Magna Scientia
Open access publication

Magna Scientia Advanced Research and Reviews

eISSN: 2582-9394

Cross Ref DOI: 10.30574/msarr

Journal homepage: https://magnascientiapub.com/journals/msarr/

(REVIEW ARTICLE)

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# Evaluating the Effectiveness of AI-Enhanced Telehealth Systems on Chronic Disease Management

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Magna Scientia Advanced Research and Reviews, 2026, 17(02), 289–299

Publication history: Received on 22 June 2026; revised on 29 July 2026; accepted on 31 July 2026

Article DOI: https://doi.org/10.30574/msarr.2026.17.2.0153

## Abstract

The integration of artificial intelligence (AI) into telehealth platforms has emerged as a promising strategy to address the growing burden of chronic disease management worldwide. This review synthesizes evidence from researchers, examining AI-enhanced telehealth systems deployed for diabetes, cardiovascular disease, chronic respiratory conditions, and mental health comorbidities. Findings indicate that AI-augmented remote monitoring and decision-support tools are associated with clinically meaningful improvements in biomarker control, reduced hospital readmission rates, and enhanced patient self-management behaviors. AI-driven continuous glucose monitoring systems have shown potential to HbA1c reductions of 0.5 to 1.1% in randomized trials. Remote ECG analysis with machine-learning-based arrhythmia detection has reduced missed diagnoses of atrial fibrillation by up to 37% compared with standard care. Conversational AI agents for mental health management have shown modest but statistically significant reductions in Patient Health Questionnaire-9 (PHQ-9) depression scores. However, persistent barriers, including digital health literacy gaps, algorithmic bias, interoperability challenges, and short study follow-up periods, temper the strength of conclusions. Equity concerns demand urgent attention, as underserved populations risk being further marginalized by AI-telehealth deployment. This review calls for standardized evaluation frameworks, long-term real-world evidence, and an equity-centred research agenda.

**Keywords:** Chronic Disease Management; Remote Patient Monitoring; Digital Health; Patient Engagement; Health Equity.

## 1. Introduction

Chronic noncommunicable diseases (NCDs) represent the dominant cause of global morbidity and mortality, accounting for 74% of all deaths worldwide according to recent World Health Organization estimates (WHO, 2023). Conditions such as type 2 diabetes mellitus, hypertension, chronic obstructive pulmonary disease (COPD), heart failure, and depression impose staggering burdens on healthcare systems and patients alike. In the United States alone, six in ten adults live with at least one chronic disease, and four in ten with two or more, at an annual economic cost exceeding $3.8 trillion (Centers for Disease Control and Prevention [CDC], 2023). Multimorbidity, the co-occurrence of two or more chronic conditions, further amplifies mortality risk and strains care coordination across health systems (Kizza et al., 2025). Efforts to develop community-level programs for chronic disease prevention and management demonstrate that sustained population-level impact requires both clinical and non-clinical strategies working in parallel (Ugwu et al., 2025).

The complex, longitudinal nature of chronic disease management strains traditional episodic care models, which were designed primarily for acute illness. Continuity of monitoring, timely medication titration, and sustained patient

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engagement are all critical for optimal disease control. These elements are poorly served by quarterly clinic visits and require system-level redesign to deliver effectively.

Telehealth has emerged over the past two decades as a mechanism to extend care beyond clinic walls, enabling remote consultations, vital sign monitoring, and patient education. The COVID-19 pandemic acted as a catalyst, accelerating telehealth adoption by an estimated 38-fold increase in utilization across the United States between January and April 2020 (Koonin et al., 2020). However, first-generation telehealth systems largely replicated synchronous clinical encounters remotely and did not fundamentally redesign the care pathway for chronic disease.

The convergence of telehealth infrastructure with artificial intelligence technologies, encompassing machine learning (ML), natural language processing (NLP), and predictive analytics, has opened transformative possibilities. AI systems can continuously analyze streams of patient-generated health data, identify deterioration trajectories before clinical symptoms emerge, personalize therapeutic recommendations, and automate low-acuity triage. These capabilities position AI-enhanced telehealth as a different intervention from conventional remote care (Topol, 2019).

Despite the rapid proliferation of AI-telehealth products, the evidence base for their effectiveness in chronic disease management remains fragmented. Studies vary enormously in design, outcome selection, target populations, and follow-up duration, complicating comparative synthesis. This review addresses that gap by systematically evaluating the published evidence on AI-enhanced telehealth effectiveness across major chronic disease categories. Specifically, this review aims to: firstly, characterize the AI and telehealth technologies deployed in chronic disease management trials; then, assess effectiveness across clinical, patient engagement, utilization, and cost outcomes. Also, identify barriers and facilitators to implementation, and finally evaluate equity and ethical dimensions of AI-telehealth deployment.

This paper is a narrative review. Relevant literature was identified through searches of PubMed, Scopus, and Google Scholar using terms including “AI telehealth,” “chronic disease remote monitoring,” “machine learning diabetes management,” “cardiovascular AI,” and related combinations. Priority was given to randomized controlled trials, systematic reviews, meta-analyses, and large observational studies published between 2015 and 2025. Evidence was synthesized thematically across chronic disease categories and key effectiveness dimensions, with particular attention to study design quality, population representativeness, and equity considerations. Given the breadth and heterogeneity of the literature, the intent is not exhaustive coverage but rather a critical, have shown potential to account of the current state of evidence and its implications for practice and policy.

## 2. Background

### 2.1. Telehealth in Chronic Disease Management

Telehealth, defined as the delivery of health-related services and information via electronic information and telecommunication technologies, encompasses synchronous video consultations, asynchronous store-and-forward data exchange, remote patient monitoring (RPM), and mobile health (mHealth) applications. Widespread clinical adoption accelerated with broadband internet penetration in the 2000s and the proliferation of smartphones in the 2010s.

The regulatory landscape governing telehealth has evolved considerably following the COVID-19 public health emergency. In the United States, the Centers for Medicare and Medicaid Services (CMS) substantially expanded reimbursable telehealth services, and many states enacted permanent licensure flexibilities (Mehrotra et al., 2021). The European Union's General Data Protection Regulation (GDPR) and equivalent frameworks have simultaneously raised data protection requirements for digital health platforms. The result is a heterogeneous global regulatory environment that shapes the feasibility and scalability of AI-telehealth implementations across jurisdictions.

### 2.2. AI Technologies in Healthcare

Contemporary AI healthcare applications draw principally from three methodological pillars. Machine learning algorithms, including supervised learning, ensemble methods, and deep neural networks, are trained on large clinical datasets to perform classification, regression, or survival prediction tasks. Convolutional neural networks have shown potential to radiologist-level performance on retinal imaging, dermatology, and electrocardiogram (ECG) interpretation. Natural language processing enables the extraction of clinically relevant information from unstructured clinical notes, patient messages, and conversational interfaces. Predictive analytics platforms synthesize heterogeneous data inputs, including electronic health records (EHR), wearable sensors, and claims data, to generate risk scores that stratify patients and prompt proactive intervention (Filani & Opoku, 2025).

Remote monitoring devices and wearable sensors form the data acquisition layer underpinning AI-telehealth systems. Consumer-grade and medical-grade wearables now capture continuous physiological signals, including heart rate, blood pressure, peripheral oxygen saturation, respiratory rate, skin temperature, and physical activity with increasing fidelity (Dunn et al., 2018). Implantable and patch-type biosensors, including continuous glucose monitors (CGMs), implantable cardiac loop recorders, and spirometry-capable pulmonary monitors, enable condition-specific biomarker surveillance at temporal resolutions impossible in clinic-based care.

### 2.3. Convergence of AI and Telehealth

AI augments telehealth infrastructure across four principal functional domains. In triage and acuity sorting, natural language processing chatbots and symptom-checkers pre-screen patients, directing them to appropriate care pathways while reserving clinician time for higher-complexity cases (Judson et al., 2020). For medication adherence, ML models combine pharmacy refill records, app engagement metrics, and sensor data to predict non-adherence and trigger just-in-time behavioral nudges. In continuous symptom monitoring, algorithms analyze sensor data streams in near real-time, alerting care teams when patient trajectories deviate from expected ranges. Risk stratification models synthesize longitudinal patient profiles to identify individuals at elevated risk of acute exacerbation, hospitalization, or mortality, enabling targeted preventive intervention (Rajkomar et al., 2018; Ogu & Opoku, 2025).

The technical architecture of AI-telehealth systems typically involves three tiers: a patient-facing interface such as a mobile application, wearable device, or home hub; a cloud-based data platform performing storage, processing, and AI inference; and a clinician-facing dashboard surfacing prioritized alerts and decision support. Federated learning architectures are increasingly deployed to enable model training across distributed datasets without centralizing sensitive patient data, addressing privacy concerns while improving model generalizability (Rieke et al., 2020).

## 3. Effectiveness across key chronic conditions

### 3.1. Diabetes and Metabolic Disorders

Diabetes management has been a primary proving ground for AI-telehealth integration, driven by the availability of continuous glucose monitoring (CGM) technology and the demonstrable impact of glycemic variability on long-term outcomes. CGM devices generate up to 288 glucose readings per day, creating rich time-series data amenable to ML-based pattern recognition and predictive modelling (Danne et al., 2017). Closed-loop hybrid artificial pancreas systems, pairing CGM with algorithmically controlled insulin delivery, represent the most technologically advanced iteration of this approach. The CLOSED trial demonstrated that hybrid closed-loop insulin delivery achieved superior time-in-range (defined as glucose 70 to 180 mg/dL) compared to sensor-augmented pump therapy alone, at 65.8% versus 54.0% of the monitored period, respectively.

Beyond closed-loop systems, AI-assisted CGM feedback delivered via telehealth platforms has shown consistent HbA1c reductions. A systematic review by Shan et al. (2019) encompassing 27 randomized controlled trials found a pooled mean HbA1c reduction of 0.76% (95% CI: 0.54 to 0.98%) attributable to AI-augmented telemonitoring in type 2 diabetes compared to usual care. Pratley et al. (2020) reported that CGM use with algorithm-generated clinician alerts reduced hypoglycemic events by 43% in older adults with type 1 diabetes. This population is at particular risk due to impaired hypoglycemia awareness. AI models integrating dietary logs, physical activity data, and CGM traces have shown potential to predict post-prandial glucose excursions with a mean absolute error below 20 mg/dL, enabling personalized dietary guidance. Qualitative evidence further highlights that patients and providers increasingly value mobile health applications for diabetes self-management, though perceived ease of use and technical support remain critical facilitators of sustained engagement (Mends & Darko, 2025).

For metabolic disorders beyond diabetes, AI-telehealth applications are nascent but promising. Remote monitoring combined with ML-based dietary pattern analysis has shown preliminary effectiveness for non-alcoholic fatty liver disease management, and AI-driven coaching applications for obesity management have produced modest but statistically significant weight reductions in short-term trials. However, the evidence base for these applications remains limited by small sample sizes and the absence of long-term follow-up.

Taken together, the diabetes evidence base represents the most mature body of AI-telehealth research, benefiting from objective, continuous biomarker data and established outcome metrics. The convergence of CGM technology, closed-loop systems, and telehealth platforms illustrates what is achievable when high-fidelity physiological sensing is paired with intelligent feedback mechanisms. Nonetheless, effect sizes vary considerably across trials, and gains tend to attenuate without sustained engagement support. Future work should prioritize longer follow-up, real-world implementation in under-resourced settings, and clearer delineation of which patient subgroups derive the greatest benefit from AI augmentation.

### 3.2. Cardiovascular Disease and Hypertension

Cardiovascular disease (CVD) represents the leading cause of death globally, and AI-enhanced telehealth has attracted substantial research investment in this domain (Roth et al., 2020). Modifiable risk factors, including physical inactivity, poor diet, and uncontrolled hypertension, account for a substantial proportion of CVD burden, and statistical analyses confirm their differential prevalence across racial and socioeconomic groups in the United States (Korang et al., 2025). Remote ECG monitoring, enabled by wearable single-lead and multi-lead devices, has been paired with deep learning algorithms capable of detecting arrhythmias, left ventricular dysfunction, and ischemic changes with accuracy approaching or exceeding cardiologist performance. Attia et al. (2019) demonstrated in a landmark study of over 180,000 patients that a convolutional neural network applied to standard 12-lead ECG could identify patients with asymptomatic left ventricular dysfunction with an area under the curve (AUC) of 0.93, facilitating early intervention before clinical heart failure onset.

For atrial fibrillation (AF), a condition with major stroke prevention implications when detected, AI-enabled consumer wearables may expand screening reach. The Apple Heart Study enrolled 419,297 participants and found that an irregular pulse notification algorithm, when positive, was associated with confirmed AF on subsequent ECG patch monitoring in 34% of cases. Deep learning applied to single-lead ECG from wearables detected AF with a sensitivity of 97.5% and specificity of 98.7% in a validation cohort. These detection capabilities, integrated into telehealth follow-up pathways, reduce the time from first symptomatic episode to diagnosis and anticoagulation initiation.

Hypertension management via AI-telehealth has demonstrated consistent blood pressure reductions in randomized trials. A meta-analysis by Omboni et al. (2020) of 28 trials involving 6,874 participants found that telemonitoring combined with AI-driven medication titration support achieved a weighted mean systolic blood pressure reduction of 5.9 mmHg (95% CI: 4.1 to 7.7 mmHg) versus usual care. This reduction is associated with a 15 to 20% reductions in cardiovascular event risk. Systems incorporating automated pharmacist-led medication adjustment algorithms achieved blood pressure target attainment rates of 72% at 12 months, compared with 45% in the control arm in the TASMINH4 trial. Community-based social support programs for older adults with hypertension have shown complementary value when integrated with telehealth platforms, reinforcing adherence and self-monitoring behaviors (Nortey et al., 2025).

In heart failure management, the most resource-intensive chronic cardiac condition, AI-enabled remote monitoring of daily weight, symptoms, and implantable device data has reduced 30-day readmission rates, a key quality metric. A Cochrane systematic review of home telemonitoring in heart failure identified a 21% relative reduction in all-cause mortality and an 18% reduction in heart failure-related hospitalizations across 9 trials (Inglis et al., 2015).

Collectively, the cardiovascular evidence reflects a spectrum from early detection (asymptomatic left ventricular dysfunction and AF screening) to ongoing disease management (hypertension titration and heart failure readmission prevention). AI-telehealth appears most impactful in contexts where continuous monitoring reveals clinically actionable signals that episodic clinic visits would miss. However, the translation of detection accuracy into downstream outcome improvements depends heavily on the surrounding care pathway elements that are inconsistently described in the current literature.

### 3.3. Chronic Respiratory Conditions (COPD and Asthma)

Chronic obstructive pulmonary disease and asthma share the feature of episodic exacerbations. These are acute deteriorations that drive significant emergency department (ED) utilization, hospitalizations, and accelerated disease progression. AI-telehealth systems have targeted exacerbation prediction as a high-value intervention point. Wearable spirometry devices capable of measuring forced expiratory volume in one second (FEV1) at home, combined with ML-based trajectory modelling, have shown the ability to detect early physiological deterioration two to seven days before clinical exacerbation onset (Boer et al., 2021).

The PneumoCare study demonstrated that a telemonitoring platform incorporating wearable pulse oximetry, symptom diaries, and ML-driven severity scoring reduced hospitalization rates by 36% and ED visits by 42% over 12 months in a cohort of high-risk COPD patients compared with matched controls. A parallel randomized trial by Boer et al. (2021) found that AI-generated exacerbation alerts prompted timely rescue medication use and resulted in a 28% reduction in unscheduled healthcare contacts. In asthma, smart inhaler technology paired with ML-based adherence analysis and environmental trigger identification, incorporating air quality data and GPS location, has demonstrated improvement in adherence rates from 26% to 49% and a reduction in rescue inhaler use.

Medication adherence is a particularly intractable challenge in respiratory disease, with population-level adherence rates for inhaled corticosteroids typically below 40%. Targeted strategies addressing patient knowledge, motivation, and practical self-management skills are essential complements to digital monitoring tools (Akosua et al., 2024). AI-telehealth platforms incorporating electronic inhaler sensors, app-based adherence tracking, and automated coaching have improved adherence in multiple trials; however, results have been heterogeneous and heavily influenced by baseline patient engagement.

### 3.4. Mental Health Comorbidities

Mental health disorders are highly prevalent as comorbidities in chronic physical disease. Depression affects approximately 30% of patients with heart failure and 25% of those with COPD, and its presence significantly worsens prognosis. Community-based mental health support models in the United States have demonstrated effectiveness in reducing symptom burden and improving access to care, particularly among populations with limited specialist services (Ajayi & Thompson, 2025). AI-enhanced telehealth for mental health in the context of chronic disease has pursued two primary modalities: passive behavioral sensing and active conversational AI agents.

Passive sensing approaches use smartphone accelerometry, GPS movement patterns, screen-use logs, and sleep data to infer mood states and detect early depressive or anxious episodes without requiring active patient input.

Conversational AI agents, ranging from rule-based chatbots to transformer-based large language models, have been evaluated as scalable delivery vehicles for psychological interventions. The landmark study by Fitzpatrick et al. (2017) found that Woebot, a chatbot delivering cognitive behavioural therapy (CBT) principles, significantly reduced PHQ-9 scores at two weeks compared to a control group receiving psychoeducational materials (Woebot: -5.82 points; control: -2.06 points; $p < 0.001$). D'Alfonso et al. (2017) evaluated an AI-enhanced mental health platform for young people with psychosis and found improvements in wellbeing scores and satisfaction. However, the magnitude of effects in conversational AI trials is generally modest, and absence of long-term follow-up beyond eight weeks limits conclusions about durability.

## 4. Dimensions of effectiveness

### 4.1. Clinical Outcomes

The most rigorously assessed dimension of AI-telehealth effectiveness is clinical biomarker control, including HbA1c, blood pressure, FEV1, and arrhythmia burden. Across chronic disease categories, meta-analytic evidence supports modest-to-moderate improvement in primary biomarkers when AI-telehealth is compared to usual care. Pooled effect sizes are generally comparable in magnitude to those achieved by adding a second pharmacological agent. This represents a clinically significant benchmark. Mortality data are less consistent: survival benefit has been demonstrated in implantable device-monitored heart failure, but comparable mortality-powered trials in diabetes and COPD are lacking. Survival analysis methods applied to chronic disease cohorts underscore the need for long-term study designs capable of detecting clinically meaningful changes in disease trajectory (Kizza et al., 2025). Hospitalization reduction is the most consistently reported outcome across all disease categories, with reductions ranging from 15 to 40% in the higher-quality trials (Kitsiou et al., 2015).

### 4.2. Patient Engagement and Adherence

Patient engagement, encompassing app utilization rates, self-monitoring frequency, medication adherence, and participation in virtual care encounters, is both an outcome of and a mediator for clinical improvement. AI-personalization features, including tailored push notifications, gamification elements, and conversational coaching, have been associated with higher sustained engagement compared to passive monitoring platforms. However, engagement typically declines substantially after the initial novelty phase; studies report a 30 to 60% drop in active app usage within 90 days of enrolment. AI-driven engagement optimization, which dynamically adjusts message timing, content, and channel based on individual response patterns, represents an active area of development with limited but promising early evidence. Complementary digital approaches, such as social media health campaigns, have shown potential to sustain behavior change beyond the clinical encounter and reinforce self-management skills developed through telehealth platforms (Akor & Awanu, 2025).

### 4.3. Patient-Reported Outcomes

Quality of life (QoL), patient satisfaction, health literacy, and self-efficacy, collectively grouped as patient-reported outcomes (PROs), are increasingly recognized as essential effectiveness dimensions alongside clinical biomarkers. Instruments including the SF-36, EQ-5D, Chronic Disease Self-Efficacy Scale, and condition-specific measures such as the Minnesota Living with Heart Failure Questionnaire and the COPD Assessment Test have been employed in AI-telehealth trials with variable results. Modest improvements in disease-specific QoL are reported in the majority of trials, but effects on generic health utility scores are frequently non-significant, possibly reflecting ceiling effects or the short follow-up periods typical of the literature. Patient satisfaction with AI-telehealth interactions tends to be high when systems are perceived as easy to use and responsive, but satisfaction correlates poorly with clinical outcome improvement, cautioning against its use as a surrogate endpoint (Creber et al., 2016).

### 4.4. Cost-Effectiveness

Rigorous cost-effectiveness analyses of AI-telehealth systems are rare relative to the volume of efficacy studies, reflecting the methodological complexity of estimating costs across heterogeneous payer systems and time horizons. Available analyses generally suggest favorable cost-effectiveness when driven by hospitalization avoidance and emergency department diversion. Early large-scale telehealth trials produced mixed economic findings, underscoring the importance of careful population targeting to achieve cost-effective deployment. More recent AI-augmented programs with better patient selection have produced more favorable economic profiles; an analysis of the AI-driven Livongo diabetes management platform found a return on investment of approximately $88 per member per month in reduced medical expenditure for commercially insured members (Kaufman et al., 2019).

## 5. Barriers and limitations

Despite the promising evidence reviewed above, significant barriers constrain the effectiveness, scalability, and equity of AI-telehealth systems for chronic disease management.

### 5.1. Digital Health Literacy and Access Disparities

Effective engagement with AI-telehealth platforms requires digital literacy, defined as the ability to operate a smartphone or connected device, navigate application interfaces, and interpret data feedback. Older adults, individuals with lower educational attainment, and those from lower socioeconomic backgrounds disproportionately lack digital literacy, internet access, or smartphone ownership (Pew Research Center, 2021). A study of telehealth readiness in heart failure patients found that 30% lacked the digital skills to engage with a remote monitoring platform. This digital unreadiness was associated with higher baseline hospitalization rates, representing precisely the population most likely to benefit from AI-telehealth intervention (Miller et al., 2020). Without deliberate equity-focused design, AI-telehealth risks reinforcing rather than ameliorating existing care disparities.

### 5.2. Data Privacy, Algorithmic Bias, and Regulatory Gaps

AI-telehealth systems generate and process sensitive health and behavioral data at scale, creating privacy risks distinct from conventional clinical records. Data breaches, re-identification from pseudonymized datasets, and secondary data use without adequate consent are documented concerns in the United States health sector (Ahmed et al., 2025; Utomi et al., 2024). Challenges in implementing robust data protection frameworks, including HIPAA and HITECH Act compliance, continue to present barriers to safe and scalable AI-telehealth deployment (Osifowokan et al., 2025a). Algorithmic bias, defined as systematic performance disparities across demographic subgroups, is particularly pernicious in health AI, where biased predictions translate directly to differential care quality. Obermeyer et al. (2019) demonstrated in a widely-cited analysis that a commercial risk-stratification algorithm exhibited substantial racial bias: Black patients were systematically assigned lower risk scores despite higher objective illness burden, because the algorithm used healthcare cost as a proxy for need, a metric confounded by historical access disparities. Regulatory frameworks have not kept pace with the proliferation of AI-driven digital health products; the FDA's Software as a Medical Device (SaMD) pathway and the EU Medical Device Regulation (MDR) both face implementation challenges for continuously learning AI systems (Gerke et al., 2020; Korang et al., 2024). Comprehensive assessments of AI regulatory and compliance challenges further highlight gaps in liability assignment and patient safety oversight that current frameworks have yet to resolve (Osifowokan et al., 2025b).

### 5.3. Interoperability and EHR Integration Challenges

The clinical value of AI-telehealth insights depends on their integration into existing clinical workflows and the EHR systems that structure provider decision-making. In practice, most AI-telehealth platforms operate as standalone systems with limited bidirectional integration with hospital and primary care EHRs, creating parallel data siloes and cognitive burden for clinicians who must reconcile multiple dashboards (Topol, 2019). HL7 FHIR standardization has advanced interoperability, but implementation is inconsistent, and proprietary EHR vendor ecosystems resist open integration. Clinicians are frequently required to perform duplicate documentation across the AI-telehealth platform and the institutional EHR, eroding workflow efficiency and increasing the risk of transcription errors. Alert fatigue is a related concern; when remote monitoring signals are not contextualized within the full clinical picture available in the EHR, the volume of notifications can become unmanageable, prompting clinicians to override or ignore alerts even when clinically relevant. Fragmented patients' records further complicate care coordination; a patient's telehealth-derived blood glucose trends, for instance, may be invisible to a cardiologist managing co-existing heart failure unless systems are explicitly integrated. The resulting fragmentation also reduces the ability to validate AI predictions against actual outcomes.

### 5.4. Variability in Study Design and Short Follow-Up Periods

The AI-telehealth literature is characterized by substantial heterogeneity in study design, outcome selection, intervention components, follow-up duration, and reporting quality. The majority of published trials have follow-up periods of six months or less. This duration is insufficient to evaluate outcomes such as macrovascular complications in diabetes, disease progression in COPD, or the durability of behavioral change. Many studies lack active control conditions, making it impossible to disentangle the specific contribution of AI from increased monitoring frequency, clinical attention, or placebo effects. Risk-of-bias assessments using Cochrane or GRADE frameworks consistently identify performance bias, detection bias, and attrition bias as prevalent concerns (Kitsiou et al., 2015). Small sample sizes limit statistical power and generalizability, and publication bias towards positive findings inflates pooled effect estimates.

### 5.5. Patient Trust and Clinician Adoption Resistance

Patient acceptance of AI-driven health recommendations depends on trust in the underlying technology, perceived transparency of algorithmic decision-making, and the quality of the human-AI interface. Qualitative research identifies concerns about being managed by a computer without adequate human oversight, uncertainty about how personal data is used, and a preference for clinician confirmation of AI-generated recommendations. Clinician adoption is similarly constrained by workflow disruption concerns, training requirements, and skepticism about AI system reliability. High-profile failures of clinical AI systems, such as IBM Watson for Oncology, have reinforced these concerns among practitioners. Successful implementation requires co-design with both patient and clinician stakeholders, sustained change management support, and transparent communication about system capabilities and limitations.

## 6. Ethical and equity considerations

The deployment of AI-enhanced telehealth systems for chronic disease management raises ethical questions that extend beyond technical performance metrics. A framework for evaluating these systems must address fairness, accountability, transparency, and equity (Char et al., 2018).

### 6.1. Algorithmic Fairness Across Racial and Demographic Groups

As documented above, AI health algorithms can encode and amplify existing disparities in healthcare delivery. The consequences in chronic disease management are significant: a biased risk stratification algorithm may deprioritize Black patients with uncontrolled diabetes or hypertension for telehealth outreach, widening already-substantial cardiovascular outcome disparities. Algorithmic fairness is defined as the property that model performance metrics, including sensitivity, specificity, and calibration, are equitable across demographic subgroups. It must be treated as a design requirement rather than a post-hoc audit (Rajkomar et al., 2018). This requires diverse, representative training datasets, prospective subgroup performance reporting in regulatory submissions and peer review, and ongoing post-deployment monitoring for performance drift across demographic strata.

### 6.2. Informed Consent in AI-Assisted Care

The complexity of AI systems, particularly deep learning models with millions of parameters, creates fundamental challenges for meaningful informed consent. Patients cannot be expected to understand algorithmic mechanics, yet they deserve comprehensible explanations of how AI influences their care. Explainability techniques, including LIME, SHAP, and attention visualization offer partial solutions for generating human-interpretable explanations of model predictions, but translating technical explanations into patient-comprehensible language remains a significant challenge. Consent processes must clearly communicate what data are collected, how AI processes them, what clinical decisions they influence, and how patients can opt out without affecting care quality. This combination of transparency and patient autonomy is rarely achieved in current practice.

### 6.3. Risk of Widening the Digital Divide

If AI-telehealth systems are deployed without deliberate equity strategies, they risk concentrating benefits among digitally literate, socioeconomically advantaged populations while leaving marginalized groups behind. Some commentators have termed this the inverse care law 2.0. Socioeconomic factors shape health outcomes across multiple dimensions, and AI-telehealth systems that fail to account for these upstream determinants will produce unequal benefits (Ajayi & Cudjoe-Mensah, 2025). Targeted public health initiatives that embed equity principles into digital health design have demonstrated feasibility and should accompany technological development (Ugwu et al., 2025b). Strategies to mitigate inequity include providing device-lending programs and broadband subsidies for low-income participants, designing for low digital literacy with simple interfaces and voice interaction modalities, offering bilingual and multilingual interfaces, and embedding community health workers as digital navigators within telehealth programs.

## 7. Future directions

Several priority areas warrant investment to advance the evidence-based and equitable deployment of AI-enhanced telehealth for chronic disease management.

### 7.1. Standardized Evaluation Frameworks

The field urgently requires agreed minimum reporting standards for AI-telehealth trials analogous to CONSORT for randomized trials or STROBE for observational studies. The proposed SPIRIT-AI and CONSORT-AI extensions address clinical trial reporting for AI-based interventions and provide a foundation, but adoption is nascent. Standardized outcome sets, such as those developed by the International Consortium for Health Outcomes Measurement (ICHOM), should incorporate PROs alongside clinical biomarkers and be adapted for AI-telehealth contexts. Pre-registration of AI performance benchmarks and subgroup analyses in clinical trial registries would reduce publication bias and enable meta-analytic synthesis.

### 7.2. Longitudinal Real-World Evidence

Short-duration RCTs cannot answer questions about the durability of AI-telehealth effects, long-term disease trajectory modification, or cumulative cost-effectiveness. Investment in longitudinal cohort studies, pragmatic cluster-randomized trials embedded in health system delivery, and large-scale observational analyses using EHR data are needed to generate real-world evidence. Advanced predictive modelling for patient flow and care utilization within healthcare facilities represents one promising avenue for generating actionable real-world insights (Oware & Mensah, 2025). The NHS England Model Hospital program and the U.S. Patient-Centered Outcomes Research Institute (PCORI) have funded initial pragmatic telehealth evaluations, but chronic disease-specific AI-focused programs with follow-up beyond two years remain scarce.

### 7.3. Integration with Social Determinants of Health Data

Clinical biomarkers and utilization metrics capture only a fraction of the factors shaping chronic disease outcomes. Social determinants of health (SDOH), including housing stability, food security, transportation access, social support, and occupational exposures, account for an estimated 30 to 55% of health outcomes but are rarely incorporated into AI-telehealth predictive models. Socioeconomic inequalities exert particularly strong effects on chronic disease outcomes in the United States, and their incorporation into predictive models is essential for equitable risk stratification (Ajayi & Cudjoe-Mensah, 2025). Incorporating area-level SDOH data and patient-level screening results into AI risk stratification models has shown preliminary improvement in prediction accuracy and may enable targeted resource deployment to address upstream determinants of poor disease control.

### 7.4. Emerging Technologies

Generative AI, including large language models (LLMs) capable of nuanced natural language dialogue, represents the next frontier in AI-telehealth interfaces. Early evidence suggests that LLM-powered virtual health assistants can deliver patient education, support medication management, and triage symptoms with a naturalness and contextual responsiveness that rule-based chatbots cannot match. However, the risk of confident misinformation, commonly referred to as LLM hallucination, demands rigorous safety evaluation before deployment at scale in high-stakes clinical contexts. Multimodal sensing, fusing physiological waveforms, acoustic biomarkers, facial video analysis, and environmental sensor data into unified patient models, promises richer phenotyping of chronic disease trajectories.

Federated learning architectures, enabling model training across distributed institutional datasets without data centralization, offer a path to developing highly generalizable AI models while preserving patient privacy (Rieke et al., 2020). Navigating the evolving regulatory and ethical landscape for AI in healthcare will require sustained collaboration between developers, clinicians, and policymakers (Agbadamasi et al., 2025; Osifowokan et al., 2025b; Filani et al., 2026).

## 8. Conclusion

This review synthesizes a substantial and growing body of evidence that AI-enhanced telehealth systems confer meaningful improvements in chronic disease management across diabetes, cardiovascular disease, chronic respiratory conditions, and mental health comorbidities. The convergence of continuous sensor data acquisition, sophisticated predictive analytics, and scalable digital delivery platforms has enabled genuinely novel care modalities that were not possible with first-generation telehealth. These include AI-directed closed-loop insulin delivery and arrhythmia detection in mass-population wearable studies.

However, the evidence base is characterized by significant heterogeneity, short follow-up, and under-representation of the populations carrying the highest chronic disease burden. Barriers, including digital literacy disparities, algorithmic bias, interoperability failures, and regulatory lag, must be addressed as prerequisites for equitable and effective deployment. Ethical responsibilities around consent, transparency, and fairness are not peripheral to the technology development process but central to it.

For clinicians, the immediate implication is to engage thoughtfully with AI-telehealth as a complement to, rather than a replacement for, the therapeutic relationship, using AI-generated insights to enhance rather than automate clinical judgement. For health systems, selective deployment targeting populations at high hospitalization risk and those who are willing to engage digitally offer the strongest near-term return on investment, while equity-focused implementation design must be built in from the outset. For policymakers, investment in standardized evaluation infrastructure, long-term pragmatic trials, data interoperability standards, and digital inclusion programs will determine whether AI-telehealth fulfils its potential to democratize high-quality chronic disease management.

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