGEMENT: A REVIEW OF EFFECTIVENESS, BEHAVIOURAL MECHANISMS, AND SOCIOECONOMIC BARRIERS

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ABSTRACT

Medication non-adherence is a major challenge in modern healthcare, with approximately half of patients with chronic conditions failing to take medications as prescribed and global economic costs exceeding US$100 billion annually in the United States alone. Mobile health (mHealth) applications, of which over 97,000 are currently available on commercial platforms, offer a scalable approach to supporting adherence behaviours. This narrative review synthesises evidence published between 2018 and 2025 on the effectiveness of mHealth applications in chronic disease management, the behavioural mechanisms underpinning observed effects, and the socioeconomic barriers shaping equitable access, with particular attention to the European context. Peer-reviewed literature was identified through structured searches of MEDLINE, Scopus, and the Cochrane Library. Recent meta-analyses demonstrate consistent, moderate improvements in adherence, with pooled mean differences of 0.57 on the 8-item Morisky Medication Adherence Scale (95% CI 0.33–0.80) and absolute improvements of 15–20% on percentage-based measures across hypertension, type 2 diabetes, HIV, cardiovascular disease, and other chronic conditions. Effectiveness is mediated by reminder mechanisms, self-monitoring, social-support features, gamification, and educational content informed by behaviour change theory. However, populations with the highest baseline non-adherence — older adults, individuals with low health literacy, those of lower socioeconomic status, and patients in low- and middle-income countries — remain underserved by current applications, reflecting a persistent digital health equity gap. Within the European Union, the German Digital Health Applications framework and the forthcoming European Health Data Space provide important precedents for statutory reimbursement and interoperable digital health infrastructure.

KEYWORDS

mHealth; Medication Adherence; Chronic Disease; Behaviour Change; Digital Health Equity; European Health Data Space

CITATION

Natalia Zienkiewicz, Jarosław Rachoń, Adela Dzwonkowska, Jakub Dzwonkowski, Alicja Kozłowska, Daria Trocka, Karolina Przybysz, Luiza Stadnik, Natalia Woroniecka, Nicol Szerenos. (2026) Mobile Health Applications for Medication Adherence in Chronic Disease Management: a Review of Effectiveness, Behavioural Mechanisms, and Socioeconomic Barriers. *International Journal of Innovative Technologies in Social Science*. 3(51). doi: 10.31435/ijitss.3(51).2026.6023

1. Introduction

Chronic non-communicable diseases now constitute the dominant burden on healthcare systems worldwide (World Health Organization, 2023). Most chronic diseases require sustained pharmacological therapy across years or decades, making medication adherence a pivotal determinant of clinical outcome and healthcare cost. The World Health Organization defines adherence as the extent to which a person's behaviour corresponds with agreed recommendations from a healthcare provider (Sabaté, 2003). Empirical evidence has consistently demonstrated that only approximately 50% of patients with chronic conditions in high-income countries take their medications as prescribed (Sabaté, 2003; Osterberg & Blaschke, 2005).

The downstream consequences of non-adherence are substantial. In the United States, suboptimal adherence is implicated in 33–69% of all medication-related hospitalisations and contributes to an estimated US$100 billion in avoidable annual healthcare costs (Cutler et al., 2018; Osterberg & Blaschke, 2005). Comparable estimates from European Union member states suggest that non-adherence accounts for approximately €125 billion in excess healthcare expenditure annually and contributes to nearly 200,000 preventable deaths (OECD, 2018). Poor adherence to antihypertensive therapy is associated with substantially increased risks of stroke and cardiovascular mortality (Kim et al., 2016).

Traditional adherence interventions — motivational interviewing, pharmacist-led medication therapy management, and structured patient education — have demonstrated modest efficacy but are resource-intensive and difficult to scale to population level. The global expansion of smartphone ownership, now exceeding 6.8 billion devices worldwide (GSMA, 2024), has transformed the landscape of possible interventions. Mobile health (mHealth) applications offer a uniquely scalable platform, delivering personalised, real-time prompts directly to patients at marginal cost per user. Current estimates place the number of available health applications on commercial platforms at over 97,000, with medication management representing one of the largest categories (Aitken et al., 2017).

Despite this proliferation, important questions persist regarding the actual effectiveness of mHealth applications, the design features that drive outcomes, and the equity implications of digital-first approaches to chronic disease management. This narrative review pursues three interrelated objectives: first, to synthesise contemporary evidence (2018–2025) on the effectiveness of mHealth applications in improving medication adherence; second, to examine the behavioural and design mechanisms that mediate intervention effects; and third, to critically appraise the socioeconomic and policy barriers shaping equitable access, with particular reference to the European Union regulatory landscape, including the German Digital Health Applications (DiGA) framework and the European Health Data Space initiative.

2. Methodology

This narrative review synthesises evidence on mobile health applications for medication adherence in chronic disease management published between January 2018 and June 2025. Peer-reviewed literature was identified through structured searches of three principal bibliographic databases — MEDLINE (via Ovid), Scopus, and the Cochrane Library — using combinations of the search terms “mobile health”, “mHealth”, “smartphone application”, “medication adherence”, “chronic disease”, “hypertension”, “diabetes”, “HIV”, and “behaviour change”. Search results were supplemented by hand-searching the reference lists of recently published systematic reviews and meta-analyses, and by targeted searches for European Union regulatory and policy documents.

Sources were selected by the authors on the basis of methodological quality, recency, and contribution to the analytical themes of the review. Priority was given to systematic reviews, meta-analyses, and randomised controlled trials. As a narrative — rather than systematic — review, this article does not employ the formal PRISMA methodology of comprehensive search documentation, dual independent screening, and quantitative pooled estimation; the selection of evidence consequently reflects authorial judgement. Inclusion was restricted to English-language sources, with the implications of this restriction acknowledged in the Limitations section.

3. Theoretical Framework: Behaviour Change Models in mHealth

Effective mHealth applications are increasingly recognised not as mere technological artefacts but as structured behaviour change interventions whose design is grounded in established theoretical frameworks. Four theoretical perspectives have particular relevance to medication-adherence applications.

The **Health Belief Model (HBM)** proposes that health-related behaviour is determined by perceived susceptibility to a health threat, perceived severity, perceived benefits and barriers, and cues to action (Rosenstock, 1974). Within mHealth applications, educational content addresses susceptibility and severity, while reminder notifications function as cues to action. HBM-informed apps have demonstrated particular effectiveness in conditions where perceived asymptomatic risk — hypertension, hyperlipidaemia — is a key adherence barrier (Al-Arkee et al., 2021).

Self-Determination Theory (SDT) distinguishes autonomous motivation, in which individuals engage in behaviours aligned with their values, from controlled motivation driven by external pressures or rewards (Deci & Ryan, 2000). Sustained behaviour change is more reliably produced by autonomous motivation. mHealth applications that support the three basic psychological needs — autonomy (meaningful choices), competence (achievable goals and feedback), and relatedness (social and peer support) — are theoretically better positioned to produce durable adherence improvements than purely cue-based designs.

The **COM-B Model and Behaviour Change Wheel** conceptualise behaviour (B) as the product of Capability (C), Opportunity (O), and Motivation (M), with the Behaviour Change Wheel mapping specific intervention functions onto these components (Michie et al., 2011). COM-B has become the most widely adopted framework in mHealth intervention design over the past decade. Medication-adherence apps typically address capability through education and reminders, opportunity through always-available access and care integration, and motivation through goal-setting and progress visualisation.

The **Fogg Behaviour Model** posits that behaviour occurs when three elements converge simultaneously: motivation, ability, and a prompt (Fogg, 2009). The model has been particularly influential in the design of habit-forming technology and explains why context-aware reminders outperform context-blind notifications. **Nudge Theory**, drawing on behavioural economics, suggests that small changes in choice architecture — defaults, framing, and salience — can produce substantial behavioural effects without restricting freedom (Thaler & Sunstein, 2008). Digital nudges in medication adherence include automatically-set reminder defaults, positive streak framing, and visual salience of missed doses.

These frameworks are not mutually exclusive; high-quality mHealth interventions typically integrate elements from several. A persistent critique of the broader mHealth literature, however, is that many commercially-available applications are designed without reference to behaviour-change theory and consequently achieve disappointing outcomes when subjected to rigorous evaluation (Bondaronek et al., 2018).

4. Effectiveness Across Chronic Disease Categories

The evidence base supporting mHealth applications for medication adherence has expanded substantially since 2018, with multiple condition-specific systematic reviews and meta-analyses now available. Effectiveness varies across disease categories, reflecting differences in regimen complexity, patient demographics, and symptom salience.

4.1 Cardiovascular Disease and Hypertension

Hypertension represents the most extensively studied condition in mHealth-adherence research, in part because of its high global prevalence — affecting over 1.28 billion adults worldwide (NCD Risk Factor Collaboration, 2021) — and its strong dependence on chronic pharmacological therapy. A systematic review and meta-analysis by Mikulski et al. (2022) pooled data from twelve randomised controlled trials and demonstrated significant improvements in medication adherence among smartphone-app users compared to usual care, with concomitant reductions in systolic blood pressure. The landmark MedISAFE-BP trial, randomising 412 hypertensive participants to the Medisafe application or usual care, found a 0.4-point improvement on the 8-item Morisky Medication Adherence Scale (MMAS-8) in the intervention arm (Morawski et al., 2018).

For cardiovascular disease more broadly, the meta-analysis by Al-Arkee et al. (2021) synthesised sixteen randomised trials and demonstrated that mHealth applications produced statistically significant improvements in adherence to cardiovascular medications across diverse populations, with effects particularly robust in post-acute coronary syndrome care.

The most recent and methodologically rigorous synthesis is provided by Lanke et al. (2025), which integrated data from fourteen randomised controlled trials across hypertension, atrial fibrillation, coronary heart disease, and other chronic conditions. On the MMAS-8 scale, app-based interventions produced a pooled mean difference of 0.57 (95% CI 0.33–0.80; $p<0.001$) compared to controls, with no statistical heterogeneity ($I^2=0\%$). Percentage-based adherence measures demonstrated absolute improvements of 18.85% (95% CI 2.17–35.53; $p=0.03$). These effect sizes, while moderate in absolute terms, are clinically meaningful in populations where baseline adherence is poor.

4.2 Type 2 Diabetes Mellitus

In type 2 diabetes mellitus, mHealth applications often combine medication-reminder functionality with broader self-management features, including glucose monitoring, dietary tracking, and physical activity logging. The systematic review and meta-analysis by Nkhoma et al. (2021), focused on diabetes self-management education and support (DSMES) applications, demonstrated significant improvements in both medication adherence and glycaemic control, with reductions in haemoglobin A1c of 0.3–0.5 percentage points compared to usual care.

4.3 Human Immunodeficiency Virus

Adherence to antiretroviral therapy in HIV care has historically been one of the most active fields of mHealth research, given the well-established link between consistent adherence and virological suppression. Early text-message-based interventions established the principle that mobile-mediated prompts could improve adherence (Lester et al., 2010); this evidence base has been extended to smartphone applications integrating reminders, education, and peer support. Recent applications targeting men who have sex with men using stimulants have demonstrated improvements in self-reported adherence and reductions in viral load (Horvath et al., 2019).

4.4 Other Chronic Conditions

Smart inhaler devices — Bluetooth-enabled inhalers paired with smartphone applications — represent a hybrid technology of particular promise in asthma and chronic obstructive pulmonary disease, with randomised trials demonstrating improvements in adherence and reductions in exacerbation frequency in paediatric asthma populations (Chan et al., 2015). In chronic dermatological conditions, Svendsen et al. (2018) demonstrated, in a randomised controlled trial, that a smartphone application supporting topical psoriasis treatment significantly improved adherence and reduced symptom severity. For oncology populations, mHealth applications integrating reminders with symptom tracking show emerging promise for oral anticancer therapies, although the evidence base remains less mature. Mental health conditions — including depression and schizophrenia — present distinctive challenges, as symptoms of the underlying condition themselves impair medication-taking behaviour; effects in this domain are smaller and less consistent than in cardiovascular or metabolic conditions (Armitage et al., 2020).

4.5 Synthesis

Across disease categories, mHealth applications produce consistent, moderate improvements in medication adherence, with the largest effect sizes observed in conditions characterised by asymptomatic risk, regimen complexity, or strong external motivation. Effects are smaller and less consistent in conditions where the underlying pathology itself compromises adherence behaviour. The clinical translation of these statistical effects depends critically on patient selection, application design, and integration with broader care pathways.

5. Behavioural Mechanisms and Design Features

The effects observed across disease categories are not produced by mHealth applications as undifferentiated objects, but rather by specific design features that operationalise the theoretical mechanisms outlined in Section 3. A summary of representative applications evaluated in the recent literature, with their target conditions, principal design features, and supporting evidence, is presented in **Table 1**.

5.1 Reminders, Self-Monitoring, and Visualisation

Medication reminders represent the most ubiquitous and best-evidenced feature, present in approximately 86% of applications evaluated in randomised trials (Lanke et al., 2025). However, reminder effectiveness is highly sensitive to design choices. Fixed-time reminders produce notification fatigue, while adaptive reminders that adjust timing based on user response patterns, location, or daily routine demonstrate superior sustained engagement. The framing of reminder messages also matters: positively-framed messages consistently outperform neutral or negatively-framed alternatives.

Allowing users to log medication intake and visualise patterns over time supports both the SDT mechanism of competence and HBM mechanism of internalised feedback. Colour-coded weekly adherence visualisations appear effective in producing “missing-dose aversion” — the salience of missed days motivates corrective behaviour in subsequent periods (Horvath et al., 2019). Integration with patient-facing data export, such as generating reports for clinical appointments, increases the perceived value of the application beyond the reminder function alone.

5.2 Gamification and Social Support

The application of game design elements — points, badges, streaks, leaderboards — has attracted both enthusiasm and criticism. Edwards et al. (2016) documented widespread use of game elements but inconsistent evidence of effectiveness, particularly over extended follow-up periods. From an SDT perspective, heavy gamification may crowd out intrinsic motivation by shifting the locus of reward from internal health values to external arbitrary tokens. Light-touch gamification — streak tracking, milestone acknowledgement — appears beneficial in medication adherence, whereas heavily-gamified competitive designs show weaker and more variable effects.

Approximately one-third of evaluated applications incorporate some form of social-support functionality, ranging from passive (read-only patient communities) to active (peer messaging, designated family-member alerts). The Medisafe “Medfriend” feature exemplifies the latter, granting designated supporters access to missed-dose alerts (Morawski et al., 2018). Social-support features are particularly valuable in older patient populations, where family involvement in medication management is common, and in conditions associated with stigma — HIV, severe mental illness — where anonymous peer support may complement formal care.

5.3 Educational Content and Artificial Intelligence

Many applications incorporate educational content delivered as text, video, or interactive modules, addressing the COM-B mechanism of psychological capability. However, evaluations of content quality have raised concerns: a substantial proportion of applications present material at reading levels exceeding average health literacy in target populations, undermining accessibility for those most in need (Stoyanov et al., 2015).

The integration of machine-learning approaches has accelerated rapidly since 2022. Predictive models now identify users at elevated risk of non-adherence based on response patterns and engagement metrics, triggering escalated interventions before missed doses accumulate (Topol, 2019). While early evidence is promising, robust randomised comparisons of AI-enhanced applications against simpler reminder-only designs remain scarce, and concerns about algorithmic bias — particularly in populations underrepresented in training datasets — have not yet been adequately addressed (Obermeyer et al., 2019).

5.4 Integration with Clinical Care and the Evaluation Gap

The strongest theoretical and empirical case can be made for applications that integrate with clinical care pathways rather than function as standalone consumer products. Integration may take the form of direct data sharing with electronic health records, automatic alerts to clinical teams when adherence drops below thresholds, or shared decision-making interfaces accessed during clinical encounters. The German DiGA framework — discussed further in Section 7 — explicitly privileges applications that demonstrate measurable clinical benefit and integrate with the statutory health insurance system (Federal Institute for Drugs and Medical Devices, 2022).

A persistent challenge in the field is the disconnect between research-evaluated applications and those actually available to consumers in app stores. The Mobile App Rating Scale (MARS) provides a standardised instrument for evaluating application quality (Stoyanov et al., 2015). Independent MARS evaluations of commercially-available medication-adherence applications consistently identify substantial quality variability and a small minority of applications with robust evidentiary backing. Patients selecting applications independently — without clinical recommendation — face a substantial information asymmetry that current consumer-app marketplaces do not address.

Table 1. Representative mobile health applications evaluated for medication adherence in chronic conditions, with their target indications, principal features, and supporting evidence.

Application	Target Condition(s)	Principal Features	Languages	Supporting Evidence
Medisafe	Hypertension; multi-condition use	Customisable reminders; biometric tracking; weekly adherence reports; “Medfriend” peer-support alerts	11+ languages	MedISAFE-BP randomised controlled trial; demonstrated MMAS-8 improvement (Morawski et al., 2018)
MyTherapy	General multi-condition use	Reminders; medication database; symptom and mood tracking; PDF report export; family sharing	30+ languages	Observational and feasibility studies; widely adopted across European markets
ALICE	Multiple chronic conditions in elderly patients	Tablet-optimised interface with large elements; prescription images and audio playback; caregiver communication	Spanish	Randomised trial in elderly Spanish patients with polypharmacy (Mira et al., 2014)
MyKidneyDiet-Phosphate Tracker	Hyperphosphataemia in haemodialysis	Animated educational videos; food database; personalised phosphate binder dose calculator	English, Malay, Mandarin	Multicentre randomised clinical trial (Teong et al., 2022)
APP+	HIV antiretroviral therapy	Daily educational content; interactive storyline scenarios; colour-coded weekly adherence visualisation	English	Pilot randomised trial in men who have sex with men using stimulants (Horvath et al., 2019)
Smart inhaler ecosystems (e.g., Propeller Health)	Asthma; chronic obstructive pulmonary disease	Bluetooth-enabled inhaler with paired application; objective monitoring of inhaler activations	English	Multiple randomised trials in paediatric and adult asthma (Chan et al., 2015)

Notes: MMAS-8 — 8-item Morisky Medication Adherence Scale. The table reflects applications described in the published peer-reviewed literature reviewed for this article; the broader consumer-app marketplace contains tens of thousands of additional applications, the majority of which have not been subjected to formal evaluation.

6. Socioeconomic and Structural Barriers to Equitable Access

While the effectiveness evidence reviewed in Sections 4 and 5 demonstrates the potential of mHealth applications, this potential is not realised uniformly across populations. A growing body of literature documents systematic inequities in access to, uptake of, and benefit from digital health technologies — inequities that risk transforming mHealth from an instrument of health-system reform into a vehicle for the widening of existing disparities.

6.1 The Digital Divide and Age

The most fundamental barrier is differential access to the underlying digital infrastructure. Although global smartphone penetration has reached approximately 86% of the world's population, in high-income European countries smartphone ownership among adults under 65 typically exceeds 95% but falls to 60–70% in adults over 75 — precisely the demographic with the highest burden of chronic disease and medication complexity (Friemel, 2016). The International Telecommunication Union estimates that 2.6 billion people worldwide remained without internet access in 2024, with the gap concentrated in rural areas and low-income households (International Telecommunication Union, 2024).

The intersection of age, chronic disease, and digital fluency produces what has been termed the "grey digital divide" (Friemel, 2016). Wildenbos et al. (2018) identified four principal age-related barrier categories in mHealth use: cognition, motivation, motor function, and physical conditions, including visual and dexterity impairments. Applications designed without explicit attention to these dimensions consistently produce lower adoption and retention in older populations. Notable counter-examples of age-friendly design include the ALICE application for older Spanish patients with multiple chronic conditions (Mira et al., 2014).

6.2 Health Literacy and Linguistic Barriers

Health literacy is a robust predictor of medication adherence, healthcare utilisation, and outcomes (Berkman et al., 2011). Digital health literacy extends this construct to the digital domain. Patients with limited health literacy demonstrate reduced uptake of mHealth applications, lower engagement once enrolled, and smaller adherence benefits when evaluated (Mackert et al., 2016). The educational content embedded in many applications frequently exceeds the reading level of average users.

The dominant language of mHealth application development is English. For multilingual populations — including migrant communities within European countries and indigenous populations in many regions — language barriers represent a substantial obstacle to engagement. Beyond simple translation, cultural appropriateness of content shapes uptake among diverse communities. The MyKidneyDiet-Phosphate Tracker application, developed in Malay, English, and Mandarin for Malaysian dialysis populations, illustrates the value of locally-developed multilingual design (Teong et al., 2022).

6.3 Economic Barriers, Privacy, and Trust

Although many medication-adherence applications are available without direct user charges, the underlying device costs, mobile data charges, and time investment required for engagement represent meaningful economic barriers. Premium application features are increasingly subject to subscription models, creating tiered access. Reimbursement of mHealth applications by statutory health systems remains the exception rather than the rule.

mHealth applications collect substantial volumes of sensitive personal data. Concerns about data privacy, secondary use, and commercial exploitation of personal health information represent meaningful barriers to adoption. In the European Union, the General Data Protection Regulation (GDPR; Polish: Rozporządzenie o Ochronie Danych Osobowych, RODO) establishes a comprehensive legal framework, but compliance among commercial application developers — particularly those headquartered outside the EU — is variable. Trust in application developers, in clinical recommenders, and in the health system itself shapes individual adoption decisions in ways that policy intervention alone cannot fully address.

6.4 The Inverse Care Law in Digital Health

Synthesising these barriers, several authors have observed what amounts to a digital health expression of Hart's classic Inverse Care Law: those most in need of healthcare-supporting interventions are systematically least likely to access and benefit from them (Hart, 1971). In the mHealth context, populations with the highest baseline non-adherence — older adults, those of lower socioeconomic status, those with low health literacy, those in low- and middle-income countries — are precisely those least reached by current applications. Without deliberate intervention to address this pattern, mHealth risks exacerbating rather than ameliorating disparities in chronic disease outcomes (Sieck et al., 2021).

7. Policy and Regulatory Implications

The translation of mHealth research evidence into population-level benefit requires policy and regulatory infrastructure that addresses three interrelated challenges: ensuring quality and safety, financing access, and protecting individual rights.

In the European Union, the Medical Device Regulation (MDR; Regulation (EU) 2017/745), in force since 2021, classifies software applications intended for diagnosis, monitoring, treatment, or alleviation of disease as medical devices, requiring CE marking, conformity assessment, and post-market surveillance (Regulation (EU) 2017/745, 2017). The pace of regulatory adaptation has lagged the pace of technological development, with most consumer-facing medication-adherence applications operating in a regulatory grey zone — not formally classified as medical devices despite making health-related claims.

Germany's Digital Health Applications (Digitale Gesundheitsanwendungen, DiGA) framework, introduced by the Digital Healthcare Act in 2019, represents the most developed pathway for statutory reimbursement of mHealth applications globally (Federal Institute for Drugs and Medical Devices, 2022). Under the DiGA framework, applications meeting specified criteria — including evidence of positive healthcare effect, data protection compliance, and interoperability — can be prescribed by physicians and reimbursed by statutory health insurance. As of 2025, over fifty applications have completed the DiGA evaluation process, covering indications including depression, chronic pain, type 2 diabetes, and cardiovascular disease. The DiGA model has been observed with interest by other European health systems, including those of France, Belgium, and increasingly Poland, where pilot reimbursement programmes for digital therapeutics have begun to emerge.

The European Health Data Space (EHDS) regulation, agreed in 2024 and entering progressive force from 2025, establishes a harmonised framework for both primary use and secondary use of health data across EU member states (European Commission, 2022). The EHDS creates legal mechanisms for cross-border health data exchange, citizen access to their own electronic health records, and standardised data formats — all of which have direct implications for mHealth applications operating across multiple jurisdictions. From a Polish perspective, the EHDS represents a major opportunity for integration of mHealth tools with the national P1 electronic health record platform and the Internetowe Konto Pacjenta (IKP) patient portal.

Notwithstanding the importance of regulatory and reimbursement frameworks, the most direct determinant of equitable mHealth uptake remains the recommendation, support, and integration of applications by healthcare professionals. Integrating mHealth recommendation into routine clinical workflows — through electronic prescribing systems, patient information materials, and continuing medical education — represents an underexploited policy lever.

8. Discussion

This narrative review has examined the contemporary evidence base for mHealth applications in medication adherence across chronic disease, the theoretical and design mechanisms that mediate observed effects, and the socioeconomic and structural barriers shaping equitable access. Three principal themes emerge from the synthesis.

First, the empirical case for mHealth applications as effective tools for medication-adherence support is now well-established but moderate in magnitude. Meta-analytic effect sizes consistently demonstrate statistically significant improvements in adherence across diverse populations (Lanke et al., 2025; Mikulski et al., 2022; Al-Arkee et al., 2021; Nkhoma et al., 2021), but the absolute clinical magnitude — improvements of approximately 15–20% on percentage-based measures, or 0.4–0.6 points on validated scales — is modest compared to the gap between current and ideal adherence in many chronic conditions. mHealth applications should therefore be understood as one component of a multi-modal adherence strategy.

Second, effectiveness is shaped substantially by design choices that operationalise behaviour-change theory in concrete features. Reminder mechanisms vary substantially in effectiveness depending on adaptiveness, framing, and contextual relevance. Self-monitoring with progress visualisation, social-support integration, and educational content tailored to user health literacy each contribute additive effects in well-designed applications. Conversely, applications developed without theoretical grounding show weaker and less consistent effects (Bondaronek et al., 2018).

Third — and most importantly from a social-science perspective — the populations with the greatest baseline non-adherence are systematically least likely to access and benefit from mHealth applications as currently designed. The grey digital divide, low health literacy, linguistic barriers, economic constraints, and reduced trust in digital health interventions concentrate in older adults, lower socioeconomic populations, and patients in low- and middle-income countries. Without deliberate equity-focused design, mHealth applications risk widening rather than narrowing disparities in chronic disease outcomes.

For practising clinicians, the evidence supports cautious recommendation of mHealth applications as adjuncts to standard adherence support, guided by evidence of efficacy in the specific clinical context and tailored to patient digital fluency, language, and accessibility needs. For health-system policymakers, the priority interventions are those that address structural barriers: investment in broadband infrastructure, public funding of digital literacy training, reimbursement frameworks modelled on the German DiGA pathway, and integration with broader e-health infrastructure including the forthcoming European Health Data Space.

Three priority directions for future research emerge from this review. First, more research is needed in underrepresented populations — older adults, lower-income populations, patients in low- and middle-income countries, and ethnic and linguistic minorities. Second, the long-term sustainability of mHealth effects remains poorly characterised; most randomised trials report follow-up periods of three to six months. Third, the integration of artificial intelligence and personalisation features, while increasingly common in commercial applications, has been inadequately evaluated against simpler comparators in rigorous trial designs.

9. Limitations

This review is subject to several limitations. As a narrative rather than systematic review, the synthesis does not employ the formal PRISMA methodology and consequently reflects authorial judgement in source selection. The review is restricted to English-language literature, introducing a language bias that is particularly relevant to a review whose central themes include digital health equity across linguistic communities. The pace of technological change in mHealth means that applications evaluated in randomised trials published two or more years ago may already differ substantially from those currently available to consumers. Finally, the heterogeneity of adherence measurement across primary studies complicates direct comparison of effect sizes across the evidence base. These limitations notwithstanding, the consistency of findings across multiple recent systematic reviews and meta-analyses provides reasonable confidence in the principal conclusions advanced.

10. Conclusions

Mobile health applications have transitioned over the past decade from speculative innovation to an established component of the digital infrastructure supporting chronic disease management. The contemporary evidence base demonstrates consistent, moderate improvements in medication adherence across diverse chronic conditions, mediated by reminder mechanisms, self-monitoring, social-support features, and educational content. These effects, while statistically robust, are clinically modest, and mHealth applications should therefore be understood as one element of a multi-modal approach to adherence support rather than as standalone solutions.

The defining challenge for the field over the coming decade is not technological but social. The populations bearing the greatest burden of chronic disease and non-adherence are systematically underserved by current mHealth applications. Realising the full public health potential of digital adherence interventions requires deliberate, equity-focused design; sustained public investment in digital infrastructure and digital literacy; regulatory frameworks ensuring quality and protecting privacy; and reimbursement pathways modelled on emerging European initiatives such as the German DiGA framework. The forthcoming European Health Data Space provides an important infrastructure layer for integrated, interoperable, citizen-centred digital health across member states, and represents a particularly significant opportunity for Central and Eastern European health systems to integrate digital adherence tools with existing national e-health infrastructure.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflicts of Interest: The authors declare no conflicts of interest.

Use of Generative AI: The authors acknowledge the use of large language model tools to assist with drafting and language refinement. All scientific content, references, interpretations, and conclusions are the responsibility of the authors.

REFERENCES

1. Aitken, M., Clancy, B., & Nass, D. (2017). *The growing value of digital health: Evidence and impact on human health and the healthcare system*. IQVIA Institute for Human Data Science.
2. Al-Arkee, S., Mason, J., Lane, D. A., Fabritz, L., Chua, W., Haque, M. S., & Jalal, Z. (2021). Mobile apps to improve medication adherence in cardiovascular disease: Systematic review and meta-analysis. *Journal of Medical Internet Research, 23*(5), e24190. https://doi.org/10.2196/24190
3. Armitage, L. C., Kassavou, A., & Sutton, S. (2020). Do mobile device apps designed to support medication adherence demonstrate efficacy? A systematic review of randomised controlled trials, with meta-analysis. *BMJ Open, 10*(1), e032045. https://doi.org/10.1136/bmjopen-2019-032045
4. Berkman, N. D., Sheridan, S. L., Donahue, K. E., Halpern, D. J., & Crotty, K. (2011). Low health literacy and health outcomes: An updated systematic review. *Annals of Internal Medicine, 155*(2), 97–107. https://doi.org/10.7326/0003-4819-155-2-201107190-00005
5. Bondaronek, P., Alkhaldi, G., Slee, A., Hamilton, F. L., & Murray, E. (2018). Quality of publicly available physical activity apps: Review and content analysis. *JMIR mHealth and uHealth, 6*(3), e53. https://doi.org/10.2196/mhealth.9069
6. Chan, A. H. Y., Stewart, A. W., Harrison, J., Camargo, C. A., Jr., Black, P. N., & Mitchell, E. A. (2015). The effect of an electronic monitoring device with audiovisual reminder function on adherence to inhaled corticosteroids and school attendance in children with asthma: A randomised controlled trial. *The Lancet Respiratory Medicine, 3*(3), 210–219. https://doi.org/10.1016/S2213-2600(15)00008-9
7. Cutler, R. L., Fernandez-Llimos, F., Frommer, M., Benrimoj, C., & Garcia-Cardenas, V. (2018). Economic impact of medication non-adherence by disease groups: A systematic review. *BMJ Open, 8*(1), e016982. https://doi.org/10.1136/bmjopen-2017-016982
8. Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01
9. Edwards, E. A., Lumsden, J., Rivas, C., Steed, L., Edwards, L. A., Thiyagarajan, A., Sohanpal, R., Caton, H., Griffiths, C. J., Munafò, M. R., Taylor, S., & Walton, R. T. (2016). Gamification for health promotion: Systematic review of behaviour change techniques in smartphone apps. *BMJ Open, 6*(10), e012447. https://doi.org/10.1136/bmjopen-2016-012447
10. European Commission. (2022). *Proposal for a regulation of the European Parliament and of the Council on the European Health Data Space* (COM(2022) 197 final).
11. Federal Institute for Drugs and Medical Devices. (2022). *The fast-track process for digital health applications (DiGA) according to Section 139e SGB V: A guide for manufacturers, service providers and users*. BfArM.
12. Fogg, B. J. (2009). A behavior model for persuasive design. In *Proceedings of the 4th International Conference on Persuasive Technology* (Article 40). ACM. https://doi.org/10.1145/1541948.1541999
13. Friemel, T. N. (2016). The digital divide has grown old: Determinants of a digital divide among seniors. *New Media & Society, 18*(2), 313–331. https://doi.org/10.1177/1461444814538648
14. GSMA. (2024). *The mobile economy 2024*. GSM Association.
15. Hart, J. T. (1971). The inverse care law. *The Lancet, 297*(7696), 405–412. https://doi.org/10.1016/S0140-6736(71)92410-X
16. Horvath, K. J., Lammert, S., MacLehose, R. F., Danh, T., Baker, J. V., & Carrico, A. W. (2019). A pilot study of a mobile app to support HIV antiretroviral therapy adherence among men who have sex with men who use stimulants. *AIDS and Behavior, 23*(11), 3184–3198. https://doi.org/10.1007/s10461-019-02597-3
17. International Telecommunication Union. (2024). *Measuring digital development: Facts and figures 2024*. ITU.
18. Kim, S., Shin, D. W., Yun, J. M., Hwang, Y., Park, S. K., Ko, Y.-J., & Cho, B. (2016). Medication adherence and the risk of cardiovascular mortality and hospitalization among patients with newly prescribed antihypertensive medications. *Hypertension, 67*(3), 506–512. https://doi.org/10.1161/HYPERTENSIONAHA.115.06731
19. Lanke, V., Trimm, K., Habib, B., & Tamblyn, R. (2025). Evaluating the effectiveness of mobile apps on medication adherence for chronic conditions: Systematic review and meta-analysis. *Journal of Medical Internet Research, 27*, e60822. https://doi.org/10.2196/60822
20. Lester, R. T., Ritvo, P., Mills, E. J., Kariri, A., Karanja, S., Chung, M. H., Jack, W., Habyarimana, J., Sadatsafavi, M., Najafzadeh, M., Marra, C. A., Estambale, B., Ngugi, E., Ball, T. B., Thabane, L., Gelmon, L. J., Kimani, J., Ackers, M., & Plummer, F. A. (2010). Effects of a mobile phone short message service on antiretroviral treatment adherence in Kenya (WelTel Kenya1): A randomised trial. *The Lancet, 376*(9755), 1838–1845. https://doi.org/10.1016/S0140-6736(10)61997-6
21. Mackert, M., Mabry-Flynn, A., Champlin, S., Donovan, E. E., & Pounders, K. (2016). Health literacy and health information technology adoption: The potential for a new digital divide. *Journal of Medical Internet Research, 18*(10), e264. https://doi.org/10.2196/jmir.6349

22. Michie, S., van Stralen, M. M., & West, R. (2011). The behaviour change wheel: A new method for characterising and designing behaviour change interventions. *Implementation Science, 6*, Article 42. https://doi.org/10.1186/1748-5908-6-42
23. Mikulski, B. S., Bellei, E. A., Biduski, D., & De Marchi, A. C. B. (2022). Mobile health applications and medication adherence of patients with hypertension: A systematic review and meta-analysis. *American Journal of Preventive Medicine, 62*(4), 626–634. https://doi.org/10.1016/j.amepre.2021.11.003
24. Mira, J. J., Navarro, I., Botella, F., Borrás, F., Nuño-Solinís, R., Orozco, D., Iglesias-Alonso, F., Pérez-Pérez, P., Lorenzo, S., & Toro, N. (2014). A Spanish pillbox app for elderly patients taking multiple medications: Randomized controlled trial. *Journal of Medical Internet Research, 16*(4), e99. https://doi.org/10.2196/jmir.3269
25. Morawski, K., Ghazinouri, R., Krumme, A., Lauffenburger, J. C., Lu, Z., Durfee, E., Oley, L., Lee, J., Mohta, N., Haff, N., Juusola, J. L., & Choudhry, N. K. (2018). Association of a smartphone application with medication adherence and blood pressure control: The MedISAFE-BP randomized clinical trial. *JAMA Internal Medicine, 178*(6), 802–809. https://doi.org/10.1001/jamainternmed.2018.0447
26. NCD Risk Factor Collaboration. (2021). Worldwide trends in hypertension prevalence and progress in treatment and control from 1990 to 2019. *The Lancet, 398*(10304), 957–980. https://doi.org/10.1016/S0140-6736(21)01330-1
27. Nkhoma, D. E., Soko, C. J., Banda, K. J., Greenfield, D., Li, Y.-C. J., & Iqbal, U. (2021). Impact of DSMES app interventions on medication adherence in type 2 diabetes mellitus: Systematic review and meta-analysis. *BMJ Health & Care Informatics, 28*(1), e100291. https://doi.org/10.1136/bmjhci-2020-100291
28. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science, 366*(6464), 447–453. https://doi.org/10.1126/science.aax2342
29. OECD. (2018). *Health at a glance: Europe 2018*. OECD Publishing. https://doi.org/10.1787/health_glance_eur-2018-en
30. Osterberg, L., & Blaschke, T. (2005). Adherence to medication. *New England Journal of Medicine, 353*(5), 487–497. https://doi.org/10.1056/NEJMra050100
31. Regulation (EU) 2017/745 of the European Parliament and of the Council of 5 April 2017 on medical devices. (2017). *Official Journal of the European Union, L 117*, 1–175.
32. Rosenstock, I. M. (1974). Historical origins of the health belief model. *Health Education Monographs, 2*(4), 328–335. https://doi.org/10.1177/109019817400200403
33. Sabaté, E. (2003). *Adherence to long-term therapies: Evidence for action*. World Health Organization.
34. Sieck, C. J., Sheon, A., Ancker, J. S., Castek, J., Callahan, B., & Siefer, A. (2021). Digital inclusion as a social determinant of health. *NPJ Digital Medicine, 4*(1), Article 52. https://doi.org/10.1038/s41746-021-00413-8
35. Stoyanov, S. R., Hides, L., Kavanagh, D. J., Zelenko, O., Tjondronegoro, D., & Mani, M. (2015). Mobile App Rating Scale: A new tool for assessing the quality of health mobile apps. *JMIR mHealth and uHealth, 3*(1), e27. https://doi.org/10.2196/mhealth.3422
36. Svendsen, M. T., Andersen, F., Andersen, K. H., Pottegård, A., Johannessen, H., Möller, S., August, B., Feldman, S. R., & Andersen, K. E. (2018). A smartphone application supporting patients with psoriasis improves adherence to topical treatment: A randomized controlled trial. *British Journal of Dermatology, 179*(5), 1062–1071. https://doi.org/10.1111/bjd.16667
37. Teong, L. F., Khor, B. H., Ng, H. M., Sahathevan, S., Purba, K. R., Narayanan, S. S., Gafor, A. H. A., Goh, B. L., Bee, B. C., Yahya, R., Bavanandan, S., & Karupaiah, T. (2022). Effectiveness of a nutritional mobile application for management of hyperphosphatemia in patients on hemodialysis: A multicenter open-label randomized clinical trial. *Journal of Personalized Medicine, 12*(6), Article 961. https://doi.org/10.3390/jpm12060961
38. Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness*. Yale University Press.
39. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine, 25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7
40. Wildenbos, G. A., Peute, L., & Jaspers, M. (2018). Aging barriers influencing mobile health usability for older adults: A literature-based framework (MOLD-US). *International Journal of Medical Informatics, 114*, 66–75. https://doi.org/10.1016/j.ijmedinf.2018.03.012
41. World Health Organization. (2023). *Noncommunicable diseases: Fact sheet*. https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases