

REVIEW ARTICLE

Artificial intelligence in healthcare: Transforming services in low-resource settings—Evidence from Bihar, India

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Abstract

Healthcare systems in low socioeconomic regions struggle with numerous challenges, including inadequate infrastructure, severe shortages of healthcare workers, limited access due to geography, and poor health outcomes. Bihar, a state in eastern India and home to more than 120 million people with nearly one-third living in poverty, exemplifies the urgent need for innovative and scalable healthcare solutions. This review evaluates the potential of artificial intelligence (AI) to address healthcare gaps in resource-constrained settings, using Bihar as a case study, and aims to develop practical AI implementation frameworks with global applicability. The approach combines analysis of Bihar's healthcare data with an assessment of AI applications in other low-resource settings, focusing on interventions that are both cost-effective and scalable. Findings indicate that AI can address critical gaps in diagnostics, disease surveillance, resource management, and care coordination. Notable applications include AI-based diagnostic imaging, outbreak prediction tools, teleconsultation systems with integrated decision support, and technologies for smarter resource allocation. Effective deployment depends not only on local adaptation and digital skill-building but also on robust ethical oversight and sustained funding. The evidence indicates that well-targeted AI initiatives can democratize healthcare delivery for underserved populations by enhancing diagnostic accuracy, optimizing scarce resources, extending specialist expertise to remote areas, and reducing health disparities. Achieving these outcomes depends on unified efforts across policy-making, technology development, clinical practice, and community engagement, anchored in principles of equity and inclusivity.

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Citation: Kumar Y, Sivasubramanian N. Artificial intelligence in healthcare: Transforming services in low-resource settings—Evidence from Bihar, India. *Artif Intell Health*. 2026;3(3):025420089. doi: 10.36922/AIH025420089

Received: October 13, 2025**Revised:** November 23, 2025**Accepted:** December 4, 2025**Published online:** December 24, 2025

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Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Keywords: Artificial intelligence; Healthcare disparities; Resource-constrained settings; Health systems strengthening; Health equity

1. Introduction

The persistent healthcare divide between populations with differing socioeconomic statuses represents one of the most pressing challenges confronting global health systems in the 21st century. Regions with concentrated poverty experience compounded healthcare deficits that perpetuate cycles of poor health outcomes, diminished economic productivity, and growing inequity.¹ These settings typically manifest critical shortages across multiple dimensions, including insufficient healthcare infrastructure, with inadequate primary health centers (PHCs) and hospital beds per capita; severe human

resource gaps well below World Health Organization (WHO) recommendations, particularly for specialist physicians; geographic barriers that limit access; and financial constraints that create significant obstacles for families already struggling with poverty.^{2,3}

Bihar, India's third most populous state with over 120 million residents, provides a compelling illustration of these systemic challenges. The state's healthcare infrastructure remains severely underdeveloped relative to population needs, with healthcare workforce densities among the lowest nationally and doctor-to-population ratios far below recommended standards.⁴ Geographic dispersion across rural areas, seasonal flooding, and inadequate road connectivity exacerbate access barriers, while health outcome indicators, including maternal mortality ratio, infant mortality rate, and communicable disease burden, remain substantially worse than national averages.⁵ Approximately 33% of Bihar's population lives below the poverty line, with high out-of-pocket healthcare expenditure pushing additional families into poverty annually.⁶ These conditions are not unique to Bihar but are representative of similar regions across South Asia, Sub-Saharan Africa, and other low-resource settings globally, making insights from Bihar's context potentially applicable to hundreds of millions of people worldwide. Bihar presents a particularly instructive case study beyond its poverty metrics. The state's unique combination of a massive population (over 120 million), recent digital infrastructure investments paradoxically juxtaposed against persistent epidemiological challenges, and existing artificial intelligence (AI) pilot implementations creates an ideal natural laboratory for examining AI's potential in resource-constrained settings. Unlike contexts with either adequate health systems or absent digital infrastructure, Bihar occupies a critical transition zone where foundational digital connectivity exists but has not yet translated to improved health outcomes—precisely the juncture where AI interventions may prove most impactful and where lessons learned have the greatest global applicability (Table 1).

Traditional approaches to addressing these healthcare deficits have largely focused on infrastructure expansion, workforce recruitment, and increased financial allocation. While necessary, these strategies face fundamental limitations in resource-poor environments where competing development priorities, constrained budgets, and vast unmet needs hinder their effectiveness.¹⁵ The emergence of AI technologies, however, offers a promising alternative paradigm.¹⁶ By enhancing diagnostic accuracy, enabling predictive analytics, supporting clinical decision-making, and improving operational efficiencies, AI

has demonstrated the potential to improve healthcare delivery without requiring proportional infrastructure expansion.^{17,18}

Several factors make the current moment particularly conducive to AI-enabled healthcare transformation in settings like Bihar. Mobile phone penetration has reached even remote rural areas, with smartphone adoption accelerating rapidly and data costs declining substantially over the past decade.¹⁹ Government initiatives, including the Ayushman Bharat Digital Mission and National Digital Health Mission, have established foundational digital health infrastructure and policy frameworks that support technology integration.²⁰ The global health technology sector has increasingly focused on developing solutions specifically designed for resource-constrained environments, moving beyond simple technology transfer to context-appropriate innovation.²¹ Furthermore, the COVID-19 pandemic accelerated the adoption of digital health tools and underscored the importance of telemedicine and disease surveillance capacities, areas where AI is particularly effective.²²

This review aims to systematically examine how AI can transform healthcare delivery in low socioeconomic states, using Bihar as a detailed case study while developing generalizable principles applicable to similar contexts. We analyze the specific healthcare challenges characterizing these settings, evaluate evidence on AI applications most relevant to these challenges, propose implementation frameworks accounting for resource constraints and contextual factors, assess barriers and enablers to successful adoption, and outline policy recommendations for stakeholders. Our objective is to provide evidence-based guidance to policymakers, healthcare administrators, technology developers, and implementation partners seeking to harness AI's potential to advance health equity rather than inadvertently exacerbate existing disparities.

2. Study selection and synthesis methodology

This review presented a narrative synthesis situated within Bihar's healthcare context. Its primary objective is to evaluate how established and emerging AI technologies can strengthen healthcare delivery in a specific, low-resource setting, using Bihar, India, as a representative case study. Given the novelty and heterogeneity of AI applications in global health, a narrative synthesis approach allows for the critical integration of diverse evidence, including pilot studies, validation trials, implementation research, and health system data, to develop a contextually relevant framework. Transparent reporting of the search strategy

Table 1. Healthcare system indicators of Bihar versus national averages (India)

Indicator	Bihar	National average	Gap (%)	Source
Demographic and socioeconomic				
Population (millions)	129.0	-	-	7
Rural population (%)	84.0	63.1	+24.8	
Below poverty line (%)	33.0	23.9	+27.5	NITI Aayog 2021 ⁸
Literacy rate (%)	65.5	80.9	-17.8	7
Female literacy rate (%)	55.0	74.6	-26.3	7
Healthcare infrastructure				
PHCs/100,000 population	1.0	3.3	-69.7	RHS 2021 ⁹
Community health centers/100,000 population	0.1	0.6	-83.3	
Hospital beds/1,000 population	0.2	0.6	-66.6	
Doctors/10,000 population	0.4	11.9	-96.6	
Nurses/10,000 population	0.8	23.2	-96.5	
Health workforce shortages (%)				
Vacant specialist positions	68.0	60.0	+11.8	RHS 2021 ⁹
Vacant staff nurse positions	85.0	26.0	+69.4	
PHCs without doctors	0.0	8.0	-1.0	
Health outcomes				
Maternal mortality ratio (per 100,000 live births)	100.0	80.0	+25.0	SRS 2020 ¹⁰
Infant mortality rate (per 1,000 live births)	47.0	25.0	+46.8	
Under-5 mortality rate (per 1,000 live births)	56.0	27.7	+50.5	
Total fertility rate	3.0	1.9	+36.7	
Institutional delivery rate (%)	64.0	95.5	-32.9	NFHS-5 (2019–2021) ¹¹
Full immunization coverage (%)	92.5	93.5	-1.1	
Stunting in children under 5 years (%)	47.3	34.7	+26.6	
Anemia in women 15–49 years (%)	64.0	57.0	+10.9	
Healthcare utilization and access				
Average distance to health facility (km)	30.0	14.5	+51.7	District Level Household Survey-4 ¹²
Out-of-pocket health expenditure (% of total health expenditure)	65.0	39.4	+39.4	National Health Accounts 2018–2019 ¹³
Households with health insurance coverage (%)	15.0	55.0	-72.7	NFHS-5 (2019–2021) ¹¹
Population covered by Ayushman Bharat (%)	70.0	45.0	+35.7	National Health Authority 2023 ¹⁴

Notes: Gap calculation represents the percentage difference from the national average. Negative values indicate values below the national average; positive values indicate values above the national average.

Abbreviation: PHC: Primary health center.

and critical appraisal process was employed to enhance methodological rigor.

2.1. Search strategy and data sources

A structured search was conducted to identify relevant literature. The coverage period spanned from January 2005 to July 2024 to capture the evolution of both digital health platforms and AI-specific applications. The following databases and information sources were searched:

- Biomedical databases: PubMed, Scopus, and Web of Science.

- Engineering/technology databases: IEEE Xplore, ACM Digital Library (to capture technical AI validation studies).
- Grey literature and policy: Google Scholar, WHO Global Health Observatory, World Bank reports, and Indian government health databases (e.g., National Health Mission records) to incorporate local context and policy relevance.

We used combinations of key terms with Boolean operators (AND/OR). Key terms included: “artificial

intelligence,” “digital health,” “low-resource settings,” “health equity,” “Bihar,” “India,” “public health systems,” “AI applications,” and “predictive analytics.” One example search string included: (“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“low-resource” OR “LMIC” OR “Bihar” OR “India”) AND (“healthcare” OR “diagnosis” OR “surveillance”).

2.2. Inclusion and exclusion criteria

Sources were included if they provided empirical data, pilot results, validation studies, or detailed implementation models concerning AI applications in diagnostics, disease surveillance, primary care, population health, or health systems within resource-constrained or low- and middle-income country settings. Sources were excluded if they were opinion pieces without empirical relevance, theoretical models lacking validation data, or studies in which the methodology or context was insufficiently clear to assess generalizability.

2.3. Critical appraisal and evidence synthesis

While formal risk-of-bias assessment tools, such as Quality Assessment of Diagnostic Accuracy Studies-AI (designed for systematic reviews of AI diagnostic accuracy studies) or Prediction Model Risk of Bias Assessment Tool-AI (for AI prognostic model validation), were outside the scope of this narrative synthesis, a structured critical appraisal framework was developed specifically to assess contextual relevance and methodological rigor for the target setting. Each included study was evaluated based on three criteria:

- (i) Contextual fit: Was the AI intervention implemented in a resource-constrained setting with similar infrastructural or human resource challenges to Bihar?
- (ii) Methodological soundness: Was the evidence derived from a robust design (e.g., a large-scale validation study, observational study, or pilot with clear methodology)?
- (iii) Generalizability: Could the intervention be plausibly adapted and scaled within the public health infrastructure of Bihar?

The extracted information was then synthesized narratively and grouped thematically. The resulting synthesis informed the development of a tiered evidence classification in Table 2, categorizing evidence as high, moderate, or low. This level is a direct reflection of the structured appraisal linking the quality and context of supporting literature to the confidence in the potential impact. Each qualitative statement in Table 2 is anchored in and supported by a specific citation within the narrative sections of this review.

To enhance transparency and interpretability, qualitative impact estimates in Table 2 were derived from peer-reviewed systematic reviews, meta-analyses, large observational studies, and validated pilot implementations where available. Where evidence was limited to early-stage studies, heterogeneous designs, or contexts outside Bihar, impact estimates are expressed as ranges or described using cautious qualitative terms (e.g., “promising” and “potential”). Evidence levels (high, moderate, and low) reflect both the methodological quality and quantity of supporting literature, with particular emphasis on contextual relevance to low-resource settings. Impact estimates labeled as “potential” indicate projections based primarily on high-income or non-Bihar settings and therefore require local validation. Implementation complexity ratings reflect anticipated infrastructure, workforce, and system-integration requirements for deployment within Bihar’s public health system.

3. Epidemiological and systemic healthcare challenges in low socioeconomic settings

3.1. Health disparities and resource constraints

Healthcare disparities are deeply entrenched in low socioeconomic contexts, driven by multiple intersecting social determinants. Globally, poverty significantly contributes to unequal health service access, environmental risks, and high burdens of communicable and non-communicable diseases.¹ Health outcomes correlate strongly with socioeconomic status, geography, gender, and age, disproportionately impacting low-income rural populations.²

Resource constraints amplify these disparities, with inadequate healthcare infrastructure, drastic workforce shortages, and logistical challenges limiting service availability and quality. Numerous regions fall below WHO-recommended health worker density thresholds, restricting access to clinical care, especially specialist services.³ Geographic isolation and financial barriers further entrench disparities by limiting vulnerable populations’ physical and economic access to healthcare. Understanding the multidimensional nature of healthcare challenges in low socioeconomic settings is essential for developing appropriate AI interventions.

3.2. The healthcare landscape of Bihar

Bihar’s healthcare system operates within a complex matrix of demographic, economic, infrastructure, and outcome-related constraints that together define the opportunity space for technological solutions. The state’s population density exceeds 1,100 persons/km², yet remains predominantly rural with over 88% of residents living outside urban

Table 2. Artificial intelligence applications for healthcare challenges in low socioeconomic settings

Healthcare challenge	AI application	Specific use cases	Proposed qualitative impact	Evidence level	Implementation complexity
Limited diagnostic capacity	AI-enabled medical imaging	Chest X-ray analysis for TB detection	High sensitivity (90–95%) for TB detection on chest X-rays ^{23–25}	High (meta-analyses of more than 34 studies, pooled sensitivity 94–95%)	Moderate (requires imaging equipment and connectivity)
		Retinal imaging for diabetic retinopathy	Excellent sensitivity (90–95%) for referable diabetic retinopathy screening ^{26–28}	High (systematic reviews and meta-analyses)	Moderate
		Dermatology image classification	Promising diagnostic support for skin conditions ^{29,30}	High	Moderate
		Ultrasound interpretation for obstetric care	Promising diagnostic support for ultrasound interpretation in obstetric care ³¹	Moderate (tele-ultrasound studies)	Moderate
Inadequate disease surveillance	Predictive analytics and early warning systems	Outbreak prediction (dengue, malaria, and JE)	1–3 months advance outbreak warning capability ^{27,28}	Moderate (Systematic review of dengue prediction models)	Moderate (requires data integration infrastructure)
		Disease hotspot identification	Moderate to high accuracy (70–96%) in outbreak prediction, ^{32,33} depending on model and data quality	Moderate (heterogeneous study designs, sensitivity 50–100%, specificity 74–95%)	Moderate
		Real-time syndromic surveillance	Improved outbreak response time ³³	Low–moderate (early warning system evaluations)	Moderate
		Epidemic forecasting models	Enhanced resource pre-positioning through predictive analytics ^{33,34}	Moderate	Moderate
Specialist shortage and geographic barriers	AI-enhanced telemedicine	Virtual health assistants and chatbots	Readily available healthcare information access via mobile platforms ^{35,36}	Moderate (LMIC telemedicine reviews)	Low–moderate (smartphone-based, lower infrastructure needs)
		Clinical decision support systems	Substantial increase in specialist consultation reach (5–10× expansion potential in remote areas) ^{36,37}	Moderate (telemedicine feasibility studies, up to 87% patient reach)	Low–moderate
		Remote consultation platforms	Significant reduction in unnecessary referrals through improved triage ³⁸	Moderate (AI-based clinical decision support studies)	Low–moderate
		Automated triage and symptom assessment	Cost reduction potential of 50–60% per consultation	Low–moderate (economic evaluations, variable contexts)	Low–moderate
Maternal and child health gaps	Risk stratification and monitoring	High-risk pregnancy identification	Enhanced high-risk case identification (30–50% improvement potential) ^{39,40}	Moderate (mobile health pilot studies)	Low–moderate (mobile-based solutions possible)
		Neonatal complication prediction	Promising reduction in preventable complications (20–30% in pilot implementations) ³⁹	Moderate (implementation studies)	Low–moderate
		Growth monitoring and malnutrition detection	Enhanced monitoring capabilities ^{39,40}	Moderate	Low–moderate
		Immunization tracking and reminders	Improved immunization completion rates (15–25% increase) ⁴¹ Enhanced antenatal care coverage through mobile reminders ^{39,40}	Moderate (m-health tracking systems)	Low–moderate
Resource inefficiency	Supply chain and operations optimization	Predictive inventory management	Substantial reduction in medicine stockouts (25–40% improvement potential) ⁴²	Low–moderate (private sector implementations)	Moderate–high (requires IoT sensors+systems integration)
		Cold chain monitoring	Improved vaccine wastage rates (40–60% improvement) ^{43,44}	Low–moderate (cold chain IoT pilots)	Moderate–high

(Cont'd...)

Table 2. (Continued)

Healthcare challenge	AI application	Specific use cases	Proposed qualitative impact	Evidence level	Implementation complexity
Fragmented care continuity	Intelligent health records management	Ambulance dispatch optimization	Reduced emergency response time (15–25%) ⁴⁵	Low (limited public sector data)	Moderate–high
		Staff scheduling and allocation	Modest improvement in staff productivity (10–20%) ⁴⁶	Low–moderate (operations research studies)	Moderate–high
		Automated clinical documentation	Substantial reduction in documentation time (60–80% in high-income settings) ⁴⁷	Low (limited LMIC data, emerging implementations)	High (requires a comprehensive EHR infrastructure)
		Patient record linkage across facilities	Improved care coordination (40–60% improvement potential) ⁴⁸	Low (early-stage implementations)	High
		Natural language processing for data extraction	Enhanced data accessibility and analysis ⁴⁹	Low	High
		Longitudinal care tracking	Enhanced treatment adherence tracking ⁵⁰ Reduced redundant testing (30–50% reduction potential) ⁵¹	Low	
Workforce capacity constraints	Clinical decision support	Evidence-based treatment recommendations	Moderate improvement in guideline adherence (20–35%) ^{51,52}	Moderate–high (extensive evidence from other settings, limited LMIC validation)	Moderate
		Drug interaction checking	Significant reduction in prescribing errors (30–50%) ^{51,53}	Moderate–high (clinical decision support system evaluations)	Moderate
		Diagnostic assistance	Enhanced diagnostic accuracy (15–30% improvement) ⁵²	Moderate (AI diagnostic support studies)	Moderate
		Protocol adherence monitoring	Standardized care quality across facilities ⁵¹	Moderate	Moderate
		Continuing education delivery	Enhanced healthcare worker competency ⁵⁴	Moderate	Moderate
Chronic disease management	Personalized care and remote monitoring	Diabetes and hypertension management	Meaningful improvement in disease control (25–40%) ^{55,56}	Moderate (growing evidence from diverse settings)	Moderate (requires patient engagement and devices)
		Medication adherence support	Improved medication adherence (40–60%) ⁵⁰	Moderate (digital health interventions)	Moderate
		Lifestyle modification coaching	Enhanced patient self-management ⁵⁶	Moderate	Moderate
		Complication risk prediction	Reduction in acute complications (20–30%) ^{50,57}	Moderate (remote monitoring studies)	Moderate
		Continuous glucose/BP monitoring integration	Reduced hospitalization rates (15–25%) ⁵⁶	Moderate (chronic disease management programs)	Moderate
Mental health service gaps	AI chatbots and virtual counseling	Depression and anxiety screening	Readily available mental health support ⁵⁸	Moderate (pilot evidence, needs cultural validation)	Low (app/web-based delivery)
		Crisis intervention and support	High patient satisfaction rates (70–80%) ⁵⁸	Moderate (limited validation studies)	Low
		Cognitive behavioral therapy delivery	Substantial increase in service capacity (10–15×potential expansion) ^{58,59}	Moderate (scalability analyses)	Low
		Counseling access in underserved areas	Reduced stigma-related access barriers ⁶⁰	Moderate (user acceptability studies, needs cultural validation)	Low
		Stigma-free anonymous support	Enhanced service accessibility ^{58,60}	Moderate	Low

(Cont'd...)

Table 2. (Continued)

Healthcare challenge	AI application	Specific use cases	Proposed qualitative impact	Evidence level	Implementation complexity
Health literacy and behavior change	Personalized health education	Multilingual health information delivery	Moderate improvement in health knowledge (30–50%) ^{60,61}	Low–moderate (limited rigorous evaluations)	Low (digital content delivery via mobile)
		Interactive health education modules	Enhanced learning engagement ^{60,61}	Low–moderate	Low
		Behavior change reinforcement	Promising increase in preventive behavior adoption (25–35%) ^{62,63}	Low–moderate (mobile health education studies)	Low
		Preventive care reminders	Enhanced screening participation (20–30% increase) ⁴¹	Low–moderate (reminder system evaluations)	Low
		Nutrition and lifestyle guidance	Culturally appropriate content delivery	Low (context-specific implementations)	Low

Notes: Implementation complexity: Low: Minimal infrastructure needs, primarily software/mobile-based; Moderate: Some infrastructure/equipment requirements, moderate training needs; High: Substantial infrastructure investment, extensive system integration required. Evidence level: High: Multiple RCTs or systematic reviews with concordant findings; Moderate: Well-conducted observational studies, large-scale pilots, or validation studies with consistent results; Low: Proof-of-concept studies, early-stage implementations, or evidence requiring further validation in LMIC contexts.

Abbreviations: AI: Artificial intelligence; BP: Blood pressure; EHR: Electronic health record; HIC: High-income country; IoT: Internet of Things; JE: Japanese encephalitis; LMIC: Low- and middle-income country; RCT: Randomized controlled trial; TB: Tuberculosis.

centers.⁷ This demographic distribution creates substantial challenges for healthcare delivery, as facilities must serve dispersed populations across geographically challenging terrain while maintaining economically viable operations. Literacy rates, while improving, remain below 70%, with significant gender disparities, creating additional barriers to health information dissemination and healthcare-seeking behavior, particularly for women.⁶⁴ Economic constraints persist with poverty rates significantly above the national average, widespread informal employment, and limited health insurance coverage.

The healthcare infrastructure inventory reveals significant gaps across all facility tiers. PHCs, intended to provide basic healthcare to populations of approximately 30,000, fall short of requirements both in absolute numbers and functional capacity, with many lacking essential equipment, medications, and adequate staffing.⁹ Community health centers (CHCs) that should provide first-referral care for approximately 120,000 people similarly operate with severe resource constraints, often without specialist physicians, functional operating theaters, or blood storage facilities. District hospitals face overwhelming patient loads that exceed their bed capacity, with inadequate diagnostic capabilities forcing referrals to distant tertiary centers for even moderately complex cases.

A critical shortage of healthcare workers affects all cadres, with specialists, nurses, and allied health professionals being particularly scarce.⁶⁵ Rural postings remain unfilled despite government recruitment efforts, as healthcare workers prefer urban assignments with better living conditions, educational opportunities for children, and professional development prospects. The resulting

workforce distribution leaves rural populations with minimal access to qualified healthcare providers, forcing reliance on informal practitioners with questionable training and creating conditions where preventable diseases progress to advanced stages before receiving appropriate care.

Health outcome indicators reflect these systemic inadequacies. Bihar's maternal mortality ratio, though improved from previous decades, remains among the highest in India, with institutional delivery rates lower than optimal and substantial proportions of births occurring without skilled birth attendance.⁶⁶ Infant mortality similarly exceeds national averages, driven by neonatal complications, preventable infectious diseases, and malnutrition. Communicable disease burden remains substantial, with endemic tuberculosis, malaria, dengue, and Japanese encephalitis, alongside emerging challenges from non-communicable diseases such as diabetes, hypertension, and cardiovascular conditions.⁶⁷

Immunization coverage, while expanding, has not achieved levels necessary for herd immunity against vaccine-preventable diseases, leaving populations vulnerable to outbreaks. Malnutrition affects substantial proportions of children under five, creating lifelong health and developmental consequences. These outcomes reflect not only resource constraints but also systemic inefficiencies, including delayed diagnosis, inadequate disease surveillance, poor care coordination across facility tiers, and limited capacity for preventive interventions.⁶⁸

Several cross-cutting challenges further complicate healthcare delivery. Geographic accessibility remains problematic, with numerous villages lacking all-weather road connectivity, leaving medical emergencies unable to reach facilities in time for effective intervention.⁶⁹ Seasonal flooding isolates communities for extended periods. Financial obstacles, including consultation fees, transportation costs, income loss, and caregiver expenses, discourage timely care-seeking.⁷⁰ Low health literacy and culturally rooted gender inequities especially restrict women's autonomy and access to healthcare.¹¹ Quality inconsistencies within and across facilities fuel distrust and deter service utilization.⁷¹ This confluence of structural, economic, social, and systemic factors creates a complex environment in which traditional healthcare interventions face significant implementation barriers and where innovation is urgently needed.

Figure 1 compares key healthcare and socioeconomic indicators between Bihar and national averages. Negative gaps (red bars) indicate that Bihar's value is significantly lower than the national average, representing a critical deficit or shortage. The largest gaps are in healthcare infrastructure and workforce, with doctors per 10,000 population (−96.6%) and nurses per 10,000 population (−96.5%) being critically low. In addition, the proportion of households with health insurance coverage is 72.7% below the national average, highlighting a major financial protection gap. Positive gaps (blue bars) indicate that Bihar's value is significantly higher than the national average. The largest positive gaps are in adverse health outcomes and access barriers, notably the under-5 mortality rate (+50.5%) and infant mortality rate (+46.8%). The high vacancy rate among staff nurses (+69.4%) further exacerbates the workforce crisis.

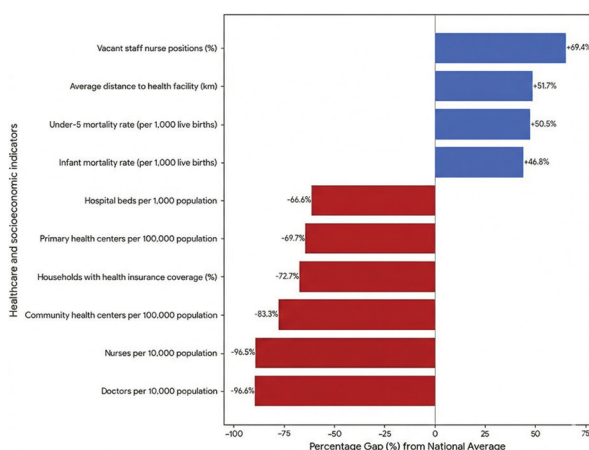


Figure 1. Comparison of key healthcare and socioeconomic indicators between Bihar and national averages. Image created by the authors.

4. AI applications in healthcare

The potential of AI to address healthcare challenges in resource-constrained settings stems from several fundamental capabilities: the ability to analyze complex data patterns at scales and speeds beyond human capacity; to make consistent, evidence-based decisions without fatigue or cognitive biases; to function continuously without time-off requirements; to be deployed simultaneously across multiple locations after initial development; and to improve systematically through exposure to additional data.⁷² These characteristics align remarkably well with the specific needs of low socioeconomic healthcare settings, where extending limited expertise across large populations, maintaining quality consistency, providing around-the-clock availability, and learning from population-level patterns could substantially enhance care delivery. In healthcare, AI tools have increasingly demonstrated their ability to complement human expertise and bridge resource and capacity gaps, especially in economically disadvantaged settings like Bihar. Table 2 shows the applications of AI for healthcare challenges in low-socioeconomic settings.

4.1. Scientific implications of AI case studies in low-resource settings

AI-driven diagnostic imaging tools, such as deep learning models for tuberculosis detection on chest radiographs, have demonstrated sensitivity and specificity comparable to those of expert radiologists across multiple low-resource evaluations.^{23,73} Their scientific significance lies in their ability to standardize interpretation quality, reduce inter-observer variability, and expand access to diagnostic accuracy in settings with severe radiologist shortages.^{24,74} These models also enable large-scale screening programs by processing high image volumes with minimal incremental cost, directly addressing delays in diagnosis and treatment.²⁵

AI-enabled outbreak prediction systems, such as those used for dengue and malaria forecasting in parts of India and Southeast Asia, demonstrate the ability of machine learning models to integrate climate variables, vector indices, mobility data, and historical epidemiology.^{29,75} Scientific implications include earlier detection of outbreak trajectories, improved allocation of rapid response resources, and reduction in disease transmission through pre-emptive interventions. For Bihar, where vector-borne diseases remain highly endemic, these models highlight the feasibility of real-time surveillance systems that outperform traditional manual reporting mechanisms.

Telemedicine platforms integrated with AI decision-support algorithms have shown measurable improvements in clinical triage accuracy, reduction in unnecessary

referrals, and faster identification of high-risk cases.^{26,30} Studies from rural Africa and India indicate that AI-supported community health worker triage can achieve diagnostic performance comparable to junior clinicians. The scientific implications include enhanced continuity of care, reduced care delays, and optimization of scarce specialist time—critical considerations in states such as Bihar with extremely low doctor-to-population ratios.

4.2. Diagnostic imaging and clinical decision support

AI-enabled diagnostic imaging is among the most mature and impactful applications in low-resource settings. Deep learning algorithms have achieved expert-level or superior performance in interpreting chest radiographs for tuberculosis detection, a critical capability given tuberculosis's substantial burden in Bihar and similar regions.²³ Automated chest X-ray analysis can function as a first-line screening tool in PHCs lacking radiologist access, flagging suspicious cases for confirmation and treatment while providing immediate feedback to healthcare workers. Similarly, retinal imaging analyzed by AI algorithms enables diabetic retinopathy screening, potentially preventing blindness in populations with limited access to ophthalmologists.²⁶ Portable retinal cameras, combined with cloud-based AI analysis, enable screening programs to reach remote populations and identify individuals requiring intervention before irreversible vision loss occurs. Dermatology applications help identify skin cancers, leprosy, and other dermatological conditions through smartphone images, extending specialist dermatology expertise to areas where such specialists are completely absent.²⁹ Importantly, these diagnostic AI applications have been specifically developed and validated for resource-limited settings, accounting for variations in image quality from lower-cost equipment, differences in disease presentation across populations, and integration into the workflows of busy, understaffed healthcare facilities.

4.3. Predictive analytics for disease management

Traditional disease surveillance relies on passive reporting from healthcare facilities, creating substantial time lags between disease occurrence and public health response while missing cases entirely in populations not accessing formal healthcare.⁷⁶ AI-based surveillance systems integrate multiple data streams, including climate data, mobility patterns, healthcare facility reports, pharmaceutical sales, and even social media mentions to detect outbreak signals earlier and more accurately than conventional approaches. Predictive machine learning models analyze vast datasets to forecast disease outbreaks, identify high-risk patients, and tailor interventions. Machine learning models

trained on historical patterns can predict seasonal disease outbreaks, including dengue and malaria, with sufficient lead time to enable preventive interventions, such as vector control intensification and public awareness campaigns.³⁴ For individual patients, risk stratification algorithms can identify pregnant women at elevated risk for complications, enabling enhanced monitoring and timely interventions, or predict which chronic disease patients face a higher hospitalization risk, allowing proactive management adjustments.⁵⁵ These predictive capabilities enable shifting from purely reactive healthcare delivery toward preventive, proactive approaches, even in settings where resource constraints have traditionally forced exclusive focus on acute treatment of already-ill patients.

4.4. Telemedicine and digital health platforms

Telemedicine platforms enhanced by AI offer solutions to the geographic access barriers characterizing low socioeconomic states. While basic video consultation technology has existed for decades, AI augmentation significantly enhances the utility and efficiency of telemedicine. AI-powered chatbots and virtual health assistants can conduct initial symptom assessment and triage, handling straightforward queries independently while escalating complex cases to human providers, effectively multiplying healthcare system capacity to respond to patient needs.⁵⁹ These conversational AI systems can be designed to function in local languages, accommodate low literacy through voice interaction, and operate on basic smartphones with intermittent connectivity. During teleconsultations with physicians, clinical decision support systems provide evidence-based treatment recommendations, flag potential medication interactions, and suggest differential diagnoses, augmenting the capabilities of less experienced providers and reducing diagnostic errors.⁵¹ Automated medical history compilation before consultations improves efficiency, ensuring comprehensive information gathering without extending consultation time. For post-consultation, AI systems can provide medication reminders, answer follow-up questions, monitor symptom progression, and flag deteriorations requiring urgent attention, extending the episode of care beyond the brief consultation period and improving treatment adherence.

4.5. Operational optimization and supply chain management

Operational and resource optimization represents a less clinically visible but critically important AI application domain. Healthcare facilities in resource-constrained settings operate in a state of perpetual resource scarcity, making efficient utilization essential yet challenging amid competing

priorities and unpredictable demands. AI-powered supply chain management systems predict medication and supply requirements based on historical consumption patterns, disease trends, and seasonal variations, reducing stockouts of essential items while minimizing wasteful overstocking of items with limited shelf life.⁴² Vaccine cold chain monitoring using Internet of Things sensors and AI analytics prevents vaccine wastage from temperature excursions while ensuring populations receive properly maintained vaccines. Ambulance fleet management algorithms optimize vehicle deployment and routing, reducing emergency response times in settings where every minute matters, yet ambulances are limited.⁴⁶ Healthcare workforce scheduling systems account for multiple constraints, including staff availability, competency requirements, patient load predictions, and regulatory requirements to generate optimized schedules that maximize coverage while minimizing overwork. These operational improvements may lack the immediate, dramatic appeal of diagnostic AI, but cumulatively create substantial improvements in healthcare system functioning and patient outcomes while reducing waste of scarce resources.

Electronic health record management enhanced by AI addresses the challenge of care fragmentation in settings where patients often receive care across multiple facilities without effective information transfer. Natural language processing algorithms can extract structured data from handwritten or poorly formatted clinical notes, creating searchable databases from information that would otherwise remain locked in paper records.⁴⁹ Patient identification and record-linking algorithms connect encounters across facilities even when patients lack unique identifiers or provide inconsistent demographic information, enabling longitudinal care tracking. Automated clinical documentation assistants reduce the documentation burden on healthcare workers, allowing sufficient time for patient interaction while ensuring comprehensive record-keeping. Integration with the national digital health infrastructure, including the Ayushman Bharat Digital Mission, lays the foundation for truly portable health records that follow patients across their healthcare journey, eliminating redundant testing, preventing medication errors due to incomplete history, and enabling better chronic disease management through comprehensive information availability.

5. The opportunities and early implementations of AI deployment in Bihar

5.1. Digital infrastructure readiness

In recent years, Bihar has made remarkable strides in digital health infrastructure, laying a robust foundation for AI integration within its healthcare system.⁷⁷ Mobile network

penetration now extends into numerous rural and remote areas, with smartphone ownership increasing steadily. This expanded connectivity, combined with declining data costs, has enabled both patients and providers to access digital health services at unprecedented scale.

Government-led initiatives play a central role. The Ayushman Bharat Digital Mission and National Digital Health Mission have established core digital infrastructure, including interoperable electronic health record platforms, health data exchanges, and telemedicine frameworks.⁷⁸ These foundational efforts provide an environment for introducing AI tools tailored to Bihar's unique challenges while aligning with national health system priorities.

Despite these advances, infrastructure gaps remain. Numerous rural areas face intermittent internet, unreliable electricity, and insufficient hardware.⁷⁹ Digital literacy among frontline health workers and the general population varies widely, necessitating ongoing capacity-building programs. Customizing technological solutions to local infrastructure realities—such as offline functionality, low-bandwidth algorithms, and rugged hardware—is crucial. Innovative approaches, including solar-powered devices and battery backups, can ensure continuous operation during power interruptions, while ruggedized hardware can withstand environmental challenges, such as dust, humidity, and rough handling.^{80,81}

5.2. Case studies of AI-powered healthcare interventions in resource-limited states

Despite infrastructural and socioeconomic hurdles, Bihar has piloted several AI-driven healthcare interventions demonstrating substantial promise. A project utilizing AI-assisted chest X-ray interpretation for tuberculosis was deployed by the Bihar State TB Cell's "qXR-TB" program from 2022 to 2024, in collaboration with Qure.ai, across 15 district hospitals in Patna, Gaya, Muzaffarpur, Darbhanga, and Bhagalpur districts. A 2023 Government of Bihar Health Department report indicated that 12,847 chest X-rays were analyzed, with an 18% improvement in TB case detection compared to the 2021 baseline.⁸² Similarly, the "Netra.ai" pilot project was launched under Bihar Health Vision 2025. Since 2023, eight CHCs in Rohtas and Buxar districts have been selected for this project. A total of 3,214 diabetic patients were screened, and 287 referable retinopathy cases were detected (8.9% positivity rate).⁸³

Telemedicine platforms integrated with AI-powered virtual assistants have expanded access to specialist care in remote areas, reducing patient travel burden and improving adherence to chronic disease monitoring. Since 2021, eSanjeevani OPD, integrated with a symptom-checker AI, has been deployed statewide across 534 health and

wellness centers. With this facility, more than 1.2 million teleconsultations were conducted from 2022 to 2023; 23% utilized AI triage, reducing physician consultation time by an average of 4.2 min.⁸⁴

These case studies underscore critical factors influencing successful AI deployment in Bihar: adaptability of AI tools to low-resource contexts; integration with existing health information systems; intensive capacity building targeting healthcare workers' digital and clinical skills; robust data privacy and governance mechanisms; sustainable financial models combining public investment and partnerships; and culturally sensitive community engagement to foster trust and uptake.

5.3. Cultural and linguistic adaptation

Technical adaptation alone cannot guarantee AI success; cultural and linguistic factors are equally critical. User interfaces must be in local languages, such as Hindi and Bhojpuri, and voice assistants should support regional dialects to accommodate low literacy levels and improve accessibility.⁸⁵ Health education and messaging integrated within AI platforms must reflect local cultural beliefs, practices, and communication styles rather than imposing foreign narratives. Such localization bolsters trust and engagement.

Algorithmic fairness requires training models on datasets representative of Bihar's diverse ethnic, genetic, and phenotypic characteristics to ensure equitable decision support. Without this, AI risks perpetuating bias and underperformance in marginalized subgroups.⁸⁶ Community health workers and traditional healers, trusted individuals within the healthcare ecosystem, should be engaged as AI facilitators, augmenting existing health-seeking pathways rather than replacing culturally embedded practices. This social alignment acknowledges that successful technology adoption in healthcare rests on human factors and cultural contexts as much as on technical efficacy.

6. Implementation strategies and frameworks for sustainable AI in low-resource settings

Successfully translating AI's potential into practical healthcare impact in low-socioeconomic states mandates carefully crafted implementation frameworks responsive to local realities. A phase-wise approach is effective for managing risks, nurturing capacity, generating evidence, and allowing iterative refinement.

6.1. Phased AI integration with operational metrics

The implementation of AI-driven healthcare interventions follows a phased approach—foundation, expansion,

and integration—linking infrastructure, workforce, and workflows with measurable process and outcome indicators to ensure effective adoption and scalability.

Foundation phase (months 0–12): Infrastructure assessment using standardized readiness checklists establishes baseline capacity at pilot sites.⁸⁷ Operational steps include: (i) facility audits documenting power availability (hours/day), connectivity bandwidth, and cold chain integrity; (ii) stakeholder workshops establishing governance committees with defined roles; and (iii) procurement following transparent bidding processes. Process indicators include infrastructure readiness score ($\geq 70\%$ threshold), stakeholder meeting frequency (minimum monthly), and staff baseline digital literacy assessment. Outcome indicators: time from patient registration to AI-assisted diagnosis (< 15 min), system uptime ($\geq 95\%$), and user acceptance scores ($\geq 4/5$).

Expansion phase (months 13–36): Deployment strategies are operationalized through mobile AI units with defined catchment areas (50–100 villages/unit), standardized training modules (a 40-h curriculum with competency assessments), and tiered technical support (helpdesk response time < 4 h).⁸⁸ Key indicators: geographic coverage of AI-enabled PHCs (%), training completion rates ($\geq 80\%$ of staff), reduction in vaccine stockout rates (baseline vs. post-intervention), and improvement in ambulance response time (< 45 min in covered areas).

Integration phase (months 37+): Embedding AI into standard workflows requires documented clinical pathways, quality assurance protocols (monthly audits), and continuous monitoring dashboards.⁸⁹ Indicators: AI utilization rate in eligible cases ($\geq 60\%$), clinical concordance between AI recommendations and provider decisions ($\geq 85\%$), and patient outcome metrics (e.g., diabetic retinopathy detection-to-treatment interval < 30 days).

6.2. Total cost of ownership and financing models

Sustainable financing demands a transparent total cost of ownership analysis. Hardware costs include ruggedized tablets/smartphones (₹15,000–40,000/device, 3-year lifecycle), portable diagnostic devices (₹80,000–4,00,000/unit), and solar backup systems (₹40,000–1,20,000/site). Connectivity costs vary by deployment model: cloud-based solutions require reliable internet (₹4,000–15,000/month/site) versus edge computing with periodic synchronization ($< ₹1,500$ /month). Maintenance and support encompass software updates, technical assistance (estimated 15–20% of annual capital costs), and hardware replacement reserves.

Blended financing combines: (i) public budget allocation (60–70% of recurring costs); (ii) development

partner grants for capital investment; (iii) performance-based financing incentivizing quality metrics; (iv) public-private partnerships with shared-risk revenue models.⁹⁰ Cost-effectiveness thresholds should align with WHO benchmarks ($\leq$ ₹12,500 per disability-adjusted life year averted for low-income contexts). Budget allocation must prioritize open-source solutions and interoperable platforms to prevent vendor lock-in.

6.3. Data governance and sovereignty

For populations exceeding 100 million, robust data governance transcends basic privacy. Federated learning architectures enable model training across decentralized sites without sharing raw data, preserving local control while enabling system-wide learning.⁹¹ Data sovereignty frameworks establish that: (i) patient data remains under public health system ownership; (ii) data-sharing agreements require explicit consent and benefit-sharing provisions; and (iii) algorithmic audits ensure transparency in AI decision-making.

Vendor lock-in prevention strategies include: Mandatory use of open standards (e.g., Fast Healthcare Interoperability Resources and Digital Imaging and Communications in Medicine), contractual clauses that ensure data portability, and a preference for open-source platforms with community governance. Data protection measures align with national digital health strategies and WHO guidance on AI ethics, including provisions for audit trails, breach notification protocols (<72 h), and patient rights to data access and deletion.⁹²

6.4. Human capital development

Training initiatives follow competency-based frameworks with defined learning objectives. Core curricula (40–60 h) cover AI fundamentals, clinical workflow integration, data interpretation, quality assurance, and ethical considerations.⁵⁴ Certification programs with periodic recertification (every 2 years) maintain standards. Pre-service health professional education integrates AI and digital health modules (minimum 20 h) to build future workforce capacity.

6.5. Cultural adaptation and technology design

AI applications must address connectivity constraints through offline-capable algorithms, data compression (enabling operation at <10 kbps), and asynchronous synchronization. User interfaces incorporate local languages, voice interaction for low-literacy populations, and culturally appropriate health messaging co-designed with community representatives. Integration with community health worker programs and traditional medicine systems requires participatory design processes that build trust and acceptance.

6.6. Alignment with international standards

Implementation adheres to established AI reporting frameworks: WHO's Ethics and Governance of AI for Health guidelines inform governance structures; the Consolidated Standards of Reporting Trials-AI standards guide the reporting of AI interventions in trials; and the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis-AI principles ensure transparent reporting of prediction models. Regular external audits assess compliance with these frameworks, with findings informing iterative improvements. This alignment enhances credibility, facilitates knowledge exchange with global health communities, and supports scale-up through standardized evidence generation.

7. Enablers, barriers, and future directions

7.1. Technological and infrastructural challenges

Implementing AI in resource-limited settings, such as Bihar, faces major technological and infrastructural barriers. Intermittent electricity and unstable internet connectivity jeopardize continuous AI operation and data integrity. Existing healthcare facilities often lack the necessary computing power, hardware, and physical space to support sophisticated AI tools.⁷⁹ These infrastructure deficits cannot be resolved quickly or cheaply, requiring sustained investment and potentially limiting where AI deployment is initially feasible. Technical solutions for these challenges include offline-capable AI systems that synchronize data when connectivity is restored, rugged, energy-efficient devices designed for harsh environments, solar and battery backup power, and edge computing models that reduce dependence on cloud services.⁸¹ These adaptations ensure AI's reliability and sustainability within Bihar's real-world healthcare infrastructure.

7.2. Sociocultural factors and community engagement

User acceptance is a critical determinant of AI implementation success and requires systematic engagement rooted in community-based participatory research (CBPR) principles. Healthcare worker resistance stems from legitimate concerns, including fear of deskilling, loss of clinical autonomy, erosion of the patient-provider relationship, and potential job displacement—particularly among paramedical staff and community health workers. Studies from comparable settings document 30–40% initial resistance rates among frontline workers, driven by inadequate digital literacy (estimated at $<50\%$ among rural health workers in Bihar), skepticism toward algorithmic decision-making in complex clinical scenarios, and hierarchical professional cultures that devalue technology-mediated care.^{85,86}

Community-level barriers operate through multiple mechanisms. Patient preferences for interpersonal care are shaped by relational trust built over years with known providers—trust that cannot be easily transferred to technological interfaces. Digital health literacy among rural populations remains limited (estimated 15–25% smartphone proficiency among women in Bihar),⁹³ compounded by linguistic barriers when interfaces lack Hindi, Bhojpuri, Maithili, and other regional languages. Gender dynamics constrain technology access, with women requiring male family member permission for healthcare decisions in ~40% of rural households.¹¹ Caste-based discrimination may be inadvertently encoded in algorithms trained on biased historical data, perpetuating health inequities.

Limitations of current approaches include superficial community consultations that fail to achieve meaningful co-design, technology-push models that prioritize innovation over user needs, and inadequate attention to power dynamics between technology developers and marginalized communities. The failure rate of digital health interventions in low-resource settings (estimation of 60–80% not achieving scale) underscores these challenges.⁹⁴

Framework-based engagement strategies grounded in the WHO community engagement framework and the United Nations International Children's Emergency Fund's community-driven AI principles provide structured approaches.⁹⁵ The WHO framework's five-stage continuum—inform, consult, involve, collaborate, and empower—guides progressive community participation. Implementation requires:

- (i) Formative research phase: Ethnographic studies documenting health-seeking behaviors, technology perceptions, and trust dynamics through focus groups, in-depth interviews, and participatory workshops with diverse community segments (women, elderly, marginalized castes, and adolescents).
- (ii) Co-design processes: Community advisory boards with decision-making authority (not merely consultative roles) shape interface design, language selection, workflow integration, and consent procedures. Bihar's Accredited Social Health Activists and Anganwadi workers serve as cultural brokers, bridging communities and technology teams.
- (iii) Iterative user testing: Rapid prototyping with community feedback loops ensures interfaces reflect local mental models, literacy levels, and cultural appropriateness. Testing must occur in actual use contexts (e.g., rural health subcenters and home visits) rather than in controlled laboratory settings.

- (iv) Transparency mechanisms: Explaining AI functioning in accessible terms (avoiding technical jargon), clarifying human clinician roles, and establishing clear accountability for AI-influenced decisions. Visual aids, community radio programs, and street theatre can effectively communicate AI concepts.
- (v) Ongoing engagement: Establishing community health committees with mandates to monitor AI implementation, report concerns, and influence program adaptations. Regular feedback sessions (at least quarterly) sustain dialogue and trust.

Addressing power asymmetries requires recognizing that technology introduction is not value-neutral but reflects and potentially reinforces existing inequities. CBPR principles demand equitable partnerships where communities shape research priorities, own the data generated, and benefit from innovations. Consent processes must be culturally appropriate, ensuring comprehension beyond mere signature collection. Benefit-sharing agreements should specify how AI-generated insights improve local services, rather than merely extracting data for external research.

Gender-responsive implementation necessitates deliberate strategies, including women-only focus groups, female health worker involvement in design teams, flexibility for women's household responsibilities, and privacy protections addressing gender-based violence risks. Technology access programs targeting women and adolescent girls build foundational digital literacy.

The complexity of achieving authentic community engagement should not be understated—it requires substantial time investments (12–18 months for meaningful co-design),⁹⁶ cultural competence among implementation teams, and willingness to modify technology based on community input, even when technically inconvenient. However, evidence from successful digital health initiatives demonstrates that community-engaged approaches yield high adoption rates (60–75% for top-down models),⁹⁷ enhanced sustained usage, and equitable outcomes. Without this foundational engagement, AI risks becoming another well-intentioned intervention that fails to achieve impact in the communities most in need.

7.3. Policy and regulatory landscapes

Robust policy frameworks are essential to enabling safe and equitable integration of AI into healthcare. At present, numerous developing contexts lack clear regulations for AI device approval, data privacy, liability management, and quality assurance. Effective governance requires establishing standards for algorithm validation on local populations, legally defining responsibilities and liabilities

for AI-aided clinical decisions, enforcing data security, and fostering interoperability across health data systems. Creating multi-stakeholder governance bodies inclusive of government, medical, technical, and community representatives ensures balanced oversight and equitable AI deployment.

8. Policy recommendations and future directions

To harness AI's transformative potential sustainably, Bihar and similar regions must pursue comprehensive policy actions, including:

- (i) Government leadership with clear AI health strategies, investment priorities, and accountability frameworks.⁸⁷
- (ii) Infrastructure development guaranteeing broadband access, stable power, and technical support capacity across healthcare tiers.⁷⁹
- (iii) Workforce development embedding AI literacy, ethical AI education, and continuous clinical training in curricula and professional development.⁵⁴
- (iv) Regulatory frameworks defining AI device criteria, data governance standards, liability provisions, and quality assurance mechanisms.^{91,92}
- (v) Innovative financing combining public budgets, donor funds, and private investments, aligned with cost-effectiveness evidence.⁹⁰
- (vi) Stakeholder engagement, integrating community representatives, healthcare workers, and technologists in design and governance.⁸⁶
- (vii) Research support facilitating local evidence generation, impact evaluation, and responsible AI development attuned to regional epidemiology and culture.
- (viii) Integration strategies linking AI with existing health programs and digital infrastructure to prevent fragmentation and amplify benefits.⁷⁸

Emerging technologies, such as 5G, blockchain, Internet of Medical Things (IoMT), and edge AI, should be leveraged cautiously with strong governance and sustainability in mind. Edge AI, enabling sophisticated processing on local devices, reduces cloud dependency and improves real-time responsiveness.⁸¹ 5G connectivity, where available, enables bandwidth-intensive applications, including high-resolution medical imaging transmission and remote surgical guidance. Blockchain technologies may enhance the security of health records and enable secure data sharing across institutions. IoMT integrating wearable sensors, home monitoring devices, and clinical equipment creates continuous data streams that support predictive analytics and chronic disease management. Ongoing AI

advances in areas such as genomics, drug discovery, mental health support, and personalized medicine may eventually become accessible even in resource-constrained settings as costs decline and implementation models mature.

9. Conclusion

Addressing Bihar's healthcare challenges requires innovation beyond conventional resource expansion. AI presents a promising avenue to extend expertise, enhance care quality, optimize limited resources, and expand equitable access. Evidence shows AI's effectiveness in comparable settings, yet realization depends on navigating infrastructural, human, financial, sociocultural, and regulatory challenges through equity-focused, inclusive strategies. Sustained commitment, multi-sector collaboration, and patient-centered approaches are vital to ensure AI benefits the most vulnerable populations. Bihar has the potential to pioneer AI-empowered health systems advancing universal health coverage and equity, providing lessons for similarly constrained regions worldwide.

Acknowledgments

None.

Funding

None.

Conflict of interest

The authors declare that they have no competing interests.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Not applicable.

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