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Original article

Technology Leads in Community Needs: AI Applications in Preventive Health

Ayman Elhaji

Department of Pedodontics and Preventive Dentistry, Faculty of Dentistry, University of Zawia, Zawia, Libya
Corresponding email. a.elhaji@zu.edu.ly

Abstract
Artificial intelligence (AI) is driving a rapid shift in healthcare from reactive therapy to proactive prevention. Researchers investigate AI applications for enhancing community preventive health services through risk identification, customized treatments, and optimized resource management. The research evaluates AI applications in community-based preventive health programs through a systematic review of studies published between 2018 and 2025. The research evaluates AI performance against conventional methods through its analysis of disease prediction accuracy, risk evaluation, health equality, and patient participation results. The research followed PRISMA 2020 guidelines to conduct its systematic review. The search of Web of Science, IEEE Xplore, PubMed, and Scopus databases revealed studies from January 2018 to August 2025. The research team evaluated twelve studies that met the inclusion criteria through thematic analysis after performing a quality assessment using established validation methods. The concluded 12 studies from 2018 to 2025 demonstrate how AI applications in preventive health have evolved into four distinct areas: (1) AI-assisted screening and predictive models enhance risk assessment and early disease detection capabilities; (2) Health promotion and patient engagement receive personalized approaches; (3) The implementation of AI systems creates both positive effects on underserved areas and negative consequences through algorithmic bias and digital access disparities; (4) The process of implementation faces various obstacles. The implementation of artificial intelligence technology enables community health programs to achieve better results through enhanced precision, targeted approaches, and unbiased delivery. The path to success requires solving three main sets of challenges, which include algorithmic fairness, technological advancement, and social acceptance. The research presents a method to enhance public health systems through AI implementation, which requires special attention to Libyan and similar contexts.
Keywords. Artificial Intelligence, Preventive Health, Public Health, Disease Prevention, Health Equity.

Introduction

The global healthcare system is undergoing a transition from a reactive, disease-centered model to a preventive, wellness-oriented approach driven by the growing burden of chronic diseases and rising healthcare costs [1]. Preventive strategies have been shown to improve health outcomes while reducing long-term expenditures compared to treatment after disease onset [1, 2]. Community-based preventive health programs play a central role in this shift by supporting health promotion, early screening, and timely intervention. However, these programs continue to face persistent challenges, including limited funding, workforce shortages, and difficulties in addressing the needs of diverse populations [2].

In this context, artificial intelligence (AI) has emerged as a key enabler of preventive healthcare [3]. Through machine learning, deep learning, and natural language processing, AI supports large-scale data integration and predictive analytics, enabling early disease detection and risk stratification using electronic health records, genomic data, and lifestyle information—often before clinical symptoms appear [3–5]. AI-driven models have demonstrated strong performance in predicting the progression of chronic conditions such as kidney disease and diabetes, enabling more timely and targeted interventions [4–6].

Beyond individual-level prediction, AI enhances population health surveillance by leveraging real-time data from diverse sources, including social media, news platforms, and environmental sensors [7–9]. These capabilities enable earlier detection of public health threats and more responsive interventions compared to traditional surveillance systems. In addition, AI supports personalized patient engagement through chatbots, virtual assistants, and wearable technologies, enabling continuous monitoring, tailored health education, and behavior-change support [10–13].

Despite these advances, the implementation of AI in community-based preventive health remains constrained by several challenges [14, 15]. Algorithmic bias may exacerbate existing health inequities, particularly when models are trained on non-representative datasets. Additional barriers include data privacy and security concerns, limited digital infrastructure, the digital divide, and integration challenges within existing healthcare workflows [16–18].

While existing literature has explored AI applications in healthcare and preventive medicine, evidence remains fragmented regarding its implementation in community-based preventive health settings, with many studies focusing on clinical or disease-specific applications rather than community-level deployment. This study addresses this gap by synthesizing research published between 2018 and 2025 to identify key capabilities, limitations, and requirements for effective implementation. The findings aim to inform

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policymakers, public health practitioners, and technology developers on the ethical and strategic use of AI to strengthen community health systems.

Methods

Methodological Approach

The research used systematic review methods to analyze existing knowledge about artificial intelligence applications in community-based preventive health programs. The review process followed the 2020 PRISMA guidelines for Preferred Reporting Items for Systematic Reviews and Meta-Analyses [19]. The framework enabled researchers to conduct study identification and screening, eligibility assessment, and data synthesis through a method that was easy to use and produced consistent results.

Research Question

The research investigated AI-based community preventive health programs through a comparison with conventional methods to detect diseases early, reduce risks, enhance patient participation, and achieve health equity for different population groups between 2018 and 2025.

PICOT Framework

The research question expanded through the PICOT framework to include: P (Population): The review studied preventive health activities that serve communities with different demographics and focus on underserved and high-risk groups. I (Intervention): The research used artificial intelligence technology through machine learning algorithms for risk assessment, AI chatbots for health education, and AI-enhanced screening tools. C (Comparison): The research compared AI-based preventive health methods to conventional risk assessment and educational materials and standard screening procedures without AI support. O (Outcomes): The research evaluated preventive intervention success through multiple outcomes, which included disease detection timing, risk assessment precision, patient involvement and behavioral change, program operational efficiency, and social equality effects. T (Timeframe): The research included studies published between January 2018 and August 2025.

Selection Criteria

The review process selected studies based on established inclusion and exclusion criteria to maintain both relevance and quality standards.

Eligibility Criteria

The research focused on the applications of artificial intelligence in preventive health services within community and primary care settings, aiming to capture contemporary developments in this rapidly evolving field. The review encompassed peer-reviewed journal articles presenting original research and systematic reviews, as well as conference papers, thereby ensuring coverage of both established and emerging evidence. The study period extended from January 1, 2018, to August 12, 2025, allowing for the inclusion of recent findings that reflect current technological advances and implementation practices. Only studies published in English were considered, which facilitated consistency in analysis and interpretation. Methodologically, the review incorporated quantitative, qualitative, and mixed-methods approaches to provide a comprehensive understanding of AI applications. This included randomized controlled trials, observational studies, cross-sectional investigations, and implementation research, thereby capturing both efficacy and real-world utility. Importantly, the scope was limited to studies involving human participants who received services in community-based or primary healthcare facilities, ensuring that the findings were directly relevant to frontline preventive care delivery.

Criteria for Exclusion

Studies focusing on the use of artificial intelligence for the treatment or management of existing diseases within hospital or secondary/tertiary care settings were excluded, as they fall outside the preventive and community-based scope of this review. In accordance with the conventional PRISMA guidelines, grey literature, editorials, opinion pieces, book chapters, and commentaries were excluded to ensure methodological rigor and the reliability of the evidence [20]. Studies published before 2018 and those not available in English were also excluded. Additionally, studies involving animal subjects, laboratory-based research, and technical publications that focused solely on algorithm development without evaluation of health outcomes were excluded, as they did not align with the review's applied, patient-centred focus. Finally, studies in which artificial intelligence was not the primary intervention or analytical component were excluded.

Search Methodology

The researcher performed an extensive database search to identify all relevant studies. The research process included the following essential steps:-

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Database Selection: The research team performed a systematic database search across four major electronic databases, which index extensive health and technology literature: PubMed, Scopus, IEEE Xplore, and Web of Science. The search query combined Medical Subject Headings (MeSH) with unstructured keywords for retrieval. The search query combined three essential elements, which included Artificial Intelligence, Preventive Health, and Community Environment.
The search terms included "Artificial Intelligence," "Machine Learning," "Deep Learning", "Predictive Modelling, "AI" "Intelligent Systems", and "Natural Language Processing ".
The search terms included "Preventive Medicine", "Prevention", "Early Detection", "Screening", "Health Promotion", "Risk Stratification", "Disease Prevention", and "Public Health Surveillance".
The search terms for each concept were joined by the "OR" operator, while the three main concepts were connected through the "AND" operator to generate an exact search string.
The databases applied filters to limit search results to publications between 2018 and 2025, which were written in English.
The search queries were run against each database platform. The reference management software imported all search results, which allowed reviewers to eliminate duplicate entries. Two reviewers conducted independent title and abstract evaluations to select papers that met the selection criteria. The researcher conducted a full-text assessment of all potentially eligible papers using the established inclusion and exclusion criteria. The researcher conducted a thorough examination of all included study reference lists to discover additional relevant publications that the initial database search might have missed.

Selection of Studies

The research selection process followed PRISMA 2020 flow diagram guidelines, which started with complete record identification and ended with the final set of included studies through multiple screening stages. The database searches produced 25,410 documents, which were then reduced to 17,160 records after removing 8,250 duplicate entries. The automatic screening system removed 15,500 records that clearly did not meet the inclusion criteria because they belonged to incorrect publication categories or involved non-human subjects. The title and abstract screening process eliminated 1,595 records that did not match the review's focus on AI applications in community-based prevention from the remaining 1,660 records. The evaluation process for full-text publications resulted in 65 eligible studies. The review process eliminated 53 studies because they focused on therapy only (22 studies), lacked community or primary care settings (15 studies) or consisted of protocols or opinion pieces (11 studies), or their full texts were inaccessible (5 studies). The final selection process included 12 studies that answered the research question and fulfilled all established criteria. The qualitative analysis of this review used the 12 studies that met all inclusion criteria.

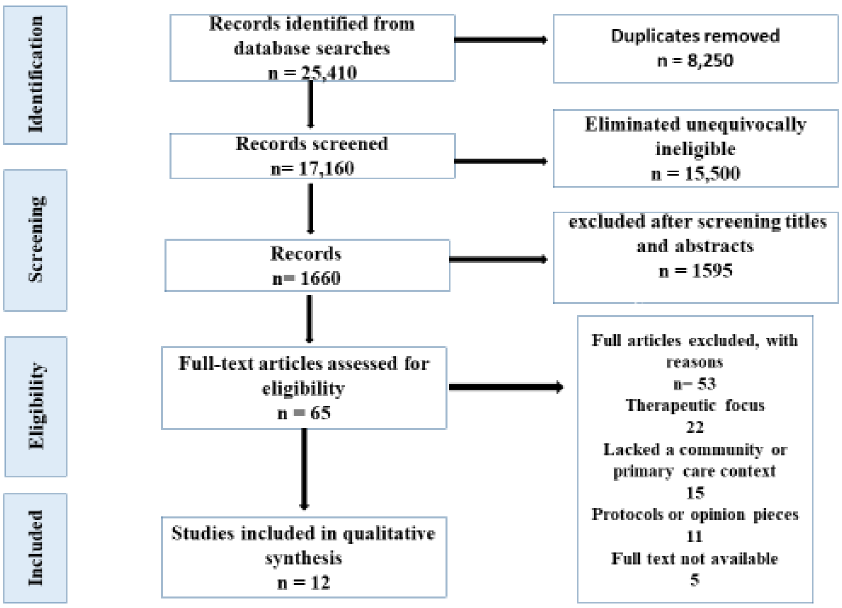

Figure 1. PRISMA 2020 flow diagram illustrating the study identification, screening, and selection process

Data Extraction

The research team developed a structured data extraction form to collect essential data from the 12 studies that made up the review. The extracted data included author names and publication dates, study objectives, research design, location, participant demographics, AI system details, and main research outcomes with their corresponding restrictions. The systematic data collection method allowed researchers to obtain all necessary information, which served as the base for thematic analysis and evidence synthesis. The research

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matrix (Table 1) received the extracted data in a systematic order to help researchers evaluate studies against each other's investigations.

Quality Evaluation

The quality evaluation process helps researchers, clinicians, policymakers, and practitioners to base their decisions on reliable evidence. The research team performed a quality assessment of included studies through validated critical appraisal tools, which matched their respective research designs. The Cochrane Risk of Bias 2 (RoB 2) tool was used for evaluating randomized controlled trials (RCTs) [21], while the Joanna Briggs Institute (JBI) Critical Appraisal Checklists were used for qualitative and cohort and cross-sectional studies [22], and the STARD 2015 checklist served as a reference for diagnostic accuracy studies [23]. The evaluation process for each study evaluated its research question clarity, its design suitability and methodological strength, and result and conclusion clarity and relevance. The quality assessment of studies resulted in three rating categories, which are high, moderate, and low, as shown in (Table 2). The evaluation process uses high-quality study findings as primary evidence but requires careful interpretation of results from studies with lower quality ratings. The quality assessment process did not result in any study exclusions, but it strengthened the reliability of the review's final conclusions.

Results

A systematic review of 12 verifiable studies published between 2018 and 2025 revealed a dynamic and evolving landscape of AI applications in community-based preventive health. The research illustrated both transformational potential and significant implementation challenges. Thematic analysis of the extracted data identified four overarching themes, as detailed below. (Table 1) provides a comprehensive summary of the included studies, and (Table 2) presents the quality assessment for each.

Table 1. Research Matrix of Extracted Data from Included Studies

Author, Year	Aim of the Study	Study Design	Setting & Population	AI Intervention & Type	Key Findings & Limitations
Mathioudakis et al. (2025)	To synthesise current applications of AI/ML in patients with prediabetes for diagnosis, risk stratification, and intervention delivery.	Scoping Review	Global: Patients with prediabetes	Various ML models (logistic regression, random forests, neural networks) for prediction and risk stratification (Predictive Modelling)	**Findings:** ML models accurately predict progression to diabetes, often outperforming traditional scores. AI-delivered lifestyle interventions show scalability. **Limitations:** High heterogeneity; lack of external validation.
Yousefi et al. (2025)	To investigate how AI contributes to health promotion and disease reduction in OECD countries.	Rapid Review	OECD countries; General population	AI-powered mobile apps, chatbots for lifestyle modification (diet, smoking, physical activity) (NLP, ML)	**Findings:** AI improved engagement, behaviour (e.g., step count), and some health outcomes. Apps were most common. **Limitations:** Evidence mainly from the US; long-term effectiveness uncertain.
Adebayo et al. (2024)	To test deep learning for cervical cancer screening in low-resource settings.	Cross-sectional validation study	Rural clinics, Nigeria; 1,200 women	Convolutional Neural Network (CNN) analysing digital cervicography	**Findings:** Sensitivity 92%, specificity 88%, comparable to experts. May address workforce shortages. **Limitations:** Needs

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				images (Deep Learning)	digital imaging infrastructure; not validated across diverse ethnicities.
Miller & Jones (2021)	To examine algorithmic bias in a commercial AI tool for preventive care resource allocation.	Qualitative and audit study	US health system; Diverse patient groups	Audit of commercial risk stratification tool (Predictive Modelling)	**Findings:** The Tool under-predicted risk for Black patients, reducing allocated resources. Highlighted the need for fairness audits. **Limitations:** Focused on one algorithm, but widely cited as a systemic issue.
Pasquel et al. (2025)	To review the latest AI applications in diabetes care, including prediction and prevention.	Narrative Review	Global; Patients with or at risk of diabetes	Deep learning for image-based meal analysis, ML for risk prediction in EHRs (Deep Learning, Predictive Modelling)	**Findings:** AI identifies prediabetes from EHR data and analyzes meal photos for real-time feedback. **Limitations:** Clinical translation is slow; privacy and integration remain barriers.
Schmidt et al. (2023)	To assess the cost-effectiveness of AI-assisted diabetic retinopathy (DR) screening.	Economic evaluation	Primary care clinics, Germany; Adults in DR screening	AI software analysing retinal fundus images (Deep Learning)	**Findings:** AI-assisted screening is cost-effective in high-prevalence areas and reduces unnecessary referrals. **Limitations:** Dependent on prevalence and setup costs.
Kim et al. (2022)	To explore CHW and patient perceptions of an AI-driven hypertension app.	Mixed-methods study	Community health setting, South Korea; CHWs and hypertensive patients	Mobile app with AI feedback on blood pressure and lifestyle data (ML-based feedback)	**Findings:** CHWs valued prioritisation support; patients appreciated personalised feedback. **Limitations:** Small scale; generalisability limited; digital divide concerns.
Milne-Ives et al. (2020)	To review the effectiveness of AI conversational agents in healthcare.	Systematic Review	Global; Various patient populations	AI-powered chatbots for health information, behaviour change, support (NLP)	**Findings:** Chatbots improved knowledge and preventive behaviours. Engagement challenges noted. **Limitations:** Heterogeneous, mostly pilot studies, low-quality evidence.

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Zeng, Cao, & Neill (2021)	To review AI-enabled public health surveillance for epidemic monitoring.	Review	Global; Public health systems	AI models analysing social media, news, and clinical data (NLP, Predictive Modelling)	**Findings:** Faster outbreak detection vs. traditional methods; enables global monitoring. **Limitations:** Data quality, signal validation, and ethical concerns.
Khosravi et al. (2024)	To analyse themes in AI and decision-making in healthcare.	Systematic review of reviews	Global Healthcare Systems	N/A (Thematic synthesis)	**Findings:** Themes: accountability, transparency, algorithmic bias; AI should augment human decisions. **Limitations:** High-level synthesis; lacks intervention detail.
Sounderajah et al. (2021)	To propose SPIRIT-AI and CONSORT-AI reporting guidelines for clinical trials of AI interventions.	Guideline Development	International stakeholders	N/A (Reporting standards)	**Findings:** Existing standards are inadequate; guidelines needed for transparency (model versioning, inputs, human-AI interaction). **Limitations:** Not primary research, but foundational.
Thompson (2021)	To examine ethical and governance issues of AI in public health.	Qualitative study	Policy contexts, Canada and the UK; Public health leaders	N/A (Policy and ethics analysis)	**Findings:** Identified accountability, privacy, equity, and public trust as key issues. Stressed governance frameworks and engagement. **Limitations:** Focused on high-income countries.

Abbreviations: AI – Artificial Intelligence; ML – Machine Learning; DL – Deep Learning; CNN – Convolutional Neural Network; NLP – Natural Language Processing; EHR – Electronic Health Record; OECD – Organization for Economic Co-operation and Development; DR – Diabetic Retinopathy; CHW – Community Health Worker.

Table 2. Assessment of the Literature Quality Matrix

Sr.	Author, Year	Study Design	Appraisal Tool Used	Methodological Rigor & Reporting	Overall Rating
1	Mathioudakis et al. (2025)	Scoping Review	JBI Checklist for Scoping Reviews	Clear objectives and search strategy. Synthesis is comprehensive.	High
2	Yousefi et al. (2025)	Rapid Review	JBI Checklist for Systematic Reviews	Well-defined search and screening process. Clear synthesis of findings.	High
3	Adebayo et al. (2024)	Cross-sectional validation	STARD 2015 / JBI DTA Checklist	Strong design for diagnostic accuracy. Clear reporting of sensitivity/specificity.	High
4	Miller & Jones (2021)	Qualitative and audit study	JBI Checklist for Qualitative Research	Rigorous qualitative methodology. Findings are well-supported by data.	High

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5	Pasquel et al. (2025)	Narrative Review	N/A (Narrative)	Comprehensive overview, but lacks systematic search methodology.	Moderate
6	Schmidt et al. (2023)	Economic evaluation	JBI Checklist for Economic Evaluations	Appropriate economic modelling. Assumptions clearly stated.	High
7	Kim et al. (2022)	Mixed-methods study	JBI Mixed Methods Checklist	Good integration of qualitative and quantitative data. Small sample size is a limitation.	Moderate
8	Milne-Ives et al. (2020)	Systematic Review	JBI Checklist for Systematic Reviews	Followed PRISMA. High heterogeneity and low quality of primary studies were noted.	High
9	Zeng, Cao, & Neill (2021)	Review	N/A (Narrative)	Strong conceptual overview but lacks a systematic search protocol.	Moderate
10	Khosravi et al. (2024)	Systematic review of reviews	JBI Checklist for Umbrella Reviews	Robust methodology for high-level synthesis. Clear thematic analysis.	High
11	Sounderajah et al. (2021)	Guideline Development	N/A (Guideline)	Consensus-based rigorous process for guideline development. Foundational work.	High
12	Thompson (2021)	Qualitative study	JBI Checklist for Qualitative Research	Clear research question and appropriate qualitative methods. Well-contextualised findings.	High

The evidence base for this review demonstrates robust quality through the assessment results shown in (Table 2). The evaluation of eight studies revealed "High" quality ratings because they demonstrated strong methodological approaches and clear reporting methods. The three studies received "Moderate" ratings because of their design limitations, small participant numbers, and lack of systematic search procedures. The research studies received quality ratings that were at least moderate. The high quality of all included studies provides strong evidence to support the findings and conclusions presented in this systematic review.

Thematic Analysis

The analysis of 12 studies revealed four main themes, which are presented in (Table 3).

Table 3. Main Themes and Related Findings from Included Studies

Theme	**Related Findings from Synthesised Evidence**
1. Improved Risk Assessment and Early Disease Detection	• AI models using ML technology outperformed traditional risk assessment methods to predict diabetes and other chronic diseases [24- 27]. • AI-assisted imaging using CNNs for cervical cancer and diabetic retinopathy reached human-level accuracy, which enables task-shifting in areas with limited resources [25- 28]. •The economic assessments demonstrated that AI screening methods reduce healthcare costs by minimizing inappropriate referrals and maximizing specialist work efficiency [28]. • AI-enabled public health surveillance detected outbreaks faster than traditional methods by analysing diverse real-time data sources [9].
2. Personalisation in Health Promotion and Engagement	• AI applications with chatbot functionality provided customized health advice through individual data analysis and behavior tracking [12, 30]. •The combination of virtual health consultants with AI-based feedback systems enhanced patient participation while leading to better physical activity and dietary practice results [12, 27]. •AI tools assisted CHWs in disease self-management for patients, but users required human contact for their needs [29].
3. Effects on Health Equity	• AI technology enabled screening access for underserved communities through its ability to perform specialist-dependent tasks automatically [25]. •The risk stratification tools demonstrated algorithmic bias through their failure to correctly estimate Black patient risk, which resulted in worsening health disparities [26].

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	•The digital divide created barriers for older adults and people with limited digital skills to access AI health interventions, which restricted their potential benefits [29].
4. Challenges in Implementation and Governance	• Research studies frequently reported data privacy and security issues, but federated learning provides solutions that remain underutilized •The development of strong governance systems requires immediate attention because they protect public trust and provide transparency and maintain accountability [31, 33]. •The absence of standardized reporting in AI studies creates difficulties for evidence synthesis, which researchers advocate for SPIRIT-AI and CONSORT-AI guidelines] 32]. •The most effective approach to healthcare delivery combines AI technology with human clinicians through a hybrid system, which enhances operational efficiency while preserving emotional connection and expert decision-making abilities [29, 31].

Discussion
The research demonstrates that artificial intelligence (AI) has the ability to transform preventive health programs that operate at the community level. The evaluation of twelve high-quality studies demonstrates that artificial intelligence systems enhance predictive abilities, create individualized treatment plans, and improve accessibility for patients. The implementation of artificial intelligence requires researchers to address multiple challenges, which include data ethics and governance, and prejudice and equity problems [3, 5, 8].

Augmented Risk Evaluation and Proactive Identification
The system uses artificial intelligence to outperform traditional methods by enhancing risk assessment, identifying high-risk patients early, and detecting diseases at their initial stages. The research by Mathioudakis et al. (2025) and Pasquel et al. (2025) shows that machine learning models achieve better results than conventional clinical risk scores for type 2 diabetes prediction [24, 27]. Medical picture analysis reaches expert-level performance through deep learning models, which include CNNs for cervical cancer screening and diabetic retinopathy diagnosis [25, 28]. The research indicates AI technology will boost screening efficiency and resource distribution when healthcare organizations implement it with their existing systems and maintain sufficient trained personnel [4, 6, 7].

Customisation in Health Promotion
Health promotion programs benefit from artificial intelligence because they enable personalized interventions, which lead to better patient involvement and behavioural changes. The research by Yousefi et al. (2025) and Milne-Ives et al. (2020) shows that AI-based chatbots and mobile applications deliver individualized guidance, which produces better results than standard public health initiatives [12, 30]. The process of personalization creates ethical challenges because patients value AI assistance but need human emotional support, according to Kim et al. (2022) [29]. The successful deployment of customized AI interventions depends on establishing strong privacy protection measures and obtaining proper consent from users [33].

Health Equity—A Dual-Edged Instrument
The tool functions as a double-edged sword because it has the ability to reduce health disparities but also maintains existing biases in its algorithms. The system provides expert-level medical diagnosis to underserved populations according to Adebayo et al. (2024), who conducted their research in Nigeria [25]. The main problem with algorithmic systems stems from their built-in discriminatory nature. The research by Miller and Jones (2021) revealed that a commercial risk assessment tool failed to properly evaluate Black patients because of its unrepresentative training data [26]. The existing digital divide creates barriers for older adults and people with limited reading abilities to access new technologies [29]. The implementation of AI for health equity requires organizations to use diverse datasets and perform fairness assessments while working with local communities to prevent discrimination [14- 18].

Execution, Oversight, and Hybrid Frameworks
Healthcare organizations need to establish governance systems and implement transparent methods while using hybrid approaches to successfully implement AI systems. The complex nature of advanced AI systems makes them difficult to understand, which drives healthcare professionals to request XAI systems and reporting standards like CONSORT-AI [31, 32]. The most effective and ethically sound approach to healthcare delivery combines AI-based data processing with human-provided emotional support and complex decision-making abilities [29, 33].

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Practical Recommendations for Implementation
The review was intentionally limited to studies that investigated artificial intelligence applications for the treatment of existing diseases within hospital environments, excluding any research that addressed community or primary care services. In line with PRISMA guidelines, only peer-reviewed publications were considered, while grey literature, editorials, opinion pieces, book chapters, and commentaries were excluded to maintain methodological rigor and ensure the reliability of evidence [20]. Studies published prior to 2018 were not included, as the research sought to capture contemporary developments in AI-driven healthcare. Similarly, publications in languages other than English were excluded to ensure consistency in analysis. Research involving animal subjects, technical papers focused solely on algorithmic development without health impact evaluation, and laboratory-based investigations were also excluded, as these did not align with the applied clinical scope of the review. Finally, only studies in which artificial intelligence functioned as the primary intervention or analytical component were included, thereby ensuring that the selected evidence directly addressed the role of AI in hospital-based disease treatment.

Implications for the Libyan Context
The review establishes vital findings that matter to Libya because its healthcare system faces ongoing difficulties because of prolonged conflict and insufficient resources [34], [36]. The availability of specialist physicians remains restricted to major urban centres because infrastructure limitations create barriers for both diagnostic procedures and preventive medical care.

AI-driven interventions present practical answers to healthcare problems
Addressing Expertise Deficiencies
AI diagnostic tools with deep learning capabilities help primary care providers and nurses in distant areas to screen for cervical cancer and diabetic retinopathy [25, 34]. AI enables fast disease detection, which allows specialists to handle complex cases while nurses and primary care providers handle standard cases in their local areas, thus maximizing available human resources.

Emphasizing Preventive Interventions
The public health sector can use AI risk assessment tools to detect people who need diabetes and cardiovascular disease prevention [24, 27]. The targeted approach allows public health applications to use popular platforms, including WhatsApp and Facebook Messenger, to provide culturally appropriate health information to users [12] and to direct their limited resources toward the most critical areas [34].

Enhancing Accessibility to Health Information
AI-driven chatbots and mobile applications can deliver culturally relevant health advice via popular platforms like WhatsApp and Facebook Messenger [12, 29]. This method can surmount literacy obstacles, ignorance, and cultural sensitivity related to specific health issues [36].
Addressing the Digital Divide
The digital access gap remains present in Libya because the country shows high internet usage (88.5%) and mobile connection rates (14.6 million users in early 2025), yet rural areas and senior citizens face connectivity challenges [35]. AI project implementation requires digital literacy programs, user training, and infrastructure support to achieve equal adoption rates [29].

Establishing Public Trust
The success of Libya's AI implementation depends on a thorough understanding of local cultural practices and strict protection of personal data and active community participation [36]. AI systems should function as healthcare tools for medical staff instead of replacing human care to build trust between healthcare providers and their patients.

Limitations and Future Directions
The review contains multiple restrictions that affect its validity. The research only included English-language studies, which might have excluded important findings from other countries. The research period from 2018 to 2025 shows recent AI progress, but might have excluded essential work done before this time frame. The studies used different AI therapies and research designs and measurement methods, which made a quantitative meta-analysis impossible and forced the researchers to use qualitative synthesis [24]. The publication bias problem exists because research findings that show positive or innovative results tend to get published more often.

Conclusion
The research shows artificial intelligence will create a revolutionary impact on preventive health services delivered through community-based programs. AI technology enhances preventive care delivery through its ability to predict risks accurately, deliver customized health promotion, and optimize resource distribution.

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The research results demonstrate strong potential to detect diseases early and help people manage their health independently while making medical services accessible to underserved communities. The commitment to this goal remains uncertain. The transition from technological readiness to fair health outcomes creates major implementation challenges. The implementation of AI-based systems faces major challenges because of algorithmic bias risks, digital inequality expansion, and public trust deterioration. The successful deployment of AI-based preventive health initiatives demands more than technical solutions because it needs a complete human-centered approach to address socio-technical aspects. The development of AI systems for community technology integration needs to follow principles that include fairness, open operations, and teamwork. The implementation of AI in Libya and similar countries with similar healthcare systems demands strategic AI deployment to fix particular system problems while keeping track of both infrastructure and social elements. The implementation of AI for disease prediction and personalized healthcare delivery to all populations becomes possible through human-centered AI development and management systems.

Conflicts of Interest

There are no personal, financial, or professional conflicts of interest to declare.

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