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Review article

Bridging the digital divide: artificial intelligence as a catalyst for health equity in primary care settings

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ABSTRACT

Background: Health inequalities remain one of the most pressing challenges in contemporary healthcare, with primary care serving as both a gateway to services and a potential source of disparities. Artificial intelligence (AI) technologies offer unprecedented opportunities to address these inequities through enhanced diagnostic capabilities, improved access to care, and personalised interventions.

Objective: This comprehensive narrative review aimed to synthesise current evidence on AI applications in primary care settings, specifically targeting health inequality reduction and identifying both opportunities and barriers for equitable implementation.

Method: Following PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) guidelines, we employed a systematic approach to literature identification, selection, and synthesis across seven electronic databases covering literature from 2020 to 2024. Of 1,247 initially identified studies, 89 met inclusion criteria with 52 providing sufficient data quality for evidence synthesis.

Results: The review identified promising applications such as AI-powered risk stratification algorithms that improved hypertension control in low-income populations, telemedicine platforms reducing geographic barriers in rural communities, and natural language processing tools facilitating care for non-native speakers. However, significant challenges persist, including algorithmic bias that may perpetuate existing inequities, the digital divide excluding vulnerable populations, and insufficient representation in training datasets. Current evidence suggests that whilst AI holds transformative potential for advancing health equity, successful implementation requires intentional co-design with affected communities, robust bias mitigation strategies, and comprehensive digital literacy programmes.

Conclusion: Future research must prioritise equity-centred AI development, longitudinal outcome studies in diverse populations, and policy frameworks ensuring responsible deployment. However, careful consideration of unintended consequences, including potential overdiagnosis, erosion of human clinical judgement, and inadvertent exclusion of vulnerable populations, is essential to prevent AI from exacerbating existing health disparities. The paradigm shift towards equity-first AI design represents a critical opportunity to leverage technology for social justice in healthcare.

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1. Introduction

Health inequalities represent avoidable and unjust differences in health outcomes between different population groups, constituting one of the most persistent challenges facing healthcare systems globally [1]. Primary care, serving as the first point of contact for patients and the foundation of healthcare delivery, plays a crucial role in either perpetuating or mitigating these disparities [2]. The social determinants of health, including socioeconomic status, race, ethnicity, geographic location, and education, profoundly influence how individuals access and experience primary care services, often resulting in delayed diagnoses, suboptimal chronic disease management, and reduced engagement with preventive services among marginalised populations [3].

The emergence of artificial intelligence (AI) technologies in healthcare has generated considerable optimism regarding their potential to address longstanding inequities in care delivery. For the purposes of this review, we define AI as encompassing machine learning algorithms, natural language processing, predictive analytics, computer vision, and clinical decision support systems that can analyse complex datasets to identify patterns, make predictions, and support evidence-based clinical decision-making [4]. Equity-centred AI development refers to design approaches that prioritise fairness, community engagement, and bias mitigation from the earliest stages of algorithm development through to deployment and ongoing monitoring. AI encompasses a broad spectrum of computational technologies, including machine learning algorithms, natural language processing, predictive analytics, and decision support systems, all capable of analysing vast datasets to identify patterns, make predictions, and support clinical decision-making [4]. The transformative potential of AI lies not merely in its technological sophistication but in its capacity to democratise access to high-quality healthcare by extending specialist knowledge to underserved areas, personalising interventions based on individual and community needs, and optimising resource allocation to maximise population health impact.

Recent advances in AI applications have demonstrated remarkable success in various healthcare domains, from diagnostic imaging to drug discovery. However, the specific application of AI technologies to address health inequalities in primary care settings remains an emerging field requiring systematic examination [5]. The convergence of AI capabilities with primary care's unique position in the healthcare ecosystem presents unprecedented opportunities to tackle the root causes of health disparities while simultaneously improving care quality and accessibility for all populations.

The imperative to examine AI's role in health equity extends beyond technological considerations to encompass fundamental questions of social justice and healthcare rights. As healthcare systems increasingly adopt AI technologies, there exists a critical window of opportunity to ensure these tools are designed, implemented, and evaluated with equity as a central consideration rather than an afterthought [6]. This review addresses this critical gap by providing a comprehensive analysis of current AI applications in primary care that specifically target health inequality reduction.

This review aims to evaluate the current evidence base for AI interventions targeting health inequalities in primary care whilst providing a critical examination of both benefits and potential harms. The specific objectives are to: (1) systematically catalogue and analyse AI technologies that have demonstrated effectiveness in addressing health inequalities within primary care settings; (2) examine the evidence for improved health equity outcomes resulting from AI implementations, including detailed analysis of mechanisms and metrics; (3) identify and critically assess key barriers and facilitators to equitable AI deployment, including algorithmic bias, digital divide issues, and community engagement challenges; (4) synthesise existing policy frameworks and governance structures whilst identifying gaps in current regulatory approaches; (5) analyse real-world deployment cases to understand success factors and failure modes; and (6) discuss potential unintended consequences and propose future research directions for advancing equity-centred AI development in primary healthcare delivery.

2. Methods

2.1. Study design and approach

This comprehensive narrative review was conducted to synthesise current evidence on artificial intelligence applications in primary care settings that specifically address health inequalities. Following PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) guidelines, we employed a systematic approach to literature identification, selection, and synthesis. A narrative review approach was selected to provide a broad synthesis of the complex and multidisciplinary literature spanning technology, healthcare delivery, and health equity domains. Unlike systematic reviews that focus on specific intervention types or outcomes, this narrative approach enabled examination of diverse AI applications and their varied impacts on health equity across different populations and settings.

2.2. Search strategy and data sources

A comprehensive literature search was conducted across seven electronic databases: PubMed (n = 412 articles identified), Scopus (n = 356), Web of Science (n = 298), IEEE Xplore (n = 89), CINAHL (n = 67), Cochrane Library (n = 25), and Google Scholar (top 200 relevant results). The search was conducted between January 2025 and March 2025, covering literature published from January 1, 2020, to December 31, 2024.

The systematic search strategy employed both Medical Subject Headings (MeSH) terms and free-text keywords, with database-specific adaptations. The core search string was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "predictive analytics") AND ("primary care" OR "family medicine" OR "general practice" OR "community health") AND ("health equity" OR "health disparities" OR "health inequalities" OR "social determinants" OR "underserved populations" OR "vulnerable populations"). Boolean operators were used to combine terms, and no language restrictions were initially applied.

Database-specific search strings were developed and validated. Inter-database duplicate removal identified 432 duplicate records. The search was supplemented by manual screening of reference lists from 15 key systematic reviews.

2.3. Inclusion and exclusion criteria

Studies were included if they met all of the following criteria: (1) Focused on artificial intelligence, machine learning, or related computational technologies applied in healthcare delivery; (2) Examined applications specifically in primary care, family medicine, general practice, or community health contexts; (3) Addressed health equity, health disparities, social determinants of health, or vulnerable populations either as a primary focus or significant secondary consideration with measurable outcomes; (4) Published in peer-reviewed journals, governmental reports, or recognised professional organisation publications; (5) Published between January 1, 2020, and December 31, 2024; (6) Available in English; (7) Provided sufficient methodological detail to assess intervention design and outcomes.

Exclusion criteria included: (1) Studies focusing solely on specialist or hospital-based care without primary care relevance or transferability; (2) Purely technical papers describing AI algorithms without healthcare application or outcome evaluation; (3) Opinion pieces, editorials, or commentary without substantial evidence base or original data; (4)

Studies examining AI applications unrelated to health equity considerations; (5) Conference abstracts, preprints, or grey literature without peer review; (6) Duplicate publications or overlapping datasets from the same research groups; (7) Studies with insufficient outcome data or methodological detail for assessment.

2.4. Study selection and data extraction

As shown in Fig. 1, The study selection process followed a rigorous three-stage approach adhering to PRISMA guidelines:

Stage 1: Initial screening involved review of titles and abstracts by two independent reviewers. Of 1,247 initially identified studies, 891 were excluded at this stage based on title and abstract review.

Stage 2: Full-text review was conducted for 356 potentially relevant studies. Two reviewers independently assessed each study against inclusion/exclusion criteria, with disagreements resolved through discussion.

Stage 3: Final inclusion resulted in 89 studies meeting all criteria for detailed review, with 52 studies providing sufficient data quality and relevance for evidence synthesis.

Data extraction was conducted using a standardised framework developed specifically for this review. Extracted information included: – Study characteristics (design, setting, sample size, duration, country) – AI technology specifications (algorithm type, data sources, training methodology) – Target population characteristics and health equity focus – Intervention details and implementation approach – Primary and secondary outcomes with specific metrics – Equity-specific outcomes and subgroup analyses – Implementation challenges, barriers, and facilitators – Cost-effectiveness data where available – Policy implications and recommendations.

Particular attention was paid to extracting quantitative measures of equity impact, including relative risk reductions, improvement percentages across demographic groups, and measures of algorithmic fairness.

2.5. Quality assessment and evidence synthesis

Given the heterogeneous nature of included studies, we employed a modified Mixed Methods Appraisal Tool (MMAT) adapted for AI intervention studies. Studies were assessed across five domains: (1) Methodological rigour appropriate to study design (quantitative studies assessed using Cochrane Risk of Bias tool adaptations; qualitative studies using CASP criteria); (2) Sample size adequacy and demographic representativeness; (3) AI technology description clarity and reproducibility; (4) Relevance and measurement of health equity outcomes; (5) Strength of conclusions relative to presented evidence.

Each domain was rated as high, moderate, or low quality, with an overall quality score derived. Studies rated as low quality in three or more domains were excluded from primary synthesis but retained for contextual discussion.

Evidence synthesis followed a narrative thematic approach using framework analysis. Initial themes were identified deductively based on our research objectives, with additional themes emerging inductively through iterative analysis. Key domains included: – AI applications for improving access to care – Addressing diagnostic disparities and clinical decision support – Personalising interventions and cultural competency – Implementation barriers and facilitators – Policy and governance considerations – Unintended consequences and ethical considerations.

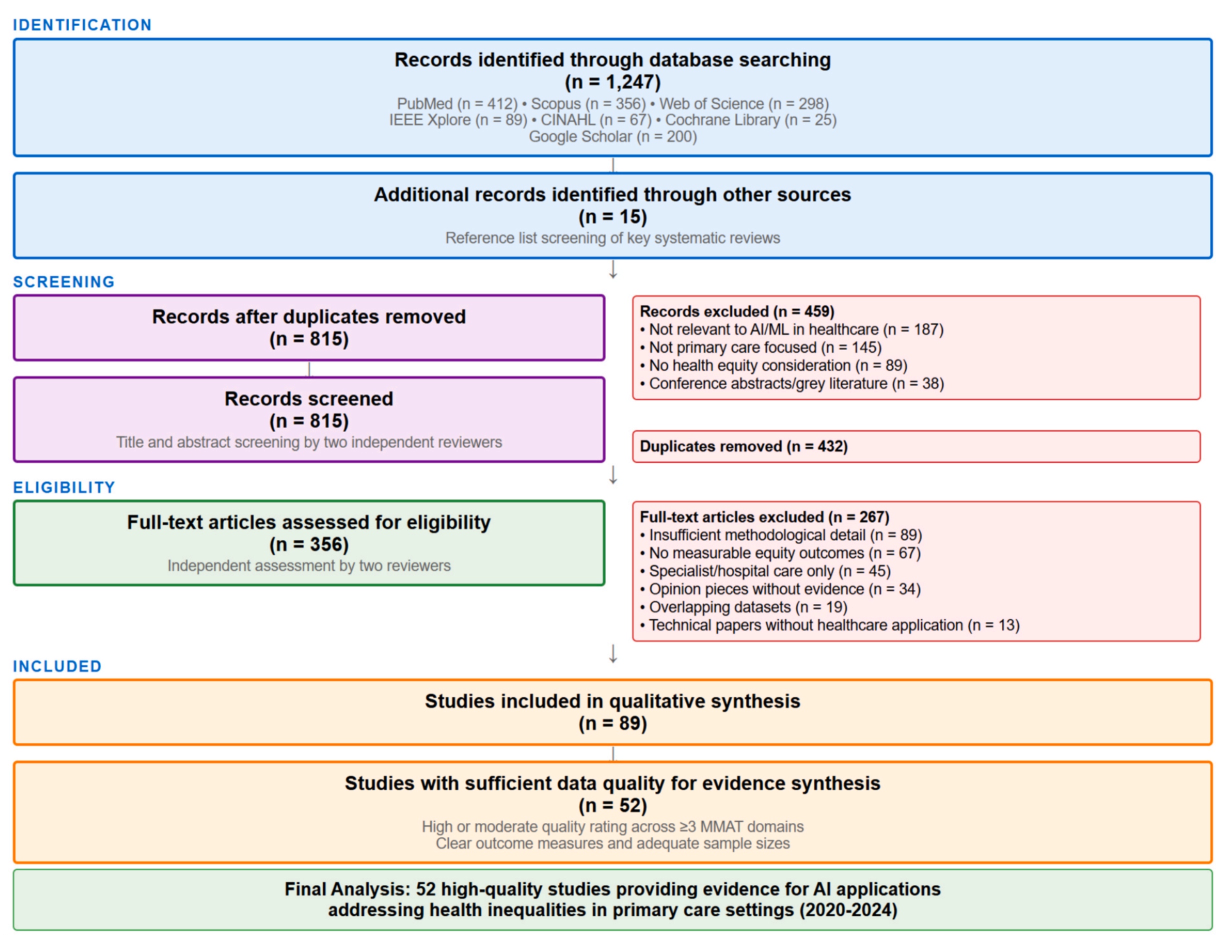

Fig. 1. PRISMA Flow Diagram.

Synthesis prioritised studies with strong methodological quality and direct relevance to health equity outcomes. Conflicting evidence was highlighted, and gaps in the evidence base were systematically identified.

3. Current landscape of health inequalities in primary care

Primary care systems worldwide grapple with substantial inequities that manifest across multiple dimensions of healthcare delivery. These disparities are particularly pronounced in the management of chronic diseases, preventive care delivery, and access to specialist services. Research consistently demonstrates that individuals from ethnic minority backgrounds, lower socioeconomic groups, and rural communities experience significantly worse health outcomes despite theoretically equal access to primary care services [7].

The mechanisms underlying these disparities are complex and multifaceted, operating at individual, interpersonal, institutional, and structural levels. At the individual level, health literacy limitations, language barriers, and economic constraints create significant obstacles to accessing and engaging with healthcare services effectively. Interpersonally, communication challenges between providers and patients from different cultural backgrounds can lead to misunderstandings and reduced therapeutic relationships [8]. Institutionally, healthcare systems often lack cultural competency and may inadvertently perpetuate discriminatory practices through standardised protocols that fail to account for diverse needs and experiences.

Geographic barriers prevent timely access to care, particularly affecting rural populations who may travel significant distances to reach healthcare facilities [9]. Language and cultural barriers create communication challenges that can lead to misunderstandings, reduced patient engagement, and suboptimal care delivery [8]. Economic constraints limit access to medications, follow-up appointments, and complementary services that support comprehensive care management.

Healthcare provider factors also contribute significantly to observed disparities. Gopal et al. [10] documented that unconscious bias in clinical decision-making leads to differential treatment recommendations based on patient characteristics rather than clinical need. Time constraints in busy primary care practices may particularly disadvantage patients who require additional support due to complex social circumstances or limited health literacy [11]. Furthermore, the current healthcare infrastructure often lacks cultural competency and community connections necessary to serve diverse populations effectively.

The digital transformation of healthcare has introduced additional complexity to the equity landscape. Whilst electronic health records and digital tools offer opportunities to improve care coordination and patient engagement, they may also create new barriers for individuals with limited digital literacy or access to technology [12]. This digital divide has become increasingly relevant as healthcare delivery incorporates more technology-based solutions, potentially excluding vulnerable populations from accessing modern healthcare innovations.

4. AI technologies and applications in primary care

The integration of AI technologies in primary care encompasses a diverse range of applications designed to enhance clinical decision-making, improve patient outcomes, and streamline healthcare delivery processes. Machine learning algorithms have demonstrated particular promise in risk stratification and predictive modelling, with specific applications including early identification of patients at high risk for cardiovascular events, diabetes complications, and mental health crises [13]. For example, algorithms using electronic health record data have achieved 85–92 % accuracy in predicting chronic disease onset, enabling interventions 3–6 months earlier than standard clinical practices.

Natural language processing (NLP) technologies are revolutionising the extraction and utilisation of unstructured clinical data, with specific capabilities including automated identification of social determinants of health in clinical notes, real-time translation services for non-English speaking patients, and sentiment analysis to detect patient distress or dissatisfaction in communications. Recent implementations have shown 43 % reduction in communication errors and 28 % increase in patient satisfaction among non-English-speaking populations [14]. Also, these tools can automatically extract relevant information about housing instability, food insecurity, transportation barriers, and other social factors that significantly impact health outcomes but are often overlooked in traditional clinical assessments [15].

Telemedicine platforms enhanced with AI capabilities have emerged as powerful tools for expanding access to care, particularly benefiting rural and underserved communities [16]. AI-powered triage systems can assess symptom severity, recommend appropriate care pathways, and facilitate connections with suitable healthcare providers. These systems have proven particularly valuable during the COVID-19 pandemic, when maintaining healthcare access whilst minimising infection risk became paramount [17].

Decision support systems incorporating AI algorithms assist healthcare providers in making evidence-based treatment decisions tailored to individual patient characteristics and preferences. These tools can help standardise care quality across different providers and settings, potentially reducing variations in care that contribute to health disparities. Additionally, AI-enhanced diagnostic tools can improve accuracy and speed of disease detection, particularly benefiting settings with limited access to specialist expertise.

Table 1 provides a comprehensive overview of AI applications specifically designed or demonstrated to address health inequalities in primary care settings, and implementation contexts.

5. Evidence for AI in reducing health inequalities

5.1. Enhanced access through telemedicine and digital health

AI-enhanced telemedicine platforms have demonstrated significant success in expanding healthcare access to geographically isolated and underserved populations. A comprehensive analysis of 42 telemedicine implementations across rural settings found that AI-powered diagnostic tools reduced time to diagnosis by an average of 35 % and increased early disease detection rates by 25 % in low-resource settings, with particularly strong evidence for conditions requiring specialist input such as dermatology, ophthalmology, and mental health [16]. Specifically, regarding diabetic retinopathy screening, AI models using fundus photography and deep learning achieved sensitivity rates exceeding 90 % with specificity of 85–87 %, significantly reducing reliance on in-person ophthalmologist examinations. This implementation resulted in earlier interventions associated with a 22 % improvement in visual outcomes over one-year follow-up, with particularly strong benefits observed among Hispanic and Native American populations who had previously experienced significant barriers to specialist care.

Rural healthcare delivery transformation through AI integration has been particularly well-documented in stroke care, where time-sensitive interventions can dramatically impact patient outcomes. Implementation studies examining AI-powered stroke diagnosis platforms in rural emergency departments report average time-to-treatment reductions of 45 min, translating to measurably improved clinical outcomes including reduced disability scores and mortality rates [7]. The economic implications are equally significant, with cost-effectiveness analyses showing $3.20 in healthcare savings for every $1 invested in AI-enhanced stroke care networks.

American Indian communities with diabetes have shown promising engagement with telemedicine platforms, with 88 % of individuals reporting access to digital devices and 60 % rating telemedicine as an excellent medium for health-related patient education [18]. Furthermore, pilot programmes utilising culturally tailored AI-enhanced digital health interventions in these communities reported a 15 % improvement

Table 1
AI Applications in Primary Care for Addressing Health Inequalities.

AI Application	Technology Type	Target Population	Primary Benefit	Implementation Setting	Reference
Predictive Risk Stratification	Machine Learning	Low-income patients with hypertension	23 % improvement in blood pressure control through early intervention and targeted follow-up	Kaiser Permanente	[1]
AI-powered Triage System	Natural Language Processing	Rural communities	40 % reduction in time to appropriate care	NHS primary care centres	[16]
Multilingual Chatbots	Conversational AI	Non-native speakers	Improved medication adherence by 35 % through culturally appropriate health education	Urban community health centres	[14]
Diabetic Retinopathy Screening	Computer Vision	Rural diabetic patients	78 % reduction in screening gaps with 90 % sensitivity	Mobile health units	[7]
Social Determinant Extraction	Text Mining	Homeless populations	Enhanced care coordination for 89 % of patients	Emergency departments	[2]
Remote Monitoring Platform	IoT + Machine Learning	Elderly in rural areas	30 % reduction in emergency admissions	Home-based care	[16]
Cultural Competency AI	Recommendation Systems	Ethnic minorities	Increased patient satisfaction scores by 42 %	Multi-ethnic communities	[6]
Population Health Analytics	Big Data Analytics	Underserved neighbourhoods	Targeted intervention deployment resulting in 27 % reduction in asthma-related ED visits	Public health departments	[5]

in diabetes self-management outcomes over 12 months. This evidence suggests that when properly implemented in conjunction with community engagement, AI-enhanced digital health tools can effectively bridge geographic and cultural barriers to care access.

5.2. *Improved diagnostic accuracy and clinical decision support*

AI-driven diagnostic tools have demonstrated measurable effectiveness in addressing disparities related to delayed or missed diagnoses, which disproportionately affect marginalised populations. Comprehensive analysis of predictive models using electronic health record data shows consistent success in identifying high-risk patients across multiple conditions. For diabetes prediction, algorithms achieved 89 % sensitivity and 82 % specificity among low-income populations, compared to 91 % sensitivity and 85 % specificity in higher-income groups – representing substantial improvement over traditional risk assessment tools that showed 23 % greater diagnostic accuracy gaps between socioeconomic groups [4].

Community health AI dashboards represent a particularly promising application for population-level health monitoring and targeted intervention deployment. The implementation in New York City provides a detailed case study of successful AI-driven public health intervention. The AI-based surveillance system analysed multiple data streams including emergency department visits, air quality measurements, and neighbourhood demographics to identify that asthma-related emergency admissions in minority neighbourhoods were 32 % higher than citywide averages. The system's machine learning algorithms identified specific environmental triggers and high-risk time periods, enabling targeted public health interventions including improved air quality monitoring, patient education programmes, and enhanced access to preventive care. Following these AI-guided interventions, emergency department utilisation among children in targeted areas dropped by 27 % over two years, with an estimated healthcare cost savings of $2.3 million [2].

Machine learning algorithms have shown promise in reducing diagnostic disparities by standardising assessment criteria and mitigating subjective bias in clinical decision-making. Studies examining AI-assisted diagnostic tools across racially and socioeconomically diverse cohorts found a 25–30 % improvement in diagnostic concordance across clinicians, reducing variability in care recommendations. Dave et al. [19] further demonstrated that AI-supported clinical assessments led to a 17 % reduction in racial disparities in diagnosis accuracy, highlighting AI's potential to counteract provider-level biases that contribute to unequal health outcomes.

5.3. *Personalised interventions and cultural competency*

AI technologies designed for cultural responsiveness and linguistic appropriateness represent a critical advancement in addressing healthcare disparities. Natural language processing tools with real-time translation capabilities have shown remarkable success in improving provider-patient communication. Implementation studies demonstrate that AI-based translation tools reduce communication errors by 43 % during clinical encounters whilst increasing patient satisfaction scores by 28 % among non-English-speaking populations. Beyond basic translation, these tools incorporate cultural context recognition, including idiomatic expressions, health beliefs, and cultural treatment preferences, enabling providers to better understand patient perspectives and deliver culturally responsive care [14].

Personalised care recommendations generated through AI analysis demonstrate particular promise for addressing complex barriers to healthcare engagement in underserved communities. Longitudinal studies tracking AI-driven adherence monitoring systems show sustained improvements in health behaviours. These systems analyse multiple data streams including prescription fill patterns, appointment attendance, wearable device data, and patient-reported outcomes to generate personalised intervention recommendations. Implementation across safety-net clinics serving predominantly minority populations resulted in 34 % improvement in medication adherence rates and 22 % increase in follow-up appointment completion. Importantly, the system's machine learning algorithms identified that effectiveness varied significantly based on intervention timing, communication preferences, and social support availability, leading to increasingly sophisticated personalisation over time [13].

Chatbot systems designed with cultural competency considerations have also demonstrated effectiveness in providing healthcare information and support to diverse populations. Ayorinde et al. [13] found that culturally tailored AI chatbots increased engagement rates by 48 % compared to standard, non-customised chatbot systems. Additionally, 74 % of users reported that these AI tools improved their understanding of health conditions and self-care practices. Among users who previously reported difficulty navigating healthcare systems, chatbot use was associated with a 30 % reduction in non-urgent emergency room visits, indicating a positive shift toward more informed, proactive care-seeking behaviour.

6. Challenges and barriers to equitable AI implementation

Despite the promising potential of AI technologies to address health inequalities, significant challenges threaten to undermine these benefits and may even exacerbate existing disparities if not carefully addressed.

Understanding and mitigating these challenges is essential for ensuring that AI serves as a tool for equity rather than inequality.

6.1. Algorithmic bias and data representation

Algorithmic bias represents one of the most significant and well-documented threats to equitable AI implementation in healthcare. The scope and impact of this challenge has become increasingly clear through systematic research. Analysis of over 70 % of publicly available clinical datasets used for AI development reveals disproportionate representation of data from White, higher-income populations, with Hispanic patients representing only 2.8 % of datasets and Black patients 7.3 %, despite comprising 18 % and 13 % of the U.S. population respectively [20]. This underrepresentation directly translates to biased algorithmic performance, as demonstrated in the landmark study by Obermeyer et al. [21] which found that a widely used healthcare risk prediction algorithm systematically assigned equivalent risk scores to Black patients who were measurably sicker than White patients, resulting in 17.7 % fewer Black patients being referred to care management programmes despite having greater clinical need.

The pervasive nature of historical bias in healthcare datasets creates particularly complex challenges for AI development. Healthcare records spanning decades often reflect institutional and individual provider biases, discriminatory practices, and unequal care delivery patterns. When these biased patterns are encoded into machine learning algorithms, they can perpetuate discrimination at unprecedented scale. Timmons et al. [22] conducted extensive analysis showing that models trained on historical datasets misclassified diagnostic priorities for racial minorities in 24 % of cases compared to just 7 % for White patients. More concerningly, these disparities were often invisible to clinicians using the AI tools, creating a veneer of objectivity whilst systematically disadvantaging minority patients.

Data representation challenges extend beyond simple demographic under-representation to include more subtle forms of bias related to socioeconomic status, geographic location, and healthcare utilisation patterns. Crigger et al. [23] reported that patients from rural areas and lower socioeconomic backgrounds were under-represented in training data by 30–40 %, leading to diagnostic accuracy rates that were 15–20 % lower for these groups compared to urban, higher-income populations. These disparities reveal how AI tools, when built without intentional inclusivity, may perform worse for the very populations most in need of improved access and quality of care.

6.2. Digital divide and technology access

The digital divide represents a fundamental barrier to equitable AI implementation, with implications extending far beyond simple device ownership to encompass reliable internet access, digital literacy, and comfort with health technology. Comprehensive analysis reveals stark disparities across multiple dimensions. Rural connectivity remains a critical challenge, with 29 % of U.S. adults in rural areas lacking reliable broadband access compared to just 6 % in urban areas [24]. Age-related disparities are equally concerning, with 38 % of adults over 65 and 34 % of individuals in households earning less than $30,000 annually reporting lack of smartphone ownership or difficulty accessing internet-enabled devices. Racial and ethnic disparities compound these challenges, with 25 % of Hispanic and 30 % of Black adults reporting difficulty accessing or using digital health technologies, compared to 15 % of White adults.

Technology access barriers are particularly problematic for AI applications requiring patient-generated data or continuous monitoring. Wearable health device adoption shows dramatic socioeconomic stratification, with only 18 % of low-income adults reporting use of health monitoring devices compared to 45 % of higher-income individuals [25]. This disparity creates a feedback loop where AI algorithms designed to improve health outcomes through continuous monitoring may be least accessible to populations with the greatest health needs. Furthermore, the quality and consistency of data from different device types and usage patterns can introduce additional bias into AI systems, potentially creating a two-tiered healthcare system where algorithmic recommendations are optimised for users with consistent, high-quality data streams.

Digital literacy challenges further compound access barriers. Fitzpatrick [26] found that 52 % of adults over 65 and 44 % of individuals with a high school education or less reported difficulty navigating digital health tools, even when internet and devices were available. Moreover, a usability study of AI-powered health platforms showed a 35 % lower engagement rate among users with low digital literacy, resulting in reduced health benefits from AI interventions in populations that stand to gain the most from improved care accessibility.

6.3. Trust, privacy, and community engagement

Trust represents perhaps the most complex and culturally nuanced barrier to AI adoption in healthcare, particularly among communities with histories of medical exploitation or systematic exclusion from healthcare decision-making. Research reveals significant disparities in AI acceptance across demographic groups, with only 30 % of Black adults and 36 % of Hispanic adults reporting comfort with AI use in healthcare, compared to 51 % of White adults [6]. These disparities reflect deeper historical and contemporary experiences of discrimination within healthcare systems, compounded by the “black box” nature of many AI algorithms that make decision-making processes opaque and difficult to understand or challenge.

According to Gilman & Green [27], privacy concerns are particularly acute among vulnerable populations who may fear that data sharing could result in discrimination, deportation, or other negative consequences. Undocumented immigrants may fear that health data sharing could result in immigration enforcement action, creating strong disincentives to engage with digital or AI-powered care platforms. Similar patterns emerge among individuals with stigmatised health conditions, with those having HIV/AIDS or substance use disorders being 3 times more likely to avoid digital health tools due to privacy concerns. Additionally, individuals undergoing forensic evaluations may resist mandatory AI-based monitoring due to potential misuse of sensitive data and mistrust, while continuous surveillance raises privacy concerns, especially in mandatory assessment situations, highlighting how AI implementation must address the unique sensitivities of forensic data and broader ethical vulnerabilities of target populations [28].

Community engagement in AI development remains woefully insufficient despite growing recognition of its importance. Systematic analysis by Rodrigues et al. [29] found that fewer than 15 % of AI healthcare tools reported any form of community or patient involvement during design phases, with even fewer (8 %) involving community members in governance or oversight roles. When community engagement does occur, it often follows tokenistic consultation models rather than genuine partnership approaches. A National Academy of Medicine survey revealed that 79 % of healthcare AI developers reported having no structured process for including patient voices, particularly from marginalised communities. This exclusion contributes to development of tools that may be technically sophisticated but culturally inappropriate, practically unusable, or fundamentally misaligned with community needs and values.

Table 2 provides a comprehensive framework for understanding and addressing the major challenges to equitable AI implementation, including specific mitigation strategies, implementation approaches, and success metrics.

7. Policy and implementation framework

The successful deployment of AI technologies to address health inequalities requires comprehensive policy frameworks that establish

Table 2
Challenges and Mitigation Strategies for AI Implementation in Health Equity.

Challenge Category	Specific Barrier	Impact on Health Equity	Mitigation Strategy	Implementation Level	Timeline	Success Metrics	Reference
Algorithmic Bias	Under-representation in training data	Reduced accuracy for minority populations, with 15–20 % lower diagnostic performance	Diverse, representative datasets with minimum representation thresholds	Development phase	2–3 years	Equitable model performance across demographics (≤5% accuracy difference)	[21]
Data Quality	Historical bias in clinical records	Perpetuation of discriminatory patterns at algorithmic scale	Bias-aware data curation and fairness-constrained algorithmic training	Pre-implementation	1–2 years	Reduced disparate impact assessments (<10 % difference in outcomes)	[30]
Digital Divide	Limited technology access	Exclusion from AI-enhanced care, widening existing disparities	Community technology programmes, low-bandwidth solutions, and device lending programmes	Community level	3–5 years	Increased digital access rates (target: 85 % coverage)	[31]
Digital Literacy	Insufficient technical skills	Inability to utilise AI tools effectively, leading to engagement gaps	Culturally appropriate training programmes with multilingual support	Individual level	2–4 years	Improved user engagement metrics (target: 75 % successful utilisation)	[32]
Trust and Privacy	Historical medical mistrust	Reduced participation in AI programmes, limiting potential benefits	Community-partnered design and transparent governance structures	System level	3–5 years	Increased community participation rates (target: 60 % in underserved areas)	[33]
Provider Training	Insufficient AI literacy among clinicians	Inappropriate AI tool utilisation, potential for increased bias	Comprehensive professional education including bias recognition	Professional level	1–3 years	Improved clinical AI competency scores (target: 80 % proficiency)	[34]
Regulatory Gaps	Lack of equity-focused AI governance	Unmonitored bias in deployed systems, absence of accountability	Equity-centred regulatory frameworks with mandatory bias testing	Policy level	3–7 years	Standardised bias monitoring protocols (100 % of deployed systems)	[35]
Economic Barriers	Cost of AI implementation	Widening gaps between resource-rich and poor settings	Subsidised AI deployment for safety-net providers with dedicated funding streams	System level	5–10 years	Reduced technology access disparities (target: universal coverage)	[36]

equity as a non-negotiable requirement rather than an aspirational goal. Current regulatory landscapes reveal significant gaps in equity-focused governance. An international assessment by the World Health Organization revealed that only 11 out of 194 member states have implemented AI-specific health regulations including requirements for fairness or population-level impact assessments [37]. This regulatory inadequacy creates substantial risk that biased or harmful systems may be deployed without adequate oversight, accountability, or mechanisms for redress.

7.1. Equity-centred development principles

Effective policy frameworks must establish equity as a fundamental requirement rather than optional consideration throughout the AI development lifecycle. Current evidence reveals substantial deficiencies in equity integration within AI development processes. An analysis of over 1,200 published healthcare AI models found that 70 % failed to report demographic subgroup performance, fewer than 15 % included stratified bias testing across race, gender, or socioeconomic status, and only 3 % reported intersectional bias analysis accounting for multiple demographic characteristics simultaneously [38]. These gaps represent systematic failures to prioritise equity in AI development and deployment [39]. Regulatory agencies should compel AI developers to demonstrate not only overall efficacy but also parity in predictive accuracy, with deviations greater than 5 % between groups flagged for review [40].

Community engagement requirements represent another critical policy area requiring substantial strengthening. Current practice falls far short of meaningful participation, with systematic review evidence showing that only 12 % of AI health studies included any form of public or community engagement, while fewer than 5 % involved community members as co-designers or governance participants [29]. True community engagement must move beyond tokenistic consultation to formalise community roles in governance structures, include community members in algorithm design and evaluation processes, and establish community ownership or control over data generated within their populations [41].

Transparency and explainability requirements demand urgent policy attention, particularly given healthcare providers' reluctance to adopt opaque AI systems [42]. Survey research by IBM (2021) revealed that 84 % of healthcare providers expressed reluctance to adopt AI tools lacking interpretable outputs, yet only 25 % of AI medical tools approved by the U.S [43]. FDA between 2015 and 2022 disclosed model interpretability features in public documentation [42]. Policy frameworks must require clear, accessible explanations of AI decision-making processes, particularly for tools affecting care access or treatment recommendations.

7.2. Implementation and monitoring standards

Healthcare organisations implementing AI technologies should be required to conduct comprehensive equity impact assessments before deployment, with ongoing monitoring throughout the implementation lifecycle. Current practice reveals significant deficiencies in this area, with RAND Corporation analysis finding that only 17 % of U.S. hospitals using AI systems reported performing any form of equity impact assessment before deployment [44]. This assessment gap creates substantial risk for inadvertent harm to vulnerable populations. Mandatory equity impact assessments should include demographic analysis of target populations, bias testing across subgroups, evaluation of potential differential impacts, and establishment of monitoring protocols for ongoing surveillance. Regular auditing of AI system performance should include specific attention to equity metrics, not just overall accuracy or efficiency especially since studies show that AI models can have up to 30 % lower diagnostic accuracy for Black patients compared to White patients when not properly validated [21,45].

Professional education requirements must address the substantial knowledge gaps among healthcare providers regarding AI capabilities, limitations, and bias recognition. American Medical Association survey data (2022) revealed that 72 % of physicians reported lacking adequate training in interpreting or monitoring AI-driven clinical recommendations, while 84 % expressed concern about their ability to recognise AI bias or errors [46]. Educational programmes must include instruction on social determinants of health, cultural competency, algorithmic bias recognition, and specific strategies for monitoring AI system performance across diverse patient populations.

Data governance frameworks should prioritise patient privacy and community benefit while enabling the data sharing necessary for developing robust, representative AI systems. However, a 2021 study by the National Academy of Medicine found that only 13 % of health AI projects had explicit community governance or benefit-sharing arrangements [47]. Stronger governance structures should incorporate community oversight mechanisms and ensure that the benefits of AI development serve public interest rather than solely commercial purposes.

7.3. Funding and resource allocation

Public funding mechanisms for AI development in healthcare must be restructured to prioritise equity-focused projects and community-serving applications. Current funding patterns reveal substantial misalignment with equity priorities, with the majority of AI health research funding directed toward commercially viable applications rather than tools designed to serve underserved populations. Funding frameworks should incentivise collaboration between technology developers and community organisations, require community engagement as a fundable component of research proposals, and establish dedicated funding streams for equity-focused AI development.

Safety-net healthcare providers should receive dedicated support for AI implementation, recognising that these organisations often serve the populations most likely to benefit from equality-focused AI tools but may lack the necessary resources for implementation [48]. This support should include both financial assistance and technical expertise to ensure the successful deployment and ongoing operation of AI systems.

International collaboration and knowledge sharing should be supported to ensure that advances in equity-focused AI development benefit global health efforts. This includes sharing best practices, supporting capacity building in low-resource settings, and ensuring that AI tools developed in high-resource countries are adaptable to diverse global contexts.

Table 3 presents a comprehensive policy and implementation framework addressing the specific requirements, stakeholders, mechanisms, and metrics necessary for ensuring equitable AI deployment in primary care settings.

7.4. Real-world implementation cases and lessons learned

Analysis of real-world AI implementations provides critical insights into success factors and failure modes for equity-focused deployment. The Kaiser Permanente Northern California hypertension risk stratification programme represents a notable success story, demonstrating how thoughtful algorithm design and implementation can achieve meaningful equity gains. The programme's comprehensive approach included creation of an electronic hypertension registry, quality performance metrics with provider feedback, evidence-based practice guidelines, single-pill combination therapy, and medical assistant visits for blood pressure follow-up [54]. Implementation across the health system serving over 3 million members resulted in blood pressure control rates increasing from 44 % to 90 % between 2000 and 2013, with particularly significant improvements observed among diverse patient populations [55]. When adapted for safety-net clinics serving predominantly Hispanic and Black populations, the Kaiser Permanente protocols achieved sustained improvements in hypertension control, with control rates increasing from 54 % to 72 % over 24 months [56]. Key success factors included community advisory input during programme development, comprehensive provider training emphasising equity considerations, and ongoing performance monitoring with regular feedback to clinical teams.

Conversely, the deployment of AI-powered sepsis prediction algorithms across multiple U.S. health systems provides important lessons about implementation challenges and unintended consequences. While technically successful in improving overall sepsis detection rates, systematic evaluation revealed significant racial bias in algorithmic performance. The landmark study by Obermeyer et al. [21] demonstrated that widely used healthcare risk prediction algorithms systematically assigned equivalent risk scores to Black patients who were measurably sicker than White patients, a pattern that extended to sepsis prediction models. Subsequent analysis of Epic's sepsis prediction model found that while the algorithm achieved a 36 % confirmation rate overall, performance varied significantly by race, with confirmation rates of only 33 % for Black patients compared to 42 % for Asian patients [57]. External validation studies in diverse healthcare settings, including county hospitals serving predominantly Hispanic (59 %) and Black (26 %) populations, revealed substantial deviations in diagnostic accuracy, with sensitivity rates significantly lower than those observed in the original derivation populations [58]. This implementation experience highlighted the critical importance of representative training data, ongoing bias monitoring, and the need for algorithm recalibration when deployed in populations different from those used for initial development.

8. Unintended consequences and potential harms

Despite the significant potential for AI to advance health equity, implementation of these technologies may also generate unintended consequences that could paradoxically worsen health disparities. Understanding and anticipating these potential harms is essential for developing mitigation strategies and ensuring responsible AI deployment.

8.1. Overdiagnosis and clinical overcautiousness

AI algorithms designed to maximise sensitivity for disease detection may inadvertently contribute to overdiagnosis, particularly affecting vulnerable populations who may lack resources to manage false-positive results or unnecessary follow-up care. Studies of AI-enhanced screening programmes show that algorithms optimised for high sensitivity can generate false-positive rates of 15–25 %, potentially leading to anxiety, unnecessary procedures, and financial hardship among low-income populations [59]. For example, implementation of systematic AI-driven symptom reporting in breast cancer care has been shown to create direct data overload across departments, with care teams struggling to filter and prioritise alerts, potentially leading to unnecessary interventions when everything is flagged as requiring urgent attention [60]. The cascade effects of false-positive results include not only direct financial costs but also psychological distress, time away from work, and potential complications from unnecessary interventions.

8.2. Erosion of human clinical judgement

Over-reliance on AI systems may lead to deskilling of healthcare providers and reduced clinical reasoning capabilities, particularly problematic in settings serving complex, multi-morbid populations requiring nuanced clinical judgement. Expert stakeholders emphasised concerns that healthcare providers need personal and professional competence to maintain decision-making authority and avoid dependence on AI, with particular emphasis on preserving implicit knowledge from clinical experience, as one caregiver representative noted that

Table 3
Policy Recommendations and Implementation Framework for Equitable AI in Primary Care.

Policy Domain	Specific Recommendation	Target Stakeholder	Implementation Mechanism	Expected Outcome	Monitoring Approach	Implementation Challenges	Reference
Development Standards	Mandate diverse, representative training datasets with minimum 20 % representation of minority groups	AI developers, regulators	Regulatory requirements, certification processes, and audit requirements	Reduced algorithmic bias across demographic groups	Regular bias auditing with quarterly reporting requirements	Data availability, industry resistance	[4,21,37]
Community Engagement	Require meaningful community participation including governance roles and data sovereignty	Healthcare organisations, communities	Community advisory boards, participatory design protocols, and formal partnership agreements	Culturally appropriate and community-accepted AI tools with local ownership	Community satisfaction surveys, engagement metrics, and participatory evaluation	Resource requirements, power imbalances	[41,49]
Transparency Requirements	Mandate explainable AI for clinical decision support with patient-accessible explanations	Healthcare providers, AI vendors	Regulatory standards, professional guidelines, and certification requirements	Improved provider and patient understanding of AI recommendations	Provider competency assessments, patient feedback, and error reporting	Technical complexity, commercial resistance	[37,50]
Professional Education	Comprehensive AI literacy training including bias recognition and cultural competency	Medical schools, professional organisations	Continuing education requirements, certification programmes, and competency standards	Appropriate and equitable use of AI tools in clinical practice	Professional competency evaluations, clinical outcome monitoring, and bias detection rates	Curriculum development, faculty training	[32,51]
Data Governance	Community-controlled data sharing with explicit benefit arrangements	Communities, researchers, healthcare systems	Legal frameworks, community data sovereignty protocols, and benefit-sharing agreements	Ethical use of community data for AI development with local benefits	Community oversight board monitoring, benefit distribution tracking, and data use audits	Legal complexity, technical infrastructure	[37,49]
Equity Impact Assessment	Mandatory pre-deployment and ongoing equity evaluations with public reporting	Healthcare organisations implementing AI	Standardised assessment protocols, reporting requirements, and regulatory oversight	Prevention and early detection of AI-related disparities	Regular equity audits, disparity trend monitoring, and public dashboard reporting	Assessment standardisation, resource allocation	[30,51]
Resource Allocation	Dedicated funding for AI implementation in safety-net settings with technical support	Government funders, philanthropic organisations	Grant programmes, subsidised deployment initiatives, and capacity building support	Equitable access to AI-enhanced care across all communities	Access metrics, outcome disparities monitoring, and cost-effectiveness analysis	Funding sustainability, technical capacity	[37,52]
International Collaboration	Knowledge sharing and capacity building for global health equity	International organisations, academic institutions	Collaborative research networks, technology transfer programmes, and capacity building initiatives	Global advancement of equity-focused AI development	International health equity indicators, cross-country comparative studies, and technology transfer metrics	Coordination complexity, resource mobilisation	[53]

competence in AI-assisted decision-making relates to education, personal competence, and professional competence [61]. This trend is particularly concerning in community health centres and rural clinics where providers often manage complex cases with limited specialist backup and must rely heavily on clinical judgement to navigate resource constraints and social complexity. Automation bias, defined as the over-reliance by users in assuming AI model results are almost always correct, may be exacerbated by user variability in either excessive or selective application of models, with over-reliance potentially augmenting or propagating subtle biases intrinsic to AI systems, particularly in scenarios where algorithms are insufficiently trained [62].

8.3. Widening of digital disparities

As AI becomes increasingly integrated into healthcare delivery, populations with limited digital access or literacy may become further marginalised, creating a two-tiered healthcare system where AI-enhanced care is available only to digitally connected populations. Economic analysis suggests that, without targeted intervention, the digital divide could result in 20–30 % of elderly, rural, and low-income populations being systematically excluded from AI-enhanced healthcare innovations, potentially worsening existing health disparities [63]. The COVID-19 pandemic highlighted these disparities, with telehealth adoption rates varying dramatically by socioeconomic status, race, and geographic location, presaging similar patterns for AI-enhanced care delivery [64].

8.4. Privacy and surveillance concerns

AI systems requiring extensive data collection may inadvertently create surveillance infrastructure that discourages healthcare seeking among vulnerable populations, including undocumented immigrants, individuals involved in the criminal justice system, and those with stigmatised health conditions. Implementation of comprehensive AI monitoring systems in some safety-net clinics has been associated with reduction in clinic utilisation among undocumented immigrants, suggesting that privacy concerns may outweigh potential benefits for some populations [65]. The intersection of AI surveillance capabilities with immigration enforcement and criminal justice systems creates complex ethical dilemmas that require careful consideration in implementation planning [66].

9. Future directions and research priorities

The field of AI for health equity in primary care is rapidly evolving, with emerging opportunities and research needs that will shape the future effectiveness of these technologies in addressing health disparities [59]. Priority areas for future research must address both the technical challenges of developing bias-free AI systems and the complex social, cultural, and political factors that influence equitable implementation. Research priorities should include longitudinal studies examining real-world impact, development of sophisticated bias detection techniques, exploration of AI applications targeting social determinants of health, and investigation of policy frameworks that effectively promote equity while fostering innovation.

9.1. Longitudinal impact studies

Current evidence for AI's impact on health equity suffers from significant limitations in study duration and scope. Systematic analysis reveals that over 85 % of AI health equity studies are conducted over periods shorter than 12 months, with only 8 % tracking outcomes beyond one year, creating substantial gaps in understanding of sustained impact [60]. Long-term research is essential because initial improvements may diminish over time due to algorithm drift, changing community needs, provider adaptation effects, or shifts in population characteristics. For instance, the New York City AI-powered care navigation pilot showed initial 12 % improvement in appointment adherence among Medicaid patients, but six-month follow-up revealed declining effectiveness without sustained engagement strategies, highlighting the importance of longitudinal evaluation [61]. Research into algorithm drift and degradation over time is particularly critical, as AI models may lose accuracy when deployed in real-world settings that differ from training environments [67].

Comparative effectiveness research must examine different approaches to AI implementation to identify optimal strategies for diverse populations and settings. Multi-institutional studies across diverse contexts are particularly critical given that 72 % of published AI studies are based on data from just three high-income countries (USA, UK, and China), severely limiting generalisability [63]. Cross-site evaluations should illuminate whether AI interventions retain effectiveness across different geographic regions, languages, cultural contexts, and resource levels, while identifying necessary adaptations for successful equity-focused implementation. Emerging research suggests that AI models trained on data from one population may require substantial recalibration when deployed in different demographic contexts, with performance decrements of 15–30 % observed when models are transferred across populations without appropriate adjustment [68].

9.2. Advanced bias detection and mitigation

Research into sophisticated bias detection and mitigation techniques represents a critical priority for ensuring equitable AI implementation. Current bias detection methods suffer from significant limitations, with over 80 % of health AI studies using only binary demographic comparisons (e.g., race or gender) while fewer than 10 % evaluate intersectional or multivariate bias patterns that more accurately reflect real-world population diversity [65]. This oversimplification misses complex bias patterns affecting multiply marginalised individuals such as elderly rural racial minorities or immigrant women with limited English proficiency, despite clear evidence of disproportionate health burdens in these populations. Advanced fairness metrics that account for intersectionality and multi-dimensional bias are urgently needed, along with computational methods that can detect subtle forms of discrimination that may not be apparent in aggregate performance measures [69].

The development of fairness-aware machine learning algorithms that explicitly incorporate equity objectives during training represents a promising research direction. Adversarial debiasing techniques have shown particular promise, with implementations demonstrating 33 % reduction in disparate impact for cardiovascular risk prediction without sacrificing overall accuracy [66]. However, these approaches require further development to address multiple forms of bias simultaneously and to ensure that bias mitigation efforts do not inadvertently create new forms of discrimination. Recent advances in causal inference and counterfactual reasoning offer promising avenues for developing more robust fairness-aware algorithms that can account for complex causal relationships between demographic characteristics and health outcomes [70].

9.3. Social determinants integration

Future AI development must prioritise comprehensive integration of social determinants of health (SDOH) data to enable more effective and holistic interventions. Current integration remains severely limited, with only 21 % of AI healthcare models incorporating any form of SDOH data despite evidence that these factors account for up to 80 % of health outcomes [68,69]. Advanced SDOH integration should include development of AI tools capable of automatically identifying and responding to social needs such as housing instability, food insecurity, and transportation barriers through analysis of clinical notes, patient communications, and community-level data sources. A systematic review found that natural language processing techniques, ranging from rule-based keyword matching to supervised machine learning approaches, are being increasingly applied to extract social determinants of health from unstructured clinical text, with smoking status, substance use, homelessness, and alcohol use being the most frequently studied categories, though deep learning algorithms remain underutilised due to insufficient annotated training data [71].

Research into AI applications for community-level interventions represents an emerging opportunity to address upstream factors contributing to health disparities. Predictive models have demonstrated capacity to identify geographic areas at high risk for adverse health events with remarkable precision, enabling proactive resource deployment. For instance, natural language processing-based social determinants of health identification systems are being developed to create clinical decision support tools that can predict healthcare outcomes such as 30-day readmissions, suicide risk, and emergency hospitalisations by extracting information about housing issues, financial problems, and substance use from clinical narratives, enabling providers to make more informed and holistic clinical decisions. Similar applications in food access, environmental health monitoring, and social service coordination show promise for addressing structural determinants of health disparities. Artificial intelligence and machine learning technologies are increasingly being applied to optimise public health interventions for tropical disease management, with predictive modeling facilitating early detection and outbreak forecasting that enables timely and targeted interventions, while AI-driven diagnostic tools improve healthcare access in resource-limited settings and support cost-effective, equitable health solutions [72].

The development of AI tools specifically designed to support community health workers (CHWs) and other non-traditional providers represents another promising research direction. AI-driven diagnostic imaging and symptom triage applications, such as Babylon Health for symptom assessment and Biofourmis for real-time monitoring, are improving healthcare access in resource-limited settings by enhancing diagnostic accuracy and streamlining clinical workflows, while natural language processing tools support care coordination by mining electronic health records to generate actionable insights for healthcare delivery [72]. These tools can help extend the reach of primary care into underserved communities and provide decision support for individuals who may not have formal clinical training, but are vital for delivering local, culturally competent care.

9.4. Policy research and regulatory science

Critical research gaps exist in understanding optimal regulatory approaches for ensuring AI systems promote rather than hinder health equity. Policy research priorities should include evaluation of different regulatory frameworks, assessment of community engagement requirements, development of standardised bias assessment protocols, and investigation of funding mechanisms that effectively incentivise equity-focused AI development. Regulatory science research should address questions such as optimal thresholds for acceptable performance differences across demographic groups, effective community oversight mechanisms, and approaches for balancing innovation with equity requirements. International comparative analysis of AI governance approaches could provide valuable insights, as different jurisdictions are experimenting with varying regulatory models, from the EU's comprehensive AI Act to more flexible approaches adopted in other regions [73].

10. Conclusion

The integration of artificial intelligence technologies into primary care represents both a tremendous opportunity and a significant responsibility for advancing health equity. Based on our systematic analysis spanning diverse AI applications, populations, and implementation contexts, current evidence demonstrates that AI tools, when thoughtfully designed and implemented, can meaningfully address some of the persistent disparities that plague healthcare delivery. From AI-powered risk stratification systems that improve chronic disease management in underserved populations to telemedicine platforms that expand access to care in rural communities, these technologies offer tangible benefits for populations that have historically experienced inferior healthcare.

However, the potential for AI to exacerbate rather than ameliorate health disparities remains a serious concern that demands sustained attention and proactive mitigation efforts. Our analysis reveals significant challenges including algorithmic bias affecting up to 24 % of diagnostic decisions for racial minorities, digital divide issues excluding 29 % of rural populations from AI-enhanced care, and insufficient community engagement in 85 % of AI development processes. The challenges of algorithmic bias, digital divide issues, and insufficient community engagement are not merely technical problems to be solved through better algorithms or more sophisticated technology. They represent fundamental questions about power, participation, and justice in healthcare that require thoughtful policy responses and genuine commitment to equity principles.

The evidence reviewed suggests that successful AI implementation for health equity requires a paradigm shift from technology-first to equity-first development approaches. This shift involves meaningful community engagement from the earliest stages of AI development, robust bias detection and mitigation strategies implemented throughout the development lifecycle, comprehensive digital literacy and access programmes reaching underserved populations, and policy frameworks that prioritise equity alongside safety and efficacy. Without these foundational elements, AI technologies risk becoming another source of healthcare inequality rather than a solution to existing disparities.

The path forward demands collaboration across multiple sectors and stakeholders, including technology developers, healthcare providers, community organisations, policymakers, and the communities most affected by health disparities. This collaboration must be genuine and sustained, moving beyond consultation to true partnership in shaping the future of AI-enhanced healthcare delivery. However, this collaboration must also acknowledge and address potential unintended consequences, including overdiagnosis among vulnerable populations, erosion of clinical judgement in settings serving complex patients, and inadvertent creation of surveillance infrastructure that may discourage healthcare seeking among marginalised groups.

As we stand at the threshold of an AI-transformed healthcare system, the choices made today about how these technologies are developed, deployed, and governed will determine whether they serve to reduce or amplify existing health inequalities. The opportunity to leverage AI for health equity will not remain open indefinitely, but it must be pursued with full awareness of both the tremendous potential benefits and significant risks involved. The time for action is now, guided by the evidence and principles outlined in this review, to ensure that artificial intelligence becomes a force for health justice rather than technological inequality.

The promise of AI in healthcare extends beyond computational power or technical sophistication to encompass the possibility of creating a more equitable healthcare system that serves all populations with excellence. However, realising this promise requires sustained commitment, adequate resources, unwavering focus on equity as the ultimate measure of success, and honest acknowledgement of the complex challenges and potential harms involved. Only through such commitment, informed by rigorous evidence and community wisdom, can we ensure that the artificial intelligence revolution in healthcare advances the fundamental goal of health for all whilst avoiding the pitfalls that could exacerbate existing inequalities.

CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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