Medical & Health Science Reviews and Letters

Digital Health and AI-Assisted Diagnosis in Resource-Limited Settings: A Narrative Review with Emphasis on India

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ARTICLE INFO

Prepared 12th October 2026, www.esrapublications.com

Edited & Published 21st October 2026

ABSTRACT

Specialists, radiology services and reliable laboratories are scarce in many low- and middle-income settings, and digital health and artificial intelligence (AI) are widely proposed as ways to extend diagnosis to people who lack access. This narrative review examines what is known, using India as the main example. About 2.2 billion people worldwide remain offline, 96% of them in low- and middle-income countries, and internet use is 23% in low-income countries compared with 94% in high-income ones. India has nevertheless built one of the largest digital health platforms in the world, with more than 93 crore (930 million) Ayushman Bharat Health Account IDs and more than 104 crore linked records by July 2026, and the eSanjeevani telemedicine service had served over 39 crore patients by July 2025. Evidence for AI diagnosis is strongest for image-based screening. A deep-learning system matched or exceeded manual grading for diabetic retinopathy in 3,049 patients at two Indian eye hospitals (sensitivity 88.9%–92.1%, specificity 92.2%–95.2%), and the World Health Organization recommends computer-aided detection for tuberculosis chest X-ray screening in people aged 15 years and older, a conditional recommendation based on low-certainty evidence. A language-model clinical copilot in Nairobi was associated with 16% fewer diagnostic errors and 13% fewer treatment errors in a preprint quality-improvement study. Real-world deployment is harder than laboratory validation: in Thai clinics, poor lighting made about one in five retinal images ungradable, and a chest X-ray model performed worse at outside hospitals in three of five comparisons. We summarise, governance frameworks from WHO and ICMR and propose a framework for responsible adoption built on need, fit to setting, local validation, governance and equity.

Key words: Digital health; artificial intelligence; diagnosis; telemedicine; diabetic retinopathy; tuberculosis; resource-limited settings; India.

1. Introduction

Many health systems face a mismatch between diagnostic need and diagnostic capacity: too few ophthalmologists, radiologists and pathologists, long distances to facilities, and unreliable infrastructure. Digital technologies promise to bridge some of these gaps through telemedicine, shared records, decision support for frontline workers and, more recently, AI that can read images or support clinical reasoning. The World Health Organization (WHO) has cautioned, however, that digital interventions are not a substitute for functioning health systems and that there are significant limitations to what digital health can address [1]. The WHO global strategy on digital health 2020–2025 set out a framework for strengthening the field [2].

This review asks four questions: what digital infrastructure exists in resource-limited settings and who is excluded from it, what evidence supports AI-assisted diagnosis there, why tools that perform well in studies often struggle in practice, and what governance and implementation choices improve the chance of benefit. India is the main example because it combines a very large burden of undiagnosed disease with a rapidly built national digital health system. This is a narrative review: evidence was selected by the author from major trials, validation studies, guidelines and official data, without a systematic search.

2. The Digital Health Landscape

Digital health in resource-limited settings includes several layers (Figure 1, Table 1): connectivity and devices; frontline mobile tools for community health workers; telemedicine; digital identity and shared health records; and, built on these, AI-assisted diagnosis. AI is most useful when it sits within these

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layers, receiving good-quality data from a connected device and returning a result that fits a referral pathway. Without the underlying layers it has little to act on [1].

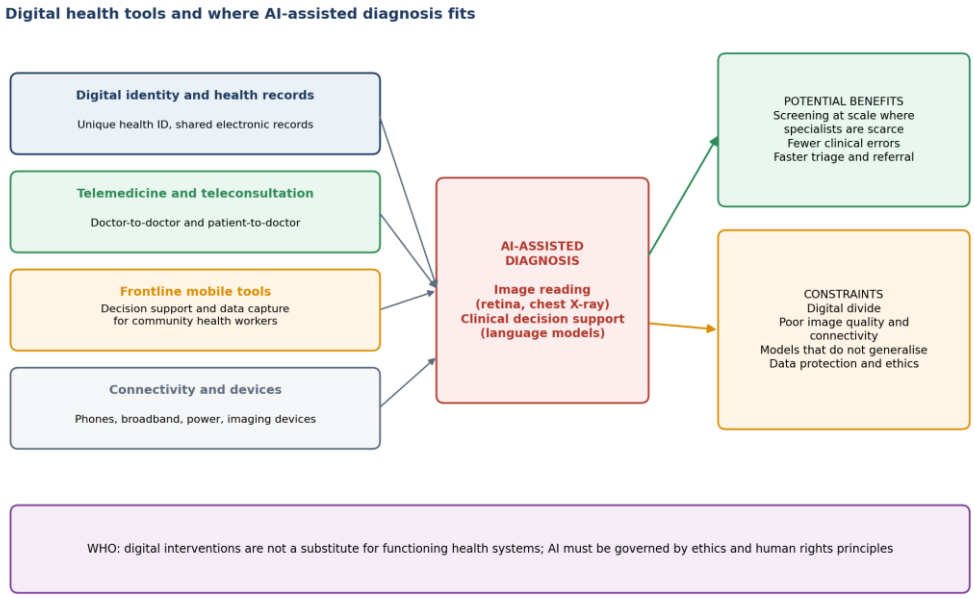


Figure 1. Layers of digital health and the position of AI-assisted diagnosis, with potential benefits and constraints. Scheme prepared from refs [1,3].

Table 1. Categories of digital health tools and examples relevant to resource-limited settings.

Category	Function	Examples	Ref.
Telemedicine	Remote consultation between patients, frontline workers and doctors	eSanjeevani (India): doctor-to-doctor and patient-to-doctor	[4]
Digital identity and records	Unique health identifier and linked records for continuity of care	Ayushman Bharat Health Account (ABHA) and ABDM	[5]
Image-based AI screening	Automated reading of retinal photographs and chest X-rays	Diabetic retinopathy grading; computer-aided TB detection	[6,7]
Language-model decision support	Real-time safety net for clinician reasoning and documentation	AI Consult copilot in Nairobi clinics	[8]
Governance tools	Ethics, validation and data protection frameworks	WHO AI guidance; ICMR AI guidelines; DPDP Act	[3,9,10]

3. Connectivity and the Digital Divide

Any digital health strategy must start from who is connected. The International Telecommunication Union estimated that about 6 billion people (74%) used the internet in 2025, leaving 2.2 billion offline, of whom 96% live in low- and middle-income countries. Internet use was 94% in high-income countries but 23% in low-income countries, 85% in urban areas but 58% in rural areas, and 77% among men but 71% among women. 5G covered 84% of people in high-income countries and 4% in low-income countries [11] (Figure 2). Those most in need of remote diagnostic services, rural, poorer and female populations, are therefore the least likely to be online. The WHO ethics guidance lists the digital divide among the key risks of health AI [3].

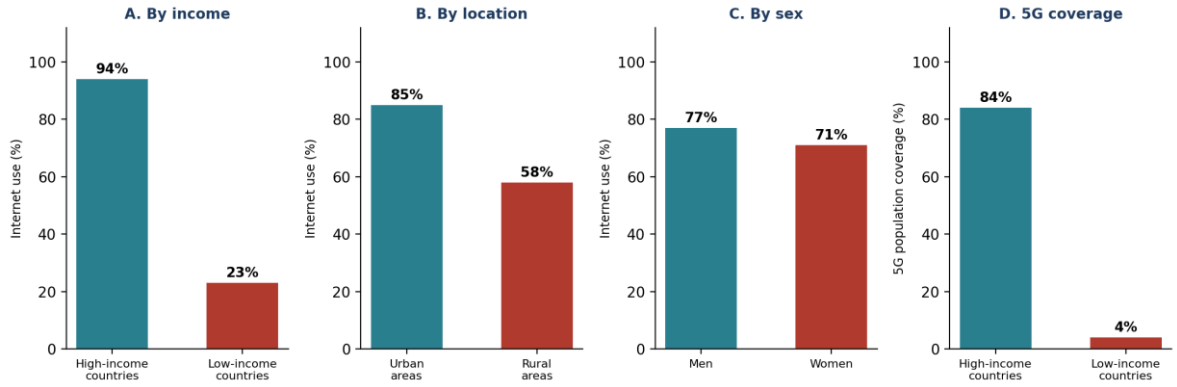


Figure 2. Digital divides that shape access to digital health, from the ITU Facts and Figures 2025 report [11]. Graphs prepared from published values.

4. India's Digital Health Infrastructure

India has built digital health infrastructure at national scale. The Ayushman Bharat Digital Mission (ABDM) provides a 14-digit ABHA health identifier that links a person's records across hospitals, laboratories and insurers with consent. By 6 July 2026, official figures showed more than 93 crore ABHA accounts and more than 104 crore health records linked, up from 79.71 crore accounts and 65.09 crore records in July 2025 [4,5]. The eSanjeevani telemedicine platform, which operates both patient-to-doctor and provider-to-provider through health and wellness centres, completed 20.41 crore teleconsultations by early 2024 [12] and had served over 39 crore patients by July 2025 [4] (Figure 3). An offline mode for ABHA registration was introduced for places without internet access or hardware [4].

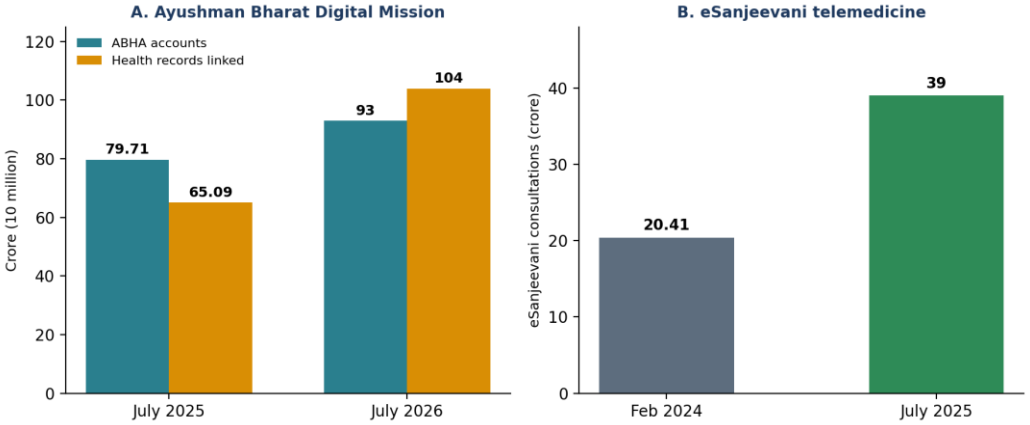


Figure 3. Scale of India's digital health platforms: (A). ABHA accounts and linked health records, July 2025 and July 2026 [4,5]. (B). eSanjeevani consultations, February 2024 and July 2025 [4,12]. Graphs prepared from published values.

Scale is not the same as clinical impact. Official counts measure registrations, records and consultations, not diagnostic accuracy or outcomes, and the ITU figures above show that connectivity remains uneven [11]. These platforms nevertheless provide the data layer and delivery channels on which AI tools could be deployed.

5. Evidence for AI-Assisted Diagnosis

5.1 Diabetic retinopathy screening

Diabetic retinopathy (DR) screening is the best-studied use. A deep-learning algorithm trained on retinal photographs from the United States and three Indian eye hospitals detected referable DR with high sensitivity and specificity in two validation sets [13]. A prospective study across two Indian centres, Aravind Eye Hospital and Sankara Nethralaya, enrolled 3,049 people with diabetes. For moderate or

worse DR, manual grading by individual graders had sensitivity of 73.4%–89.8% and specificity of 83.5%–98.7%, whereas the automated system achieved sensitivity of 88.9% and specificity of 92.2% (AUC 0.963) at Aravind, and 92.1% and 95.2% (AUC 0.980) at Sankara Nethralaya, equal to or exceeding manual grading [6] (Figure 4A).

5.2 Tuberculosis screening

For tuberculosis, WHO's 2021 screening guidelines state that, in people aged 15 years and older in populations where screening is recommended, computer-aided detection (CAD) software may be used in place of human readers to interpret digital chest X-rays for screening and triage. The recommendation is conditional and the certainty of evidence is low [7]. It was based on analysis of three software products, CAD4TB, Lunit INSIGHT CXR and qXR [7]. A multi-site evaluation has also compared the diagnostic accuracy of three deep-learning systems for TB on chest radiographs [14]. CAD has reduced accuracy in people with prior TB and in people living with HIV [7], so local calibration is important.

5.3 Language-model decision support

Generative AI is the newest entrant. In a quality-improvement study across 15 primary care clinics in Nairobi, covering 39,849 visits and 106 clinicians, a language-model copilot (AI Consult) acting as a safety net was associated with 32% fewer history-taking errors, 10% fewer investigation errors, 16% fewer diagnostic errors and 13% fewer treatment errors, as rated by independent physicians. The authors state that these results required a workflow-aligned implementation and active deployment support to encourage clinician uptake [8]. The study was funded in part by the technology developer, has been released as a preprint and is not a randomised trial of patient outcomes, so it should be regarded as promising rather than definitive (Figure 4B).

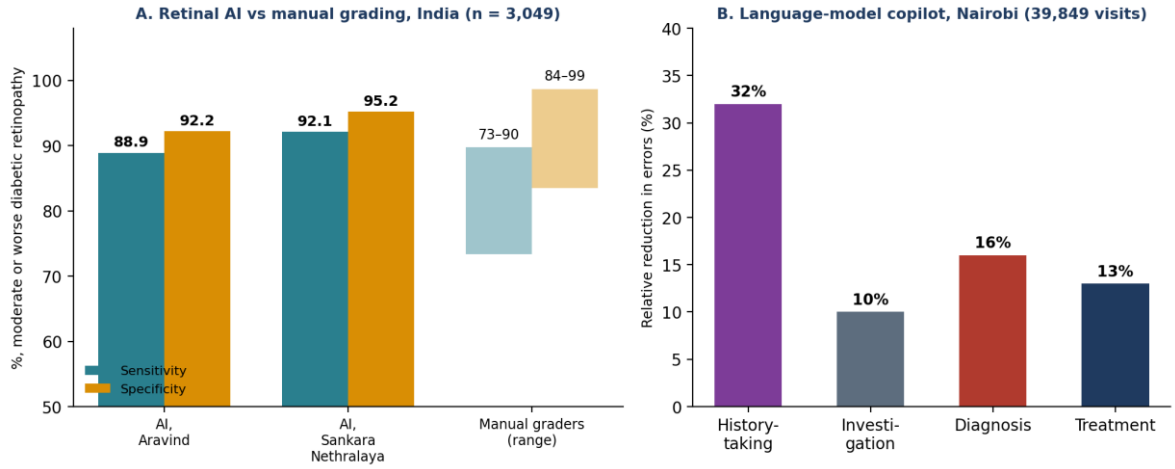


Figure 4. (A). Sensitivity and specificity of a deep-learning system for moderate or worse diabetic retinopathy at two Indian centres, compared with the range of manual grading [6]. (B). Relative reduction in clinical errors with a language-model copilot in Nairobi clinics [8]. Graphs prepared from published values.

Table 2. Evidence for AI-assisted diagnosis in resource-limited settings.

Application	Setting and design	Key finding	Ref.
Diabetic retinopathy	Two Indian eye hospitals; prospective, 3,049 patients	Sensitivity 88.9%–92.1%, specificity 92.2%–95.2%; equal to or better than manual grading	[6]
Diabetic retinopathy	Eleven Thai clinics; human-centred field study	Poor lighting caused ungradable images; connectivity delays; referral hardship for patients	[15]
Tuberculosis (chest X-ray)	WHO guideline, 2021	CAD may replace human readers in people aged 15+; conditional recommendation, low certainty	[7]
Clinical decision support	15 Nairobi clinics; 39,849 visits; quality-improvement preprint	16% fewer diagnostic and 13% fewer treatment errors	[8]
External validity	Chest X-ray model tested across three hospital systems	Performance at outside hospitals was significantly lower in 3 of 5 comparisons	[16]

6. Why Performance in Studies Does Not Always Translate to Practice

Three problems recur (Figure 5, Table 3). The first is generalisation. In a study of three hospital systems, a pneumonia-detection model performed significantly worse on chest X-rays from outside hospitals than on held-out images from its own hospital in 3 of 5 comparisons, and the networks could identify the source hospital of an image with near-perfect accuracy, showing that models can learn site-specific cues [16]. This is a central concern for deployment across different equipment and populations.

The second is fit with the working environment. In field research in 11 Thai clinics, nurses captured retinal images in rooms with poor lighting; because the system had strict image-quality thresholds, about one in five images was returned as ungradable, causing frustration and extra work, and network delays slowed screening. Some nurses worried that on-the-spot referral advice imposed time, travel and cost burdens on patients [15]. The investigators amended their protocol so that specialists reviewed ungradable images with the patient's record rather than referring automatically [15].

The third is accountability. Even where accuracy is high, someone must be responsible for errors, for monitoring performance over time and for protecting patient data. The WHO ethics guidance and the ICMR guidelines address these issues explicitly, as discussed below [3,9].

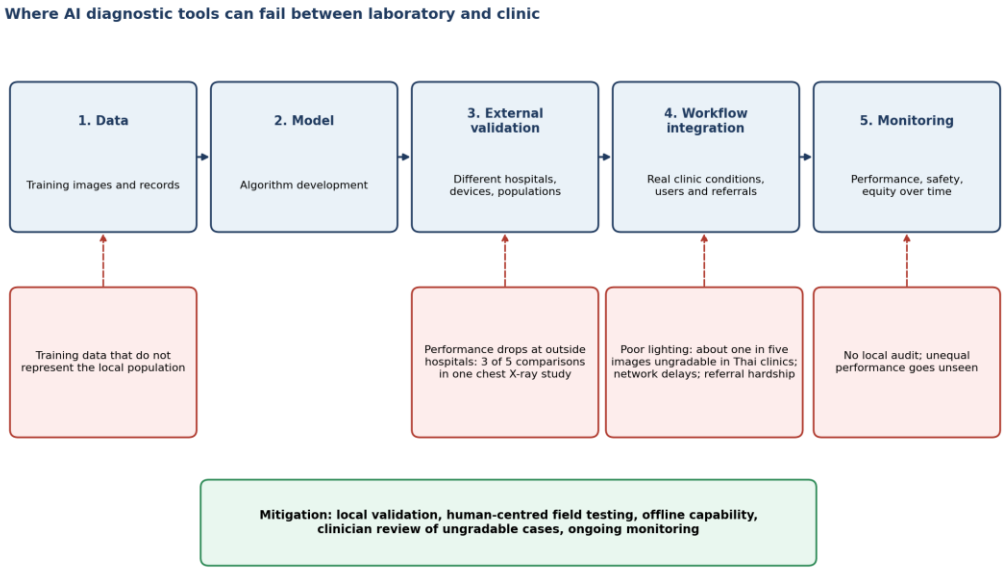


Figure 5. Points at which AI diagnostic tools can fail between development and routine use, with mitigation. Based on refs [9,15,16].

Table 3. Barriers to AI-assisted diagnosis in resource-limited settings and possible mitigations.

Barrier	Evidence	Mitigation	Ref.
Digital divide	74% of the world online; 23% in low-income countries; 58% in rural areas; 71% of women	Offline-capable tools; reach rural and female users; offline registration	[4,11]
Model generalisation	Worse performance at outside hospitals in 3 of 5 comparisons	Local validation on local devices and populations	[9,16]
Image quality and infrastructure	About one in five images ungradable; poor lighting; network delays	Training, lighting, offline inference, specialist review of ungradable images	[15]
Patient burden	Referral advice caused time, travel and cost concerns	Design referral pathways with patients; review borderline cases locally	[15]
Evidence quality	TB CAD recommendation conditional, low certainty; copilot evidence is a preprint	Prospective, independent evaluation of outcomes	[7,8]

7. Governance, Ethics and Law

WHO's 2021 guidance on the ethics and governance of AI for health, drawn up over 18 months by an expert group, identifies six principles: protecting autonomy; promoting human well-being, safety and the public interest; ensuring transparency, explainability and intelligibility; fostering responsibility and accountability; ensuring inclusiveness and equity; and promoting AI that is responsive and sustainable. It highlights the digital divide, accountability for AI-assisted decisions and bias as key risks [3].

In India, the ICMR's 2023 ethical guidelines for AI in biomedical research and healthcare provide a framework for the development, deployment and adoption of AI, with sections on ethical principles, guidance for stakeholders, ethics review, governance and informed consent [9]. Principles include safety and risk minimisation, data privacy, accountability, representative training data and clinical and field validation before use [9]. The Digital Personal Data Protection Act 2023, India's first dedicated personal data protection law, adds a legal layer for health data [10]. Table 4 summarises the landscape.

Table 4. Policy and governance instruments relevant to digital health and AI in India.

Instrument	Content	Level	Ref.
WHO guideline on digital interventions (2019)	Evidence-based recommendations; digital health is not a substitute for functioning health systems	International	[1]
WHO guidance on AI ethics (2021)	Six consensus principles; risks of the digital divide, bias and unclear accountability	International	[3]
ABDM and eSanjeevani	National health ID, linked records and telemedicine; offline registration option	National programme	[4,5]
ICMR AI guidelines (2023)	Ethical principles, ethics review, governance, informed consent; validation and representative data	National guidance	[9]
DPDP Act 2023	First dedicated personal data protection law	National law	[10]

8. A Framework for Responsible Adoption

Drawing on the evidence above, we propose five principles (Figure 6). Start from a service gap, such as screening for retinopathy or tuberculosis where specialists are scarce, rather than from a technology. Design for the actual setting, including poor lighting, intermittent connectivity and limited staff time [15]. Validate locally on the devices and populations that will be used [9,16]. Govern the tool through ethics review, consent, data protection and clear accountability [3,9,10]. And track equity, because those with the least access to connectivity are also the least likely to benefit [11]. These steps are consistent with WHO's view that digital interventions should strengthen, not replace, health systems [1].

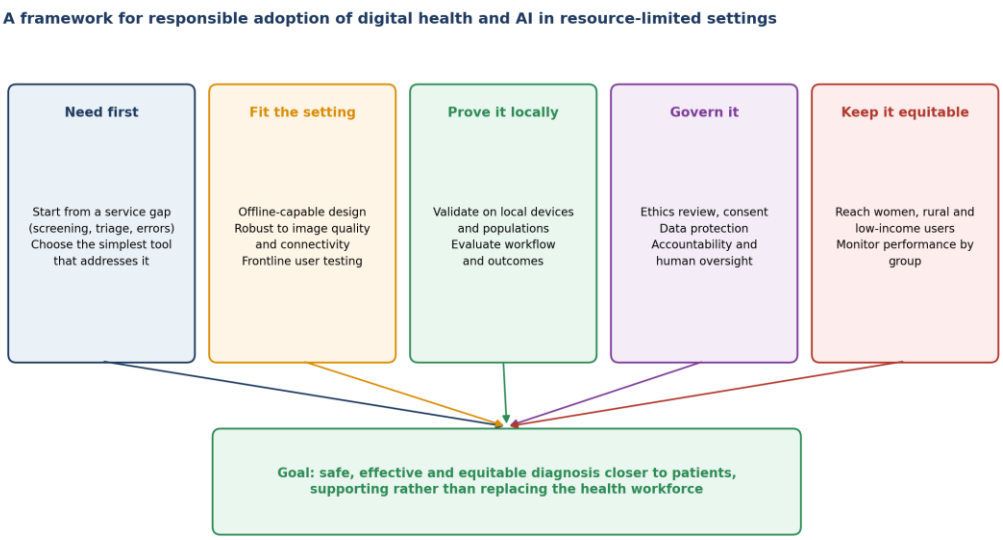


Figure 6. Framework for responsible adoption of digital health and AI in resource-limited settings. The framework is the author's synthesis of refs [1,3,9,11,15,16].

9. Research Gaps

Most published AI diagnostic studies measure accuracy, not patient outcomes. Trials are needed that test whether AI-assisted screening increases the number of people who reach treatment, and at what cost. Evidence on language-model tools comes largely from a single preprint, and independent, peer-reviewed replication in other settings, including Indian primary care, is needed [8]. TB CAD evidence is rated low certainty and weaker in people with prior TB or HIV [7]. Finally, performance should be reported by sex, age, income and geography so that inequities become visible [3,9].

10. Conclusions

Digital health and AI can extend diagnosis to people who have little access to specialists. India's national platforms show that scale is achievable, and image-based AI for diabetic retinopathy and tuberculosis has credible validation evidence. But the technology works only within a functioning system: models must be validated locally, tools must fit the working environment, data must be protected, and benefits must reach the people who are still offline. A careful, evidence-led approach, with AI supporting rather than replacing the health workforce, offers the best chance of turning promising technology into better health.

Declaration, Conflict of Interest, Funding, and Other Statements

Use of Artificial Intelligence (AI): This manuscript was prepared with the assistance of artificial intelligence (AI) tools to support the organization, development, and presentation of information relevant to researchers working in the fields of artificial intelligence in medical and health sciences. The author is responsible for reviewing and verifying the content, and maintaining the scientific integrity of the manuscript.

Funding: No specific funding was received from any public, commercial, or non-profit organization for the preparation of this review.

Conflict of Interest: The author declares no conflict of interest related to the preparation or publication of this manuscript.

Ethics Approval: Not applicable. This article is a literature-based narrative review and does not involve new research on human participants or animals.

Data Availability: No new datasets were generated or analyzed during the preparation of this review. The information discussed is derived from previously published literature and other cited sources.

Author Note

This manuscript is a narrative review intended for academic and educational purposes. It does not constitute medical advice, a clinical practice guideline, or a treatment recommendation for any individual patient. The information presented should not replace professional medical judgment or established clinical protocols. Decisions concerning diagnosis, treatment should be made in consultation with appropriately qualified healthcare professionals and specialists.

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