Digital Health Technologies in Low-Income Countries: Bridging Gaps in Personalized Preventive Care Through Telemedicine, Electronic Health Records, and AI-Driven Nursing Informatics

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Digital Health Technologies in Low-Income Countries: Bridging Gaps in Personalized Preventive Care Through Telemedicine, Electronic Health Records, and AI-Driven Nursing Informatics

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Abstract: *This review examines the role of digital health technologies in enhancing personalized preventive care in low-income countries (LICs), where non-communicable diseases continue to rise amidst chronic limitations of healthcare infrastructure, workforce, and data system. It explores telemedicine, open-source electronic health records, AI-driven analytics, and nursing informatics within LIC settings, drawing on recent evidence from 2020–2025. Real-world implementations, such as offline-first platforms and portable health clinics, demonstrate feasibility and clinical impact. However, barriers such as algorithmic bias, fragmented systems, and digital illiteracy persist. The review proposes an integration framework addressing contextual relevance, interoperability, workforce development, and ethical governance. It concludes with actionable strategies to design equitable, sustainable digital solutions for under-resourced healthcare systems.*

Keywords: Artificial Intelligence; Digital Health; Low-Income Countries; Health Informatics; Preventive Care.

1. INTRODUCTION

The World Health Organization estimates that non-communicable diseases (NCDs) contribute to 74% of global mortality, disproportionately affecting low-income countries (LICs), where healthcare systems often emphasize treatment over prevention, clinical capacity is limited by low physician-to-patient ratios, and health records frequently remain incomplete—a challenge further compounded by overlooked conditions such as dental caries and other oral diseases; limiting the potential of data-driven care [1]. Compounding this, the global nursing workforce is unevenly distributed; 78% of nurses serve only 49% of the world's population which intensifies service gaps in the most vulnerable regions [2]. This inequity underscores the need for innovative, scalable strategies to support personalized preventive care.

Digital health technologies offer a compelling set of tools to address these challenges in LICs. Telemedicine enables remote clinical consultations, reducing travel burdens and expanding access. Electronic Health Records (EHRs) streamline data management, improve continuity of care, and inform evidence-based policy. Artificial Intelligence (AI) models support risk prediction and resource optimization. Nursing informatics bridges clinical expertise with data systems to improve decision-making. Predictive analytics adds a forward-looking layer, identifying early health threats based on real-time data patterns [3].

Despite this promise, widespread adoption in LICs remains constrained. Studies from 2024–2025 cite systemic barriers such as limited IT infrastructure, unreliable internet access, inconsistent power supply, digital skill deficits among healthcare workers, and unresolved ethical concerns around data ownership and security [4]. Moreover, solutions designed for high-income environments often lack contextual relevance and business model, reducing their utility and sustainability in resource-constrained settings.

This review maps the evolving landscape of digital health in LICs, focusing on four core domains: telemedicine, EHRs, AI applications, and nursing informatics integrated with predictive analytics. Drawing on recent field evidence, it highlights practical lessons, identifies persistent gaps, and introduces a context-sensitive integration framework. The goal is to guide academic researchers, clinical leaders, and health policymakers in designing, implementing, and scaling digital interventions that truly meet the preventive care needs of LIC populations.

Search Strategy:

Databases: PubMed, Scopus, IEE Xplore, web of science
Search terms: ("digital health" OR "telemedicine" OR "electronic health records" OR "artificial intelligence" OR "nursing informatics" OR "predictive analytics") AND ("low-income countries" OR "resource-constraint settings" OR "developing countries")
Filter: Publication date (2020 -2025), English language

Identified from database searching (n=1,247)
Duplications (n=260)
After duplications removed (n=987)
Records excluded (n=924)
-Not relevant to digital health (n=412)
-Not focused on LICs (n=287)
-Published before 2020 (n=225)
Studies included in qualitative synthesis (n=63)

Fig. 1. PRISMA Flow Diagram of Literature Selection Process

2. GLOBAL HEALTH CONTEXT

2.1 The Burden of NCDs in Low-Income Countries

Non-communicable diseases (NCDs) like cardiovascular conditions, diabetes, and chronic respiratory illnesses are rising rapidly in low-income countries (LICs). NCDs cause 75% of global deaths, with 73% of those in low- and middle-income countries (LMICs). 40% of NCD deaths occur before age 70, and LMICs account for 82% of these premature deaths [5].

This shift demands a move from reactive care to proactive prevention, because economically, up to 4% of their GDP 4% of GDP annually by 2030, according to predictive analyses by the World Economic Forum [6]. Furthermore, NCDs may cost many people in LICs more than 40% of their household's income [7].

2.2 Workforce Limitations

The geographical distribution of health workers is skewed towards urban and wealthier areas. This pattern is found in nearly every country in the world, but the problem is especially acute in LICs [8] causing less than a third of the healthcare workers per capita in rural settings compared to the urbans [9]. Preventive care in LICs is also hampered by a digitally undertrained health workforce. A 2025 review by Agbeyangi and Lukose showed fewer than 25% of healthcare providers in Sub-Saharan Africa have digital health training [10].

2.3 Infrastructure Deficits

Multiple recent reports indicate that a large share of primary-care facilities in low-income and lower-middle-income countries suffer from unstable electricity and lack basic computing devices. For example, in sub-Saharan Africa, about 15% of health-care facilities have no electricity at all, and only 40% have reliable electricity. There is also a notable urban–rural divide, with rural facilities facing greater challenges [11]. These deficits hinder the deployment of technologies like telemedicine, EHRs, and AI.

3. KEY DIGITAL HEALTH TECHNOLOGIES

3.1 Telemedicine

Telemedicine is increasingly closing access gaps in LICs. According to a 2024 comparative policy analysis, Tanzania's digital health strategy is strongly aligned with global standards and demonstrates significant progress in leveraging digital technologies to improve health access in low-connectivity regions. The strategy emphasizes interoperability, client-centric solutions, and the integration of digital health tools. Importantly, it supports offline-first tools to enable care in low-connectivity zones. Thus, supporting the use of both online and offline functionalities can enable care continuity, particularly in underserved areas [12].

3.2 Electronic Health Records (EHRs)

Open-source EHRs like OpenMRS, Bahmni, and DHIS2 are gaining traction due to cost-effectiveness and local adaptability. A 2024 review stressed successful rollouts depend on phased implementation, local ownership, and robust training [13]. A 2022 systematic review of health information exchange policy and standards in Africa found that successful digital health system implementation depends on clear policy frameworks and robust standards. The review highlights persistent challenges, such as funding gaps, poor infrastructure, and lack of interoperability, which result in many health information systems across the continent operating in isolation [14].

3.3 Artificial Intelligence in Healthcare

AI is unlocking efficiencies in diagnostics, outbreak forecasting, and resource allocation. However, most models rely on high-income country data, making them poorly suited to LIC needs which is a form of "algorithmic colonialism" [15]. Newer efforts, like Stanford's 2025 generative AI tools, are tailored for LICs, factoring in local disease burdens and national protocols [16].

3.4 Nursing Informatics and Predictive Analytics

Nursing informatics empowers care through early warning tools, decision aids, and risk stratification which are vital in LICs with nurse shortages [17]. A 2025 study showed that predictive models identified high-risk patients with 83% accuracy using minimal data [18]. Barriers persist which include low digital literacy, algorithm skepticism, and unresolved ethical concerns around data use and transparency [17].

4. THE PREVENTIVE CARE GAP IN LOW-INCOME COUNTRIES

Despite the promise of digital health in preventive care, key barriers persist in LICs:

4.1 Limited Diagnostic Access: Many facilities lack essential diagnostics. In ten LMICs, median diagnostic service availability was only 19.1%, with ultrasound as low as 1.2% [19].

4.2 Fragmented Data Systems: A review of 20 countries found parallel paper–digital systems and siloed vertical programs. In 70% of cases, fragmentation across public, private, and non-governmental organizations sectors further impaired data coherence and health system integration [20].

4.3 Workforce Skill Gaps: A 2024 meta-analysis of 36 studies showed adoption of digital tools is tied to training. "Facilitating conditions" such as technical support correlated moderately ($r = 0.42$) with uptake [21].

4.4 Lack of Predictive Analytics: Without such tools, care remains reactive. In other settings, e.g., Medicare, predictive outreach reduced Emergency Department visits by 3.9 points and hospitalizations by more than twofold versus standard care [22].

5. KEY IMPLEMENTATION CHALLENGES

5.1 Infrastructure and Connectivity Gaps

The lack of reliable internet access in rural health facilities significantly hampers the implementation of digital health solutions. According to the International Telecommunication Union's 2020 global assessment, 17% of the rural population in Least Developed Countries (47 countries)—many of which are classified as low-income by the World Bank—had no mobile network coverage, while an additional 19% were limited to only 2G connectivity. This means that over one-third of rural communities in these countries lack the minimum infrastructure required to support digital health tools [23]. This connectivity gap creates fundamental barriers to real-time data exchange, teleconsultations, and cloud-based applications.

Beyond internet connectivity, Unreliable electricity remains a significant barrier to healthcare delivery in LICs [24]. These infrastructure limitations necessitate innovative approaches such as offline-first applications, low-power devices, and alternative energy solutions.

5.2 Data Quality and Interoperability

Inconsistent data collection methods and the absence of standardization in data formats lead to poor data quality in many LIC health systems. For instance, in a 2024 study of 50 EHR-enabled health facilities in Rwanda, viral load results were recorded in only about 12% of patient records in facilities without data-quality alerts—rising to 27% after implementation. This indicates substantial gaps in essential clinical data capture, especially for preventive-care indicators [25]. This data quality gap undermines the potential value of predictive analytics and decision support systems.

Interoperability between different health information systems remains a significant challenge. For example, recent assessments of digital health systems in the East African Community countries (including Kenya, Rwanda, Tanzania, and Uganda), despite Great effort for digital ecosystem, found that achieving functional interoperability between digital health implementations and national health information systems got lowest score outcomes among other assessment items. [16]. This fragmentation creates inefficiencies, increases documentation burden, and prevents the comprehensive data analysis needed for effective preventive care.

5.3 Algorithm Bias and Contextual Relevance

Many predictive models are developed using data from high-income countries, which may not be applicable to LIC populations. A 2024 analysis of AI algorithms in global health found that predominantly, most of published algorithms were developed using datasets exclusively from high income countries and African held only about 1% [26]. This bias can lead to inaccurate predictions and ineffective interventions when applied in LIC contexts.

The contextual relevance of digital health technologies is shaped not only by data representation but also by alignment with local clinical practices, resource availability, and cultural factors. Recent evaluations, including a 2025 analysis of clinical decision support systems (CDSS) in low-income countries, have highlighted that many recommendations are not fully implementable due to resource constraints and local contextual barriers [27].

5.4 Workforce Digital Readiness

The digital readiness of the healthcare workforce is critical for the successful implementation of digital health technologies. A 2025 systematic review showed health professionals' readiness for electronic medical records in LICs and found significant variations in digital literacy, with particularly low levels among older healthcare workers and those in rural settings [28].

Effective use of advanced digital health technologies requires more than basic digital literacy; healthcare professionals in low-resource settings face significant challenges due to insufficient training, limited infrastructure, and variable digital readiness, all of which impact their ability to adopt and utilize new tools. [28].

5.5 Policy, Ethics, and Equity Considerations

Ethical concerns particularly around data ownership, consent, and privacy, remain critical in digital health. A 25-year review by Sharma et al. (2025) noted that many LMICs still lack robust frameworks, with policy gaps exposing vulnerable groups to privacy risks and weakening system trust [29].

Equity challenges persist, especially for women and rural populations. Digital divides along socioeconomic and geographic lines exacerbate disparities, underscoring the need for equity-focused digital health strategies [29].

6. GLOBAL IMPLEMENTATION EXAMPLES

6.1 Telemedicine Success Stories

Mobile health Mobile health initiatives in Sub-Saharan Africa have notably improved healthcare access and outcomes. In Kenya, as reported by Owoche et al. (2025), digital tools are enhancing maternal and child health services in low-resource settings. The mHero platform supports nurses via alerts and clinical decision aids, strengthening outcomes [30].

In India, the mSakhi app equips community health workers to collect maternal data, identify risks, and guide referrals. Recent evaluations confirm its role in improving early detection and supervision [31]. Crucially, long-term sustainability remains a central concern for such innovations [32].

6.2 Electronic Health Record Implementations

Open-source EHR platforms such as OpenMRS have demonstrated promise in more than 44 low-income countries due to their flexibility and cost-effectiveness. Implementation studies document the importance of adapting these systems to local workflows, language requirements, and infrastructure constraints [33]. Key success factors included strong government support, phased implementation, and extensive end-user involvement in customization.

The integration of DHIS2 as Ethiopia's national health information system has significantly improved data quality, accessibility, and management across more than 30,000 health facilities. This shift has enabled more timely and informed decision-making, reduced reporting delays, and increased the use of health data at all levels of the health system, demonstrating the critical importance of interoperability and system integration for sustainable digital health solutions [34].

6.3 AI Applications in Resource-Limited Settings

AI-powered diagnostic tools are showing promise in resource-limited settings by supporting primary care providers in managing skin conditions where specialist access is limited. Recent evaluations, such as the 2024 WHO Skin NTDs App study in Kenya, demonstrated high sensitivity compared to dermatologist diagnoses and empowered frontline health workers to manage conditions that previously required referral [35].

Predictive analytics for disease management has improved outcomes for chronic conditions in LICs. For instance, Ghana has made significant progress in diabetes care and non-communicable disease management through collaborative initiatives that strengthen governance, workforce training, and the use of digital health solutions. The introduction of platforms like DHIS2 eTracker enables healthcare workers to collect and monitor patient data in real time, supporting more timely and data-driven care for people with diabetes and helping to build a more resilient healthcare system [36].

6.4 Nursing Informatics Innovations

Mobile nursing decision support tools are strengthening frontline care in LICs. In Bangladesh, the EPI e-Tracker helps nurses monitor vaccination schedules, send reminders, and address zero-dose/dropout cases. National rollout has improved coverage and timeliness [37].

Machine learning–based early warning systems aid early detection of clinical deterioration in low-resource hospitals. A 2021 scoping review confirmed their role in identifying high-risk patients sooner, enabling timely interventions and optimizing limited critical care capacity [38].

6.5 PORTABLE HEALTH CLINIC: A SUSTAINABLE SOLUTION FOR UNREACHED COMMUNITIES

The Portable Health Clinic (PHC), developed by Kyushu University and Grameen Communications, is a mobile telehealth system tailored for underserved communities in low-income countries. Built for low-resource settings, it integrates diagnostic tools, digital records, and remote consultations into a compact, deployable unit.

The kit in the basic NCDs model includes tests for blood pressure, glucose, cholesterol, urinalysis, and anthropometrics. Islam et al. (2024) reported 89–94% concordance with clinical standards, confirming field viability [39]. There are other models in PHC including dental care, maternal and child health, Tele-Eye Care, Tele-Pathology, COVID-19 Module. The PHC uses a four-layer model: 1) data collection by community health workers, 2) risk-based triage algorithms, 3) physician teleconsultation, and 4) structured follow-up.

A major strength is its offline-first design, ensuring continuous service in low-connectivity regions—crucial for rural LICs. PHC has improved access and outcomes. In Bangladesh, it raised antenatal care adherence by 37% and reduced pregnancy complications by 29% [40]. During COVID-19, it enabled remote care with 92% safety adherence [41]. Its sustainability is supported by the Micro Healthcare Entrepreneurship (MHE) model, which aligns income generation with Universal Health Coverage goals [42].

The model is adaptable: in Indonesia, it was customized for NCDs using national protocols [43]; in India, Yokota et al. (2018) showed that co-designed systems enhanced adoption and durability [44]. Key success factors include: 1) Early engagement of local providers, 2) Alignment with national referral pathways, 3) Localized diagnostic logic, and 4) Viable business models.

Recent advancements have extended PHC's function to predictive care. Sampa et al. (2020) developed AI models predicting uric acid with 83% accuracy [45], while Hasan et al. (2020) used machine learning to identify pediatric growth issues from minimal data [46]. These tools boost early detection, moving PHC from reactive care to anticipatory health management.

PHC exemplifies equity-focused digital health: adaptable, sustainable, and system-integrated—a scalable model for preventive care in resource-limited settings

7. AI-ASSISTED COSTEFFECTIVE PERSONALIZED CARE PLANNING IN LOW-INCOME COUNTRIES

The integration of artificial intelligence into healthcare planning represents a promising frontier for enhancing personalized preventive care in LICs. Recent innovations in this domain have focused on leveraging AI tools, particularly large language models (LLMs), to support healthcare professionals in developing individualized care plans that account for resource constraints and local contexts.

7.1 Training of Generative AI for Personalized Time-Scheduled Care Plans

Generative AI models like ChatGPT offer a promising solution for improving personalized care in low-resource settings by supporting healthcare professionals in developing context-aware, time-scheduled care plans [47]. These AI tools can integrate anonymized individual patient risk factors, local healthcare resource availability, cultural influences, and scheduling constraints to create tailored care strategies, thereby helping to overcome a key challenge in low-income communities: the shortage of time and decision-making support for clinicians. While the potential benefits are substantial, including extending the impact of limited healthcare workforces, key challenges remain such as ensuring clinical safety, mitigating data bias, establishing governance, and training healthcare providers to work effectively alongside AI. A proposed human-AI collaboration model emphasizes shared responsibility, where AI enhances but does not replace professional judgment, supporting safer and more effective care delivery in under-resourced environments.

7.2 Cost effective non-invasive Tools as Firstline Approach for Early Disease Detection

Cost-effective, non-invasive tools for early disease detection present a valuable first-line strategy to strengthen preventive care in low-income communities. By utilizing evidence-based risk algorithms and screening charts, which are particularly for non-communicable and cardiovascular diseases, healthcare providers can identify at-risk individuals without relying on costly diagnostic equipment that may be unavailable in these settings [48]. These tools are especially impactful when integrated into digital health platforms, such as the Portable Health Clinic system, as they enhance diagnostic reach while remaining affordable and scalable, making them a practical and sustainable solution for early intervention in resource-constrained environments.

7.3 Integration with Digital Healthcare systems

The convergence of AI-assisted care planning, novel screening approaches, and digital health platforms creates opportunities for comprehensive preventive care ecosystems in LICs. By integrating these components, healthcare systems can potentially identify at-risk individuals through cost-effective screening methods, generate personalized care plans tailored to individual risk profiles and local resources, deliver these plans through digital platforms that support both providers and patients, and monitor outcomes and adapt interventions based on real-world effectiveness data.

8. PROPOSED INTEGRATION FRAMEWORK

Based on the evidence reviewed, we propose a comprehensive framework for integrating digital health technologies into preventive care in LICs. This framework emphasizes contextual relevance, sustainability, and equity, addressing the unique challenges and opportunities in LIC settings.

8.1 Data Collection Layer: The foundation of the framework involves context-appropriate data collection strategies. These include: - Mobile technology and voice recognition to facilitate data collection in low-literacy settings - Offline-first applications that function in areas with intermittent connectivity - Simplified interfaces designed for users with limited digital experience - Integration with existing paper-based systems during transition periods
8.2 Analytics Layer: The second layer involves analytics capabilities adapted to LIC contexts: - Predictive models trained on diverse datasets representative of LIC populations - Simple, interpretable risk scoring systems that can be understood by end-users - Algorithms designed to function with incomplete data common in LIC settings - Contextually relevant clinical decision support aligned with local guidelines and resources
8.3 Clinical Implementation Layer: The third layer focuses on effective integration into clinical workflows: - Decision support systems designed for the specific roles and capabilities of LIC healthcare workers - Task-shifting support to enable effective delegation within interdisciplinary teams - Adaptation to local clinical protocols and available interventions - Training and support systems that build sustainable local capacity
8.4 Feedback and Improvement Layer: The final layer ensures continuous learning and adaptation: - Monitoring systems to track implementation outcomes and identify challenges - User feedback mechanisms accessible to all levels of healthcare workers - Governance structures that include community and end-user representation - Connections to policy processes to enable system-level improvements
This integrated framework emphasizes low-cost, modular solutions that actively involve healthcare workers in the design and implementation process. By addressing the full spectrum from data collection to policy feedback, it provides a comprehensive approach to digital health implementation in LIC settings.

9. ACTIONABLE RECOMMENDATIONS

Based on the evidence reviewed, we propose the following recommendations for leveraging digital health technologies to enhance preventive care in LICs:

9.1 Build Interdisciplinary Collaborations: Foster partnerships between healthcare, technology, social sciences, and community stakeholders to develop holistic solutions. A 2025 analysis of successful digital health implementations highlights that involving diverse stakeholders from the outset is crucial for sustained adoption. Participatory design, co-development, and continuous stakeholder engagement throughout the project lifecycle are associated with greater relevance, usability, and long-term success of digital health solutions compared to technology-driven approaches [49].
9.2 Invest in Workforce Development: Prioritize comprehensive digital health training for all levels of healthcare workers, with particular attention to nurses and community health workers who form the backbone of preventive care in many LICs. Training should address not only technical skills but also critical thinking for data interpretation and application.
9.3 Design Contextually Relevant Technologies: Develop and adapt digital health solutions specifically for LIC contexts, considering infrastructure limitations, workflow realities, and local health priorities. Participatory design approaches involving end-users throughout the development process have demonstrated superior adoption and effectiveness [50].
9.4 Implement Equity-Centered Approaches: Explicitly address digital divides and ensure that digital health technologies reduce rather than reinforce existing

health inequities. This includes designing for accessibility across literacy levels, accommodating cultural preferences, and ensuring benefits reach the most vulnerable populations [51].

9.5 Strengthen Data Governance: Develop comprehensive frameworks for data privacy, security, and ownership that protect individuals while enabling appropriate data use for public health. Community-based governance models that include representation from affected populations have shown promise in building trust and ensuring ethical data use [52].

10. CONCLUSION

Digital health (including telemedicine, EHRs, AI analytics, and nursing informatics) can transform preventive care in low-income countries by enabling remote access, risk prediction, and data-driven decisions. Yet adoption remains hindered by infrastructural, technical, and workforce limitations. This review outlines a context-aware roadmap emphasizing equity, sustainability, and integration with local systems. Evidence shows success hinges on user involvement, system alignment, and barrier mitigation. To ensure lasting impact, digital health ecosystem must be inclusively designed, community-governed, and evaluated across diverse populations as advancing not just innovation, but health equity as well.

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