

AI Chatbots and Conversational Agents for Health Communication in Low- and Middle-Income Countries: A Scoping Review of Applications, Outcomes, and Implementation Barriers

Anietie Akpan

`akpan.anietie.256670@unn.edu.ng`

University of Nigeria

Isaac Sandy

University of Uyo

Oluwasegun Oloko

Federal University of Agriculture

Alexander Ebubechi

University of Nigeria

Excellence Nwachukwu

University of Nigeria

Celestine Ilo

University of Nigeria

Margaret Timothy

University of Calabar

Ekpono-abasi James

University of Uyo

Inimfon Udoubom

University of Uyo

Joy Kinoti

Kabarak University

Taofeekat Odesanmi

University of the People

Ineza Patrick

Food and Drugs Authority

Godwin Ishaku

Bayero University Kano

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Abstract

Background

Conversational agents or AI-enabled chatbots are scalable digital health tools capable of delivering personalized information, supporting self-management, promoting healthy behaviors, and facilitating engagement with healthcare services. However, evidence regarding their application in low- and middle-income countries (LMICs) remains fragmented. We synthesized available evidence on the utilization of AI chatbots and rule-based conversational agents for health communication and health-related outcomes in LMICs to identify their functional roles and implementation barriers.

Methods

Following PRISMA-ScR guidelines, a systematic search was conducted across PubMed, ScienceDirect, Cochrane Library, IEEE Xplore, and Google Scholar. Primary empirical and mixed-methods studies set in LMICs that assessed the use of conversational agents or chatbots in health communication, patient education, or health-related outcomes were eligible for inclusion.

Results

Of 1,803 records identified, nine studies involving over 141,000 users were included. Chatbots or conversational agents were utilized across HIV prevention, sexual and reproductive health, tuberculosis care, diabetes, hypertension, oral health, and childhood immunization. Eight studies reported improvements in health knowledge, while seven reported positive behavioral changes such as enhanced medication adherence. Chatbot interventions demonstrated high acceptability, satisfaction, and user engagement. Although some interventions improved self-management, objective clinical outcomes were infrequently assessed and findings were mixed. Common implementation barriers included digital access inequities, language and literacy challenges, declining user engagement, and minimal health-system integration.

Conclusions

AI chatbots hold diverse potential for enhancing health literacy and behavioral outcomes across LMICs. However, more rigorous evaluations are needed to establish long-term clinical effectiveness, sustainability, and equitable implementation.

Introduction

Access to accurate, timely, and comprehensive health information remains a major problem in low- and middle-income countries (LMICs) [6, 7]. Health systems in these regions are often constrained by limited

human resources, inadequate infrastructure, lack of funding and growing disease burdens, all of which contribute to gaps in patient education, health communication, and continuity of care [8–12]. These challenges are further compounded by disparities in health literacy and access to reliable information sources, particularly among underserved populations [13, 14]. In many LMICs, shortages of healthcare professionals and unfavorable doctor–patient ratios further limit the ability of health systems to provide consistent, individualized patient education and support, with global projections estimating a shortfall of approximately 11 million health workers—predominantly in low- and lower-middle-income countries [15, 17].

To effectively address these widening communication gaps, digital health technologies have emerged as highly scalable solutions [18–20]. In 2015, a joint road-map published by the World Bank Group, USAID, and the WHO supported the use of digital technology to advance health interventions and engage society in public health measures [22]. In a 2021 report on Ethics and Governance of Artificial Intelligence (AI) for health, the World Health Organization stated that AI has enormous potential for strengthening the delivery of health care and medicine and helping all countries achieve universal health coverage [23]. This includes improved diagnosis and clinical care, enhancing health research and drug development and assisting with the deployment of different public health interventions, such as disease surveillance, outbreak response, and health systems management. This could also be of great benefit to low- and middle-income countries, especially in countries that may have significant gaps in health care delivery and services for which AI could play a role. However, for AI to have a beneficial impact on public health and medicine, ethical considerations and human rights must be placed at the centre of the design, development, and deployment of AI technologies for health [23].

In recent years, advances in artificial intelligence (AI) and mobile technology have led to the emergence of conversational agents, commonly known as chatbots. With the increased access to technological devices (eg, smartphones and computers) and the internet, AI chatbots offer the potential to provide accessible, autonomous, and engaging health-related information and services, which can be promising for technology-facilitated interventions [3]. Earlier chatbot systems were basic rule-based applications that allowed for predetermined scripts to be triggered by specific user input [4]. In contrast, today's AI chatbots combine machine learning and Natural Language Processing (NLP) techniques which have improved their ability to simulate human-like conversations, providing real-time responses, and delivering personalized health education through widely accessible platforms such as mobile applications, websites, and messaging services like WhatsApp and Facebook [5, 39]. In resource-limited settings, both advanced NLP architectures and simpler rule-based algorithmic pathways remain highly relevant digital health solutions due to differing infrastructural constraints. Their scalability, accessibility, and ability to operate continuously make them particularly attractive for use in resource-limited settings [45, 24].

A growing body of chatbot-specific literature suggests that conversational agents can support health education, health communication, behaviour change, self-management, service navigation, and user engagement across healthcare settings [29, 3, 28]. These systems range from rule-based chatbots that deliver scripted responses to more advanced AI-enabled systems that use machine learning and natural

language processing to interpret user input and generate more personalized responses [5, 4]. While global reviews have synthesized chatbot applications broadly [29, 28], there remains a critical dearth of synthesis focusing specifically on conversational agent implementation patterns, infrastructure challenges, and adoption barriers within LMIC health systems [26]. Furthermore, there remains a need to better understand the functional roles of these chatbots, their implementation patterns, and the barriers and facilitators influencing their adoption and impact [28, 27].

Our aim for this scoping review is to synthesize already existing evidence on the use of AI-driven chatbots and automated conversational agents for patient education and health communication in low- and middle-income countries (LMICs). We also sought to map the health contexts in which these chatbots are applied, and examine the range of reported outcomes, including changes in knowledge, behavior, clinical indicators, and user experience. This review also aimed to characterize chatbot functional roles, delivery platforms, and communication approaches, and to examine implementation barriers, contextual challenges, and facilitators influencing usability, effectiveness, and scalability within LMIC healthcare settings. Furthermore, we provided recommendations for future conversational agent research, design, and application.

Methods

Search Strategy

We used the framework for scoping reviews initially proposed by Arksey and O'Malley [1] and later refined by Levac et al. [2] and the Joanna Briggs Institute [46]. While indexing databases such as Embase, Scopus and Web of Science were not directly accessed, broad interdisciplinary coverage was achieved through PubMed, Cochrane Library, IEEE Xplore, Google Scholar, and backward citation tracking. PubMed provided extensive biomedical coverage, IEEE Xplore captured technical and engineering literature, while Google Scholar and reference-list screening were used to identify potentially relevant studies not indexed in the primary databases.

The search terms were constructed combining keywords and controlled vocabulary (e.g., MeSH) for three core concepts: artificial intelligence chatbots, health communication and patient education, and low- and middle-income countries (LMICs), with a special focus on health-related outcomes. The detailed terms combined variations of "artificial intelligence," "AI," "chatbot*," "conversational agent*," and "virtual assistant*" with "health communication," "patient education," "health promotion," "self-management," "digital health," and "mHealth." To these, outcome-related terms such as "health outcomes," "behavior change," "knowledge," "adherence," and "clinical outcomes" were added. Contextual terms such as "low- and middle-income countr*," "LMIC*," "developing countr*," "Sub-Saharan Africa," and "resource-limited settings" were then combined using Boolean operators (AND/OR). Given that this is an emerging area, an additional search was done in Google Scholar, where the first 12 pages of results were screened. Further backward citation tracking of included studies and relevant reviews was undertaken to identify additional studies meeting the eligibility criteria.

Eligibility Criteria

This study was guided by the Population-Concept-Context (PCC) framework for scoping reviews. The Population included in this review is patients, health care consumers, caregivers, community members, health care providers, or anyone who interacts with AI chatbots for health-related purposes in LMICs (low, lower-middle-, and upper-middle-income countries, as defined by the World Bank at the time of publication [22]). For the purposes of this review, AI chatbots were broadly defined to include conversational agents employing artificial intelligence, natural language processing, machine learning, or rule-based conversational architectures designed to simulate interactive dialogue for health-related purposes. This broader definition was adopted because many healthcare chatbot interventions in LMIC settings utilize hybrid or rule-based architectures while performing functions similar to those of more advanced AI-driven systems. The Concept is AI-driven chatbot interventions applied to healthcare, including advanced AI-driven conversational agents, virtual assistants, and rule-based or sequential automated text/messaging interfaces utilized for patient education, health communication, behavior change, adherence support, or disease management. The Context is the LMIC settings, as classified by the World Bank at the time of publication [22], in clinical, community, digital, and public health.

Studies reporting on the application of AI-Driven chatbots in health care or public health published from January 2015 to March 2026 were included. Primary empirical studies or mixed-methods studies published in English and conducted in one or more LMICs were considered for inclusion. Because the objective was to map chatbot applications and implementation patterns rather than assess effectiveness alone, development and implementation studies were retained. Excluded were studies focusing solely on non-health applications of chatbots or conversational agents; studies focusing on static informational websites or one-way broadcast SMS (without interactive, automated conversational flow or response features) were excluded; studies conducted entirely in high-income countries; editorials, commentaries, protocols, conference abstracts, and opinion papers that did not present primary data; and studies that did not report outcomes relevant to the review objective. Articles published before 2015 and those not written in English were excluded. Studies reporting insufficient data for chatbot evaluation, including those with limited or no outcome assessment; accuracy-focused analyses with no direct relevance to clinical or health-related outcomes were excluded; and purely theoretical computer science simulations were excluded. However, technical digital health design and development protocols were eligible if they mapped out functional architecture intended for near-term field deployment within public health systems.

Screening, Data Extraction and Analysis

We retrieved a total of 1,703 records from core electronic databases (PubMed, ScienceDirect, Cochrane Library, and IEEE Xplore) and an additional 100 records through Google Scholar and backward citation tracking, yielding an initial pool of 1,803 records. These records were exported to Zotero and Rayyan for reference management and screening. A total of 68 duplicates were sorted and removed prior to

screening. To ensure high inter-rater reliability and methodological consistency across the distinct screening arms, all reviewers underwent a formal calibration exercise using a pilot sample of records prior to the official screening. Studies were screened by two independent reviewers in three stages:

1. Title Screening
2. Abstract Screening
3. Full-text screening

This was strictly governed by highly operationalized, pre-defined eligibility criteria across all stages. Discrepancies were resolved by the primary investigator and reasons for exclusion at the full-text stage were documented. From the included studies, data was extracted into a standardized Microsoft Excel spreadsheet. Data extraction focused on key variables aligned with the objectives of the review, including author and year of publication, country and LMIC category, study design, population/sample, health domain, chatbot type, educational and communication functions, platform or delivery mode, and reported outcomes. Data items extracted from included studies were grouped into three analytical domains aligned with the review objective:

1. Patient education applications
2. Health communication functions
3. Health-related outcomes (e.g., behaviour change, diagnosis support, adherence, disease management)

Additional contextual data on implementation setting, target users, and technological features were also extracted.

Data extraction was performed independently across all included studies to ensure consistency and reliability, and extracted data were cross-checked between reviewers. Discrepancies were discussed and resolved through consensus. Extracted data were synthesized descriptively using numerical summary and thematic analysis. Study characteristics were summarized using frequencies and tabular mapping. Findings were then narratively synthesized across the three predefined domains:

Cross-cutting implementation patterns, barriers, and research gaps were subsequently identified and summarized.

Quality Appraisal, Protocol and Reporting

Quality Appraisal, Protocol and Reporting

Consistent with scoping review methodology, formal critical appraisal of methodological quality was not undertaken, as the primary objective was to map the extent and characteristics of available evidence rather than assess intervention effectiveness. However, study design and methodological characteristics were descriptively reported to support interpretation of the evidence base.

Although not prospectively registered in a public repository, a rigid a priori protocol was developed, finalized, and internally archived prior to the initiation of the literature search to ensure methodological transparency and minimize risk of selective reporting bias. The review methods were specified in advance and conducted in accordance with established scoping review guidance and PRISMA-ScR reporting standards.

Results and Findings

A total of 1,803 records were identified through database searching (n = 1,703) and additional sources (n = 100). Following deduplication, 68 duplicate records were removed, leaving 1,735 unique records for screening. Title screening resulted in 399 records eligible for abstract screening, out of which 55 records were retained for full-text evaluation. After full-text screening, a total of 9 studies met the inclusion criteria and were included in the final synthesis.

Characteristics of Included Studies

The included studies were conducted in India, Thailand, South Africa, Nigeria, Malaysia, and Pakistan, covering both lower-middle-income and upper-middle-income countries. Study designs were heterogeneous and included mixed-methods evaluations, pilot studies, observational studies, proof-of-concept trials, cross-sectional studies, and design/development studies. The target populations also varied, including adolescents, caregivers, people living with or at risk of infectious diseases, patients with chronic diseases, and key populations requiring HIV prevention services.

Across the included studies, chatbots were applied to several health domains, including adolescent sexual and reproductive health, pediatric oral health, tuberculosis care, diabetes self-management, hypertension self-care, HIV prevention and testing, and childhood immunization. The chatbots were delivered through commonly used digital platforms such as Facebook Messenger, WhatsApp, Telegram, SMS, and web-based interfaces. Table 1 summarizes the general characteristics, study designs, and deployment platforms of the included studies. The complete data set, including granular details on the specific educational and communication functions of each chatbot, is provided in the Supplementary Material (Supplementary Table 1).

Table 1
Characteristics of Included Studies

Study ID	Author (Year) & Setting	Health Focus, Study Design & Population	Chatbot Type & Delivery Platform
S1	Wang et al. (2022)[35] India (Lower-Middle Income)	Adolescent sexual & reproductive health, family planning, and mental health Design: Mixed-methods case study Population: 135,263 automated chatbot users (93% male, 6.8% female).	Hybrid AI chatbot using NLP (Microsoft Azure LUIS) and Regular Expressions; bilingual ("Hinglish"). Platform: Facebook Messenger
S2	Pupong et al. (2025) [33] Thailand (Upper-Middle Income)	Pediatric oral health & early childhood caries prevention Design: Mixed-methods evaluation Population: 58 caregivers evaluated (predominantly mothers).	Frame-based AI behavior change chatbot ("30-Day FunDee") with an animated dentist avatar. Platform: Facebook Messenger
S3	Mudzengi et al. (2025) [32] South Africa (Upper-Middle Income)	Tuberculosis (TB) test result notification & adherence support Design: Digital health design/development Population: Household contacts of TB patients (46 users evaluated).	Rule-based automated chatbot ("Shesha") based on the Health Belief Model; available in English and isiZulu. Platform: WhatsApp Business API
S4	Mash et al. (2022)[31] South Africa (Upper-Middle Income)	Type 2 diabetes self-management & lifestyle coaching Design: Mixed-methods implementation evaluation Population: Public-sector health users (4,577 interactive users).	Rule-based sequential chatbot ("GREAT4Diabetes") adapted from national guidelines; delivered in English, Afrikaans, and isiXhosa. Platform: WhatsApp Business Interface API
S5	Antia et al. (2025)[30] Nigeria (Lower-Middle Income)	Hypertension self-care & cardiovascular risk reduction Design: Single-arm, non-blinded proof-of-concept trial Population: 48 evaluable hypertensive adults (60.4% male).	Generative AI conversational chatbot ("Healthy Heart Assistant") built using OpenAI's GPT architecture. Platform: WhatsApp interface integration
S6	Ni et al. (2025)[37]	HIV prevention, self-testing, PrEP information, and mental health	Web-based AI chatbot embedded directly into a specialized digital

Study ID	Author (Year) & Setting	Health Focus, Study Design & Population	Chatbot Type & Delivery Platform
	Malaysia (Upper-Middle Income)	Design: National observational study Population: 334 men who have sex with men (MSM).	portal. Platform: MYHIV365 website interface
S7	Ntinga et al. (2022)[38] South Africa (Upper-Middle Income)	HIV self-testing, counseling support, and PrEP information Design: Cross-sectional pilot study Population: 120 consenting adults (median age: 24 years).	IsiZulu-speaking conversational agent ("Nolwazi_bot") featuring four selectable chatbot counselor personas. Platform: Telegram messaging application
S8	Mathur et al. (2025)[36] Nigeria (Lower-Middle Income)	HIV prevention, PrEP awareness, and risk self-assessment Design: Pilot study Population: 150 clinic waiting room participants (132 cisgender women, 18 transgender men).	Digital HIV prevention chatbot decision-support tool tailored specifically for local waiting room contexts. Platform: Digital devices in clinic waiting areas
S9	Siddiqi et al. (2024)[34] Pakistan (Lower-Middle Income)	Childhood immunization tracking & vaccine schedule tracking Design: Sequential explanatory mixed-methods study Population: 677 caregivers who actively interacted with the platform.	Local-language AI chatbot ("Bablibot") utilizing NLP, Machine Learning, and Human-in-the-Loop oversight; converses in Roman Urdu. Platform: SMS and WhatsApp

N = 9, Studies denoted as S1-S9

Functional Applications of AI Chatbots in LMIC Healthcare

To map the functional roles of the included chatbots, intervention components were grouped into six major domains: patient education, health communication, behaviour change, diagnosis or triage support, adherence support, and disease management. Because several chatbots had more than one function, individual studies could contribute to more than one functional domain. The functional domains and primary healthcare roles of these interventions are cross-tabulated in Table 2.

Table 2
Functional Applications of AI Chatbots in LMIC Healthcare

Functional Domain	Description of Use	Example Applications	No. of Studies
Patient Education	Delivery of tailored health information and disease-specific knowledge	HIV/PrEP education, hypertension education, diabetes education, TB education, oral health lessons, immunization information	9 (All)
Health Communication	Interactive communication support between users and digital systems	Answering health queries, conversational counselling, chatbot-guided self-testing, clinic information, care navigation	9 (All)
Behaviour Change	Support for modifying health-related behaviours or encouraging preventive/self-care action	Tooth-brushing improvement, diet and physical activity support, HIV testing/self-testing, PrEP consideration, medication adherence behaviour, immunization uptake support	7 (S2, S3, S4, S5, S6, S7, S9)
Diagnosis/Triage	Preliminary screening, result interpretation, risk assessment, or referral guidance	HIV self-test guidance and interpretation, depression screening, HIV risk self-assessment, TB result notification, side-effect guidance, referral/linkage to care	6 (S1, S3, S5, S6, S7, S8)
Adherence Support	Promotion of treatment adherence, appointment compliance, or follow-up behaviour	Medication reminders, appointment reminders, TPT adherence support, immunization due-date guidance, follow-up prompts	5 (S3, S4, S5, S7, S9)
Disease Management	Ongoing support for chronic disease monitoring, self-care, or structured condition management	Diabetes self-management, hypertension self-care, TB preventive treatment support	3 (S3, S4, S5)

Reported Outcomes of AI Chatbot Interventions

Reported outcomes were grouped into six domains: health knowledge, behaviour change, clinical outcomes, communication outcomes, user experience outcomes, and trust or relational outcomes. These domains reflect the range of effects reported across the included studies, including both quantitative outcomes and qualitative user feedback. A detailed breakdown of the directions of effect across the documented outcome categories is summarized in Table 3.

Table 3
Reported Outcomes of AI Chatbot Interventions

Outcome Domain	Specific Outcomes Reported	Direction of Effect	No. of Studies
Health Knowledge Outcomes	Improved disease knowledge, health awareness, health literacy, or new learning about HIV, PrEP, hypertension, diabetes, oral health, TB, or immunization	Positive	8 (S1, S2, S3, S4, S5, S6, S7, S9)
Behaviour Change Outcomes	Improved or intended changes in health behaviours, including medication adherence, tooth-brushing, PrEP consideration, HIV testing/self-testing, lifestyle practices, and immunization-related actions	Positive	7 (S2, S3, S4, S5, S6, S7, S9)
Clinical Outcomes	Changes in measurable health or screening-related outcomes, including blood pressure, HIV self-test results, depression screening, oral health behaviour indicators, and treatment/referral linkage	Mixed/Positive	3 (S1, S5, S7)
Communication Outcomes	Improved engagement, responsiveness, two-way interaction, answering health queries, guided counselling, clinic navigation, and chatbot-user communication quality	Positive	9 (All)
User Experience Outcomes	High usability, acceptability, satisfaction, ease of use, perceived usefulness, and willingness to recommend the chatbot	Positive	9 (All)
Trust/Relational Outcomes	Perceived confidentiality, non-judgmental interaction, empathy, social presence, feeling like talking to a real person, willingness to disclose, and trust in chatbot-supported communication	Mixed/Positive	6 (S1, S4, S6, S7, S8, S9)

Across the included studies, the most consistently reported outcomes were positive user experience and communication outcomes. Most studies reported high acceptability, usability, satisfaction, or willingness to recommend the chatbot. Several studies also reported improvements in knowledge, self-care confidence, medication adherence, HIV prevention awareness, oral health behaviour, or service engagement. However, clinical outcomes were less consistently measured, and findings were mixed.

Distribution of Included Studies by Health Domain

The health domains represented in the included studies were then categorized to show where AI chatbots have been most commonly applied within LMIC healthcare settings. The categorical distribution of the included studies across specific health domains is mapped out in Table 4.

Table 4
Distribution of Included Studies by Health Domain

Health Domain	Description	Applicable Studies (Count)
HIV Prevention and Testing	Chatbots used for HIV prevention education, HIV self-testing support, PrEP information, HIV risk self-assessment, linkage to care, and access to MSM-friendly or key-population-sensitive services.	S6, S7, S8 (n = 3)
Sexual and Reproductive Health	Chatbot support for adolescent sexual and reproductive health, family planning, menstruation-related questions, virginity concerns, safe sex, and gender-related social issues.	S1 (n = 1)
Pediatric Oral Health	Chatbot used to support caregiver education on child tooth brushing, fluoride toothpaste use, dental plaque self-assessment, and prevention of early childhood dental caries.	S2 (n = 1)
Tuberculosis Care and Prevention	Chatbot used for TB test-result notification, clinic linkage, Tuberculosis Preventive Treatment education, and adherence support for household contacts.	S3 (n = 1)
Diabetes Self-Management	Chatbot used for type 2 diabetes education, lifestyle coaching, medication information, foot care, mental health support, and self-care confidence.	S4 (n = 1)
Hypertension Management	Chatbot used for hypertension education, medication adherence support, lifestyle coaching, symptom tracking, appointment reminders, and blood pressure self-care.	S5 (n = 1)
Childhood Immunization	Chatbot used to answer caregiver questions about routine vaccination schedules, missed or delayed vaccination, vaccine side effects, and immunization centre information.	S9 (n = 1)

HIV prevention and testing was the most represented health domain, with three studies focusing on HIV self-testing, PrEP information, HIV risk assessment, or linkage to HIV-related services. Other health domains were represented by one study each, including sexual and reproductive health, pediatric oral health, tuberculosis care and prevention, diabetes self-management, hypertension management, and childhood immunization. This distribution shows that current evidence is still scattered across different health areas, with limited replication within most domains.

Implementation Barriers / Limitations

Implementation barriers and study limitations were extracted to identify recurring challenges affecting chatbot deployment, uptake, usability, scalability, and interpretation of findings. These barriers included both practical implementation issues and methodological limitations reported by the included studies.

Table 5
Implementation Barriers / Limitations

Study ID	Implementation Barriers and Methodological Limitations
S1	• No Direct User Data: Evaluated only via proxy Facebook analytics without collecting direct user-level demographic or motivational characteristics. • Gender-Skewed Engagement: Users were overwhelmingly male, with instances of abusive or obscene behavior recorded. • Design & Safety Risks: Faced challenges in balancing positive/negative tool affordances, safety, moderation, and inclusivity for underprivileged groups.
S2	• High Attrition & Low Completion: Suffered an 8-participant loss to follow-up, with only 32.8% of participants completing the full program. • Engagement Decay: Usage peaked in the first week and steadily declined due to long interaction durations and user workload strain. • Methodological Bias: Employed a pre-post design susceptible to maturity bias and a self-administered questionnaire that raised validity concerns.
S3	• Technical Workflow Bugs: Plagued by skipped or duplicate messages, incorrect flow sequencing, inflexible dashboards, and Meta platform delays. • Tracking & Access Barriers: Complicated by low survey completion, poor clinic follow-up, password access issues, and multiple users sharing single phone numbers. • Financial & Operational Constraints: Hampered by high development costs, delayed local translation (isiZulu), and a lack of pre-intervention user consultation.
S4	• Low Uptake & Program Completion: Only 12.56% of users received all 16 messages, heavily limited by low digital literacy and lack of smartphones among older adults. • Technical & Infrastructure Overload: Backend system overload dropped over 1,000 queued messages following national television publicity. • Methodological Restrictions: Lacked objective patient-level clinical data (e.g., glycemic control) and carried potential positive bias from implementation staff acting as researchers.
S5	• Severe Digital Exclusion: Only 35% of screened clinic attendees possessed internet-enabled, chatbot-compatible smartphones. • Declining Engagement: Chat frequencies dropped sharply after the first week of initial interest. • Methodological Limitations: Restricted by a small sample size, short 30-day follow-up, lack of statistical power for efficacy testing, and reliance on subjective, self-reported adherence data.
S6	• Algorithmic Rigidity: Failed to answer 31 complex interactions or process unprogrammed requests for human assistance/clinic information. • Minimal Sustained Use: 91% of participants interacted with the web-based chatbot only a single time.

Study ID	Implementation Barriers and Methodological Limitations
	• Methodological Gaps: Inability to fully verify user identities (tracked strictly by IP address) or evaluate actual HIV prevention behavior changes.
S7	• Impersonal Interaction: Lacked emotional support capabilities, featuring rigid one-directional dialogue and overly rapid responses that felt unnatural. • Risk of User Error: High potential for user error when interpreting HIV self-test instructions or results without human oversight. • Sampling Restrictions: Relied on a convenience sample of young users tested on a single phone brand (Samsung) and messaging application (Telegram) using an unvalidated scale.
S8	• Accessibility & Language Gaps: Lacked vital audio prompts, verbal inputs, open-ended feedback channels, large font sizes, and local language options. • Privacy & Scope Gaps: Focus was restricted purely to oral PrEP, and participants displayed privacy concerns regarding sharing bot responses with healthcare providers. • Selection Bias: Sample was restricted to cisgender women and transgender men already actively attending public health facilities.
S9	• High Algorithmic Fallback: Bablibot frequently defaulted to human-in-the-loop oversight due to a profound lack of local Roman Urdu training data, which ultimately led to unexpected system delivery delays during repeat chatbot sessions. • Methodological Restrictions: Utilized convenience sampling, lacked technology readiness assessments, and could not verify user eligibility for those recruited via mass communication.

Several cross-cutting barriers were observed across the included studies. These included limited digital access, low sustained engagement, language and literacy challenges, privacy concerns, weak integration with health systems, and technical limitations such as workflow errors, limited personalization, or high dependence on human support. Some studies also reported methodological limitations, including small sample sizes, short follow-up periods, self-reported outcomes, unvalidated tools, and limited generalization. These findings suggest that although AI chatbots are feasible in LMIC settings, successful implementation requires attention to infrastructure, accessibility, user trust, health system integration, and long-term sustainability.

Identified Research Gaps in the Evidence Base Across Included Studies

Based on the study characteristics, reported outcomes, and implementation barriers, key gaps in the evidence base were identified. These gaps reflect areas where further research is needed to strengthen the design, evaluation, and implementation of AI chatbot interventions in LMIC healthcare systems.

Table 6
Identified Research Gaps in the Evidence Base Across Included Studies

Gap Area	Description	Implication	Applicable Studies
Limited rigorous effectiveness evidence	Most studies were exploratory, pilot, feasibility, usability, observational, cross-sectional, design/development, pre-post, proof-of-concept, or mixed-methods studies. None provided definitive long-term randomized effectiveness evidence across clinical outcomes.	The evidence base supports feasibility, acceptability, and early usefulness, but stronger controlled or randomized studies are needed to confirm effectiveness.	All studies
Short follow-up or limited duration of assessment	Several studies assessed short-term outcomes, early implementation, single-session chatbot use, 30-day outcomes, 2-month follow-up, or limited deployment periods.	Long-term engagement, sustained behaviour change, adherence, service uptake, and clinical impact remain uncertain.	S2; S4; S5; S6; S7; S9
Limited objective clinical outcome measurement	Many studies focused mainly on usability, acceptability, engagement, satisfaction, knowledge, or self-reported outcomes rather than objective clinical endpoints.	The current evidence is stronger for user experience and feasibility than for measurable health improvement.	S1; S3; S4; S6; S8; S9
Small, selective, or non-representative samples	Some studies used small samples, convenience sampling, clinic-based recruitment, web-based recruitment, or selected users with smartphone/internet access.	Findings may not generalize fully to wider LMIC populations, especially rural, older, poorer, low-literacy, or digitally excluded groups.	S2; S3; S5; S6; S7; S8; S9
Digital access inequity	Barriers included smartphone ownership, internet-enabled phone access, data costs, platform dependence, shared devices, low digital literacy, and limited accessibility for some users.	Chatbot interventions may widen inequities if they assume stable internet, smartphone ownership, literacy, or familiarity with digital platforms.	S3; S4; S5; S6; S7; S8; S9
Limited language, literacy, and accessibility adaptation	Studies highlighted issues around local language, simplified text, delayed translation, audio options, verbal response options, culturally appropriate	Chatbots require stronger multilingual, audio-supported, and low-literacy designs to	S1; S3; S4; S7; S8; S9

Gap Area	Description	Implication	Applicable Studies
	language, and adaptation for low-literacy or visually impaired users.	improve inclusion in LMIC settings.	
Limited personalization and contextual response capacity	Some chatbots could not answer questions outside programmed algorithms, had high fallback rates, lacked flexible follow-up questioning, or were limited in providing individualized interaction.	Current systems may work well for structured education and navigation but may be less reliable for complex counselling, triage, or personalized care.	S3; S5; S6; S7; S8; S9
Weak healthcare-system integration and follow-up	Several studies raised issues around linkage to care, provider integration, follow-up after screening or testing, electronic registry integration, or embedding chatbots into routine service delivery.	Chatbots may provide useful information but may not ensure continuity of care unless linked to trusted healthcare services and referral systems.	S4; S6; S7; S8; S9
Privacy, confidentiality, and trust concerns	Concerns included shared devices, data privacy, provider access to chatbot responses, confidentiality of sensitive disclosures, trust in automated systems, and the need for safe disclosure spaces.	Clear privacy safeguards, consent processes, data governance, and user control over information sharing are needed.	S1; S3; S4; S6; S7; S8; S9
Limited implementation cost and sustainability evidence	Cost and sustainability evidence was uneven. Only some studies reported development, operational, support, or scale-up considerations in detail, while others provided little or no economic evidence.	It remains unclear whether many chatbot interventions can be sustained or scaled within routine LMIC health systems.	Across studies; detailed cost/sustainability evidence mainly from S3, S4, and S9
Engagement drop-off or limited sustained use	Several studies reported declining engagement, low programme completion, one-time use, survey attrition, or users stopping conversations before completion.	Sustained engagement remains a major challenge, especially for chatbot interventions requiring repeated or long-term use.	S2; S3; S4; S5; S6; S9

Gap Area	Description	Implication	Applicable Studies
Limited validation of outcome tools and reliance on self-report	Some studies used adapted, self-made, self-administered, or unvalidated tools, and several relied on self-reported outcomes such as satisfaction, behaviour change, adherence, or usability.	Outcome measures may be difficult to compare across studies and may be affected by reporting or measurement bias.	S2; S4; S5; S7; S8; S9
Underrepresentation of vulnerable or hard-to-reach groups	Some studies had gender imbalance, small transgender samples, facility-based samples, or higher participation among digitally enabled, educated, or already health-seeking users.	Evidence may not fully represent those most affected by stigma, poverty, low literacy, poor healthcare access, or digital exclusion.	S1; S2; S5; S6; S7; S8; S9
Limited safety and escalation pathways	Gaps included unanswered complex queries, unclear linkage after depression screening, limited empathy, one-directional conversations, possible user error, and uncertain escalation to human support.	Chatbots need clear human escalation pathways, especially for HIV testing, mental health, symptom concerns, clinical referral, and sensitive counselling.	S3; S5; S6; S7; S8; S9

The evidence base remains strongest for feasibility, acceptability, and user experience, but weaker for long-term effectiveness, objective clinical outcomes, cost-effectiveness, and sustained implementation. Most studies were early-stage evaluations rather than definitive trials, and several relied on short follow-up periods, selective samples, or self-reported measures. Across studies, there was also limited evidence on how chatbot interventions can be safely integrated into routine care pathways, linked to healthcare providers, or scaled sustainably within resource-constrained health systems.

Discussion

This scoping review mapped the current evidence on the utility of AI-driven chatbots for patient education, health communication, and health-related outcomes in low- and middle-income countries (LMICs). Nine studies met the inclusion criteria, reflecting the emerging nature of this field within LMIC health systems. Despite the modest number of included studies, several interventions involved large real-world user populations, indicating growing implementation activity across a diverse range of health domains, including HIV prevention, sexual and reproductive health, tuberculosis care, diabetes self-management, hypertension management, childhood immunization, and pediatric oral health. HIV-related interventions accounted for one-third of the included studies. This concentration likely

reflects both the continuing public health burden of HIV in many LMICs and the potential suitability of chatbot-mediated communication for addressing sensitive or stigmatized health issues. Several studies reported that users valued the privacy, confidentiality, and non-judgmental nature of chatbot interactions, particularly when discussing HIV prevention and testing [36–38]. These findings suggest that conversational agents may offer unique advantages in healthcare contexts where stigma, discrimination, or fear of disclosure represent barriers to care-seeking behaviour. The ability to access information anonymously and engage in confidential discussions may facilitate greater user engagement with preventive and diagnostic services.

Furthermore, the included studies demonstrated a high level of user acceptability and satisfaction associated with chatbot interventions. Positive perceptions of usefulness, ease of use, and willingness to recommend the intervention were reported across diverse populations, health conditions, and delivery platforms, including WhatsApp, Facebook Messenger, Telegram, SMS, and web-based systems [30, 31, 34, 36, 37]. These findings are consistent with broader evidence demonstrating that user acceptability is among the most robust and reproducible outcomes associated with healthcare chatbot interventions [3, 27]. Importantly, the positive user experiences observed across both rule-based and more advanced conversational systems suggest that perceived usefulness, accessibility, and contextual relevance may be more important determinants of adoption than technological sophistication alone.

Corroborating the broad utility of digital modalities, significant improvements in health knowledge were reported across eight of the nine included studies [30–35, 37, 38]. The consistency of these findings across different countries and health domains suggests that conversational agents may function as effective channels for delivering health information in contexts where healthcare professionals often face substantial workload pressures and limited consultation time. Given the ongoing shortages of healthcare workers in many LMICs and the projected global deficit of health personnel, digital approaches that expand access to reliable health education may play an increasingly important complementary role within health systems [15, 17].

The findings also suggest that chatbot interventions or conversational agents may contribute to positive behavioral outcomes. Seven studies reported improvements in health-related behavior, including medication adherence, HIV self-testing, oral health practices, lifestyle modification, immunization-related actions, and engagement with preventive services [30–34, 37, 38]. These findings align with previous evidence indicating that conversational agents can facilitate behaviour change through tailored messaging, reminders, motivational support, and repeated user engagement [3, 40]. The observed behavioral improvements are particularly relevant in LMIC contexts, where barriers related to healthcare access, workforce shortages, and limited opportunities for ongoing patient counselling may constrain conventional behaviour-change interventions. Nevertheless, the mechanisms through which chatbot interactions translate into sustained behavioral change remain insufficiently understood and warrant further investigation.

In contrast to the consistently positive findings for knowledge acquisition, communication, and behavioral outcomes, evidence regarding clinical effectiveness remains limited. Only a minority of studies assessed objective clinical outcomes, and findings were mixed. For example, [30] reported significant improvements in hypertension knowledge and medication adherence but found no statistically significant reduction in blood pressure following a 30-day intervention period. Similar patterns have been reported, where improvements in self-management behaviors and treatment adherence do not necessarily translate into immediate physiological improvements [25, 41, 42]. The predominance of short follow-up periods, small sample sizes, and exploratory study designs across the included studies likely contributes to this evidence gap. Consequently, while current evidence supports the feasibility and potential utility of chatbot interventions or conversational agents, it remains insufficient to establish their long-term effectiveness in improving clinical outcomes.

Chatbot applications in LMIC healthcare settings extend beyond traditional health education functions. Although all included interventions incorporated educational and communication components, several also provided risk assessment, symptom screening, self-testing guidance, treatment adherence support, referral recommendations, and chronic disease management functions [30, 32, 37, 38]. This expansion mirrors trends reported in broader healthcare chatbot literature, which increasingly positions conversational agents as multifunctional tools capable of supporting multiple stages of the patient journey rather than serving solely as information-delivery platforms [28, 29]. Such multi-functionality may be particularly advantageous in resource-constrained health systems where interventions that address multiple healthcare needs simultaneously are likely to provide greater implementation value.

The geographical distribution of evidence identified in this review reveals substantial gaps in current knowledge. Although studies were identified from South Asia, Southeast Asia, and Sub-Saharan Africa, some countries facing the most severe shortages of healthcare workers and the greatest barriers to accessing health information remain largely absent from the literature. Future research should therefore prioritize low-income settings to determine whether the benefits observed in lower-middle-income and upper-middle-income countries can be replicated in more resource-constrained environments.

Several implementation challenges emerged consistently across the included studies. Digital access inequities were among the most frequently reported barriers and included limited smartphone ownership, inadequate internet connectivity, data costs, low digital literacy, and restricted access among older adults and socioeconomically disadvantaged populations [30–32, 34]. These findings reinforce concerns raised by previous reviews that digital health interventions may inadvertently exacerbate existing health inequities if implementation strategies fail to account for disparities in access to digital technologies [26, 43, 44]. Consequently, equitable implementation of chatbot interventions will require careful consideration of local technological infrastructure and user capabilities.

Sustained user engagement also emerged as a major challenge. Although initial uptake was generally favourable, several studies reported declining participation over time, incomplete programme completion, or predominantly single-use interactions [31, 33, 37]. This pattern mirrors broader findings

within digital health research and suggests that maintaining long-term engagement remains a persistent obstacle. Because many anticipated benefits of chatbot interventions depend on repeated exposure and ongoing interaction, future studies should investigate strategies to enhance engagement retention, including adaptive content delivery, personalization, behavioral reinforcement techniques, and integration with human support systems.

Language, literacy, and accessibility considerations represented another recurring implementation challenge. Several studies highlighted limitations related to multilingual functionality, culturally appropriate communication, accessibility for users with low literacy levels, and support for individuals with visual impairments [32, 34, 36]. While some projects integrated multi-language capabilities into their design frameworks [31], others faced severe operational delays in deploying localized translations, such as the isiZulu framework for the Shesha chatbot [32]. Given the linguistic and cultural diversity that characterizes many LMICs, these issues should not be viewed as secondary design considerations. Rather, culturally responsive adaptation, multilingual functionality, and low-literacy-friendly interfaces are likely to be essential determinants of intervention reach, acceptability, and effectiveness.

Privacy, confidentiality, and trust also emerged as important considerations. Concerns related to shared-device use, protection of sensitive information, data governance, and uncertainty regarding information sharing with healthcare providers were reported across multiple studies [32, 36, 37]. These findings are particularly relevant in settings where users may access chatbot services through shared household devices or where concerns regarding stigma and discrimination remain significant. Consistent with WHO guidance on the ethical governance of AI in health, robust privacy safeguards, transparent data governance frameworks, and user control over information sharing should be considered essential components of future chatbot implementation strategies [23].

Study Limitations

While large-scale implementation datasets were captured in certain digital channels (e.g., S1, S4), the majority of the remaining evidence base relies on small, selective, or non-representative clinic-based samples (S2, S3, S5, S7, S8, S9) that constrain broad generalizability across rural or low-literacy LMIC regions. While such studies provide valuable insights regarding feasibility, acceptability, and implementation, they offer limited evidence regarding long-term effectiveness, scalability, and cost-effectiveness. Although a comprehensive search strategy was employed, the exclusion of Embase, Scopus, and Web of Science may have resulted in the omission of some relevant studies. To mitigate this risk, multiple databases with complementary coverage were searched, supplemented by Google Scholar screening and backward citation tracking. Additionally, our exclusion of non-English publications introduces a potential language bias that may have inadvertently omitted localized chatbot deployments across low- and middle-income country (LMIC) contexts. Accordingly, the current evidence base is strongest in demonstrating feasibility and potential utility rather than definitive effectiveness. More rigorous evaluations, including randomized controlled trials, implementation studies, and economic evaluations, are required to determine whether chatbot interventions or conversational agents can

deliver sustained improvements in health outcomes and represent efficient investments within resource-constrained health systems.

Future Research Directions and Recommendations

The evidence mapped in this review points to a field that is active, diverse, and genuinely promising but still operating largely in the register of early feasibility. Moving from that register toward robust, policy-relevant evidence will require deliberate investment in several specific directions.

The most urgent priority is rigorous effectiveness research. Future studies should move beyond pre-post designs and single-arm pilots toward randomized or quasi-experimental trials with longer follow-up periods sufficient to evaluate the sustainability of behavioural and clinical outcomes. Where randomization is not feasible, stepped-wedge designs or matched comparison groups offer credible alternatives. Standardized outcome reporting, guided by frameworks such as the mERA checklist and the CONSORT extension for digital health trials, would make findings meaningfully comparable across studies and settings.

Alongside effectiveness, the field needs a much clearer understanding of what sustains engagement over time. The consistent pattern of early drop-off documented in this review is not merely a methodological inconvenience but a public health problem. Studies that explicitly test engagement-sustaining design features, such as adaptive content sequencing, peer-network integration, gamification, and proactive human-in-the-loop support, are needed.

The geographic and demographic gaps in the current evidence base must also be directly addressed. Low-income countries, rural communities, older adults, users with low or no literacy, and populations affected by stigmatised conditions beyond HIV are substantially underrepresented. Reaching these groups will require not just research funding but a shift in how chatbot interventions are developed. Participatory and community-based design processes, in which intended users are involved from the earliest stages of development through to evaluation, consistently produce tools that are more contextually relevant, more trusted, and more used. That approach should become standard practice rather than an exception in LMIC chatbot research.

Health system integration deserves its own research agenda. Several studies in this review identified weak or absent linkage between chatbot interactions and formal care pathways which includes: unclear referral after depression screening, limited follow-up for TB household contacts, uncertain continuity of care following HIV self-testing. How chatbots can be meaningfully embedded within existing health information systems, community health worker networks, and referral structures rather than operating as standalone tools is one question that combines technical, organizational, and relational dimensions. Answering it will require health systems researchers and implementation scientists working alongside technologists, not separately from them.

Health economic evidence is almost entirely absent from the current literature. Only a small number of studies reported any cost data in detail. Robust cost-effectiveness analyses (cost per behaviour change,

cost per clinical outcome avoided, cost per quality-adjusted life year) are needed to support rational resource allocation decisions by health ministries and funders. Cost modelling that projects scale-up scenarios under different implementation conditions would be particularly valuable for planning purposes in resource-constrained settings.

Finally, the rapid expansion of large language model-based and generative AI chatbot architectures introduces a new set of questions that the field is not yet equipped to answer. The GPT-powered Healthy Heart Assistant evaluated in Nigeria [30] represents an early example of what may soon become the dominant chatbot architecture in health applications. Generative AI systems can produce contextually responsive, naturalistic phrased responses that rule-based systems cannot match, but they also carry real risks of misinformation, unvalidated clinical guidance, and culturally inappropriate outputs. Research frameworks for prospectively evaluating the safety, accuracy, and equity implications of generative AI health chatbots in LMIC contexts are needed now, before widespread deployment makes that evaluation far harder to conduct rigorously.

Conclusion

The consistently positive findings regarding acceptability, knowledge acquisition, communication support, and behavioral outcomes indicate that conversational agents or AI-Driven chatbots may serve as valuable complements to existing healthcare services in LMICs. However, substantial gaps remain regarding long-term clinical effectiveness, equity, sustainability, health-system integration, and cost-effectiveness. Addressing these gaps should be a priority for future research and implementation efforts if chatbot interventions are to move beyond pilot projects and contribute meaningfully to strengthening healthcare delivery in resource-constrained settings.

Declarations

Conflict of Interest Statement

The authors declare that they are no conflict of interest relevant to this study.

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Author Contribution

A.A. conceived and developed the study protocol and contributed to the screening process, data extraction, data presentation, drafting of the methodology and results sections, and critical review of the entire manuscript. I.S. contributed to writing the discussion, limitations, recommendations, future research directions, and conclusion sections. A.E. participated in article retrieval, screening, and drafting of the introduction. E.N. contributed to writing and editing the introduction. C.I. contributed to drafting the abstract and critically reviewing the manuscript. M.T. assisted with article retrieval and data extraction. E.J. contributed to data extraction. I.U. assisted with article retrieval and organization of retrieved studies. J.K. contributed to study screening. T.O. was responsible for reference formatting. I.P. and G.I. critically reviewed the manuscript. All authors read and approved the final version of the manuscript.

Data Availability

All data supporting the findings of this study are included within the article and its supplementary materials. The data were derived from previously published studies, all of which have been appropriately cited in the manuscript. No new primary datasets were generated during this study.

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Figures

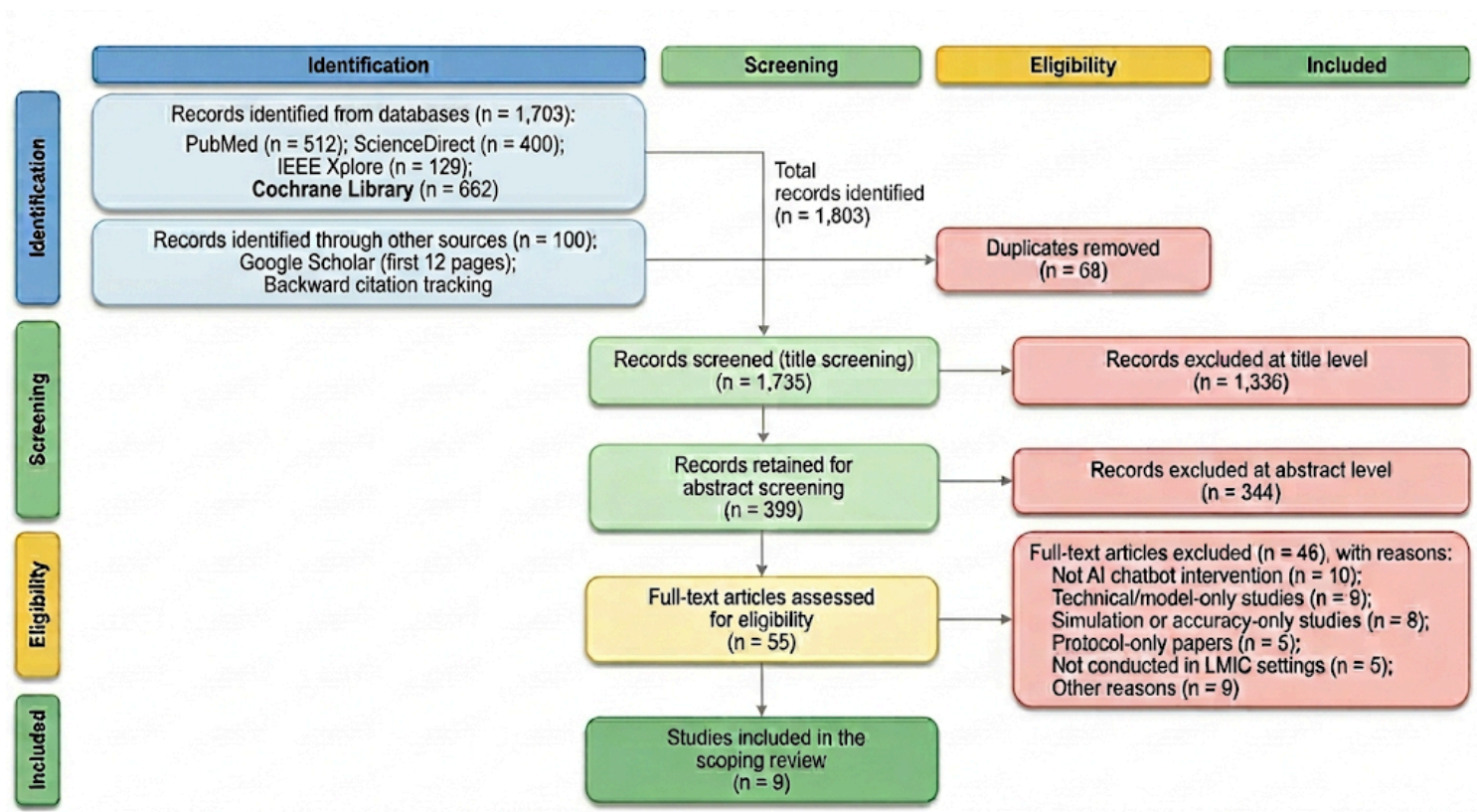


Figure 1

PRISMA Flow Chart

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