AI Augmented Radiology in Resource Constrained Settings: Addressing India's Imaging Inequality

Conference Paper

Abstract

Diagnostic imaging has become an important part of modern healthcare, yet access to imaging and specialist interpretation remains uneven. In India, this inequality is particularly visible between major urban centres and rural or underserved areas. A facility may have an imaging machine but still struggle to provide timely diagnosis because of limited specialist availability, connectivity problems, referral barriers, or inadequate technical support.

At the same time, artificial intelligence is changing the way radiological images are analysed and managed. AI can assist with image interpretation, case prioritisation, workflow management and other parts of the diagnostic process. This raises an important question for resource constrained settings: can AI help extend the reach of radiology without creating another layer of inequality?

This conference paper examines the potential role of AI augmented radiology in addressing imaging inequality in India. It draws on published literature on artificial intelligence, medical imaging, teleradiology, digital health and responsible AI, with particular attention to the Indian context. The paper considers both the opportunities and the limitations of AI, including infrastructure, cost, data quality, algorithmic bias, privacy, professional accountability, workforce preparation and the need for local evaluation.

The paper proposes a conceptual framework in which AI is treated as a supporting component of a wider diagnostic network rather than as a replacement for radiologists. The proposed model connects patient needs, local imaging services, digital infrastructure, AI assistance, specialist interpretation, clinical decision making, referral and patient outcomes, with equity, safety, accountability and continuous evaluation operating across the entire pathway.

The paper argues that the value of AI in radiology should not be judged only by algorithmic accuracy. Its wider value should be considered in terms of whether it helps bring reliable diagnostic expertise closer to people who currently have limited access to it. For India, the most promising approach may therefore be one that combines local imaging, teleradiology, carefully selected AI applications and human clinical judgement within a connected health system.

Keywords: Artificial intelligence; AI augmented radiology; diagnostic imaging; healthcare inequality; resource constrained settings; teleradiology; India

1. Introduction

A medical image can change the direction of a patient's care. It can help confirm a diagnosis, reveal the extent of disease, guide treatment and determine how urgently a patient needs attention. For this reason, diagnostic imaging has become an essential part of modern healthcare.

However, having an imaging service somewhere within a health system does not necessarily mean that every patient can benefit from it. Access involves more than the presence of a machine. Patients need to reach an appropriate facility, the equipment needs to be functioning, trained personnel need to be available, and the resulting images need to be interpreted by someone with the necessary expertise.

This distinction is particularly important in India. Research on imaging services in the country has identified an uneven distribution of radiology facilities and specialist expertise, with rural and underserved areas facing important access challenges (Chandramohan et al., 2024). The problem is therefore not simply a question of how many imaging machines exist. It is also a question of where those machines are located, who can operate them, who can interpret the images and how patients are connected to the next stage of care.

India has already demonstrated that technology can help address part of this problem. Char et al. (2010) described a teleradiology service connecting a rural hospital in northeastern India with radiologists in Bengaluru, more than 3,000 kilometres away. During the period studied, images were transmitted electronically for specialist interpretation, demonstrating that geographical distance did not necessarily have to prevent a rural hospital from obtaining radiological expertise.

The technological environment has changed considerably since then. Artificial intelligence is now being used and studied for a growing range of tasks in medical imaging. Deep learning systems can assist with image classification, detection, segmentation and other forms of image analysis (Litjens et al., 2017). Reviews of the literature have found considerable promise in these applications, although they have also identified important limitations in study design, external testing and generalisability (Aggarwal et al., 2021; Liu et al., 2019).

The growing interest in AI therefore creates an opportunity, but also a question. If specialist radiologists are unevenly distributed, could AI help extend the capacity of the radiologists who are available? Could it help prioritise urgent examinations, support image interpretation or improve the organisation of large imaging workloads? Could AI work alongside teleradiology to connect local facilities with specialists elsewhere?

These questions are especially important in resource constrained settings. A technology that works well in a highly resourced urban hospital may not necessarily provide the same value in a district hospital or rural facility. Differences in equipment, connectivity, staffing, patient populations and clinical workflows can affect implementation and performance (Kelly et al., 2019).

There is also a more fundamental concern. If AI is introduced mainly into hospitals that already have better infrastructure and specialist services, it could strengthen the parts of the healthcare system that are already advantaged while leaving underserved communities behind. The World Health Organization has emphasised that AI should be developed and deployed with attention to equity, privacy, human oversight, accountability and the diversity of health settings (World Health Organization [WHO], 2021).

This paper therefore examines the potential role of AI augmented radiology in addressing imaging inequality in India. Rather than treating AI as a replacement for radiologists, it considers how AI might work alongside local imaging services, teleradiology, specialist expertise and other parts of the health system.

The central argument is simple. The success of AI in radiology should not be judged only by what the algorithm can do. It should also be judged by whether the technology helps bring reliable diagnostic care closer to people who currently have limited access to it.

2. Background and Context

2.1 Diagnostic Imaging and Healthcare Access in India

Diagnostic imaging supports healthcare across a wide range of conditions. X ray, ultrasound, computed tomography and magnetic resonance imaging are used in emergency care, cancer diagnosis, trauma, maternal healthcare, infectious diseases and chronic disease management.

As diagnosis becomes increasingly dependent on imaging, inequalities in access to imaging can become inequalities in access to healthcare itself.

The Indian context is particularly important because healthcare resources are distributed across a very large and diverse population. Major urban centres contain large hospitals and specialist services, while lower level facilities may have more limited diagnostic capacity. Chandramohan et al. (2024), in their scoping review of technology solutions for improving access to imaging in India, identified evidence from 10 states and found that teleradiology, mobile imaging, artificial intelligence and other digital technologies were already being explored to address gaps in access.

One important lesson from this literature is that producing an image and interpreting an image are not necessarily the same thing. A facility may be able to perform an examination while still depending on expertise located elsewhere.

This distinction matters for patients. A person living far from a specialist centre may have to travel for an examination, wait for interpretation, return for a report or travel again if the findings require specialist attention. Each additional step can involve time, money and inconvenience.

Imaging inequality therefore needs to be understood as a problem of the whole diagnostic pathway rather than simply the availability of equipment.

2.2 The Radiology Workforce and Specialist Expertise

Radiology is highly dependent on professional expertise. Imaging equipment produces information, but that information needs to be interpreted within a clinical context.

The radiologist considers the reason for the examination, the patient's symptoms, previous imaging, relevant medical history and the possible significance of the findings. This makes the distribution of radiologists an important part of diagnostic access.

Teleradiology offers one way of separating the location of image acquisition from the location of specialist interpretation. Char et al. (2010) demonstrated this in rural India by transmitting images from a remote hospital to radiologists in Bengaluru. More recent Indian evidence has continued to identify teleradiology as an important mechanism for extending access to specialist interpretation (Chandramohan et al., 2024).

This creates an interesting possibility for India. Rather than trying to place a radiologist physically in every location where imaging is performed, a connected system could allow images to be acquired locally, supported by AI where appropriate, and interpreted by a specialist located elsewhere.

2.3 Understanding Resource Constraints

Resource constraints in healthcare are not limited to money. A facility may lack imaging equipment, trained personnel, electricity, internet connectivity, technical support, maintenance services or appropriate information systems. It may have some of these resources but not others.

This matters because AI depends on the environment around it. An AI system cannot repair a broken imaging machine. It cannot compensate indefinitely for poor image quality. It cannot create a reliable internet connection or replace the need for professionals who can interpret its findings.

The question should therefore not simply be whether an AI system is accurate. It should also be whether the system can function reliably in the environment where it is intended to be used. This is consistent with the broader literature on AI implementation, which identifies technical, organisational, clinical and sociocultural barriers between successful research demonstrations and routine healthcare use (Kelly et al., 2019).

3. Artificial Intelligence in Radiology

Artificial intelligence has been studied in medical imaging for decades, but recent advances in deep learning have substantially increased the range of tasks that can be automated or supported.

Litjens et al. (2017) described the expanding role of deep learning across medical image analysis, including classification, detection, segmentation and other applications. Since then, the volume of research has grown considerably.

Systematic reviews have shown that AI can achieve strong diagnostic performance in several areas of medical imaging. Aggarwal et al. (2021), for example, reviewed 503 studies and found promising diagnostic performance across several imaging applications. However, the review also identified substantial methodological variation and concerns about the possibility of overestimating performance.

Similarly, Liu et al. (2019) found that deep learning systems could show diagnostic performance comparable with healthcare professionals in some imaging tasks. Importantly, relatively few studies had strong external validation, and reporting limitations made it difficult to interpret the findings confidently.

These findings suggest that AI has genuine potential, but they also support a more cautious approach to implementation.

3.1 Supporting Image Interpretation

One of the most obvious uses of AI is assistance with image interpretation. Depending on the application, an algorithm may identify a suspected abnormality, highlight an area of interest or estimate the probability that a particular finding is present.

The value of such assistance is that it can provide another source of information to the radiologist. It does not necessarily have to produce the final diagnosis.

This distinction is important. A radiologist interprets images together with clinical information, previous examinations and the reason for the investigation. AI may analyse the image, but it does not automatically possess the complete clinical context.

For this reason, the concept of augmentation is particularly useful. The purpose is to support professional judgement rather than remove it.

3.2 Helping to Prioritise Cases

Radiology departments often manage large numbers of examinations. Some are routine, while others may require urgent attention.

AI can potentially assist with case prioritisation by identifying examinations that contain findings associated with urgent conditions. This could be particularly useful when a limited number of radiologists are responsible for a large imaging workload.

The benefit is not that the algorithm decides which patient matters more. Rather, it can help the clinical team recognise cases that may require earlier review. Any such system still needs appropriate testing and professional oversight because missed findings or excessive alerts can both create problems.

3.3 Supporting Reporting and Workflow

Radiology involves more than image interpretation. Reporting, documentation, communication and case management also require time.

AI is increasingly being explored for workflow support and reporting assistance. Topol (2019) described potential benefits of AI for clinicians and health systems, including image interpretation and workflow improvement.

This could be useful where reporting workloads are high. If technology can reduce repetitive tasks, radiologists may have more time for complex examinations and communication with clinical teams.

However, automated reporting also creates risks. A report can appear fluent and convincing while still containing an important error. Professional review therefore remains necessary.

3.4 Connecting AI With Teleradiology

The relationship between AI and teleradiology may be particularly relevant to India.

Teleradiology already allows images acquired in one location to be interpreted by a radiologist in another. AI could potentially support the process by helping organise cases, identifying examinations that may require urgent review or providing preliminary image analysis.

A possible pathway is straightforward. A patient undergoes imaging at a local facility. The images are processed through an AI supported system where appropriate and transmitted securely to a radiologist. The radiologist reviews the images together with the clinical information and provides the final interpretation.

The approach nevertheless depends on basic infrastructure. Images must be of sufficient quality, connectivity must be reliable, data must be protected and professional responsibility must be clearly defined.

3.5 Moving Beyond Detection

AI is also changing the way researchers think about the information contained in medical images.

Radiomics, for example, involves extracting quantitative features from images that may not be readily apparent through conventional visual assessment (Lambin et al., 2017). Such approaches may support research into disease behaviour, prognosis and treatment response.

These applications remain an active area of research and should not automatically be treated as ready for widespread clinical use.

The broader point is that radiology is becoming increasingly quantitative. AI provides tools for extracting and analysing information from images, but the clinical value of those tools depends on evidence, validation and appropriate integration into care.

3.6 Why Human Oversight Still Matters

The increasing capability of AI should not lead to the assumption that clinical judgement is becoming less important. In many situations, the opposite may be true.

A radiologist needs to decide what an imaging finding means for an individual patient. This involves more than recognising patterns. It requires interpretation, context and professional responsibility.

The WHO has therefore emphasised human autonomy, transparency, accountability, safety, equity and appropriate governance in the use of AI for health (WHO, 2021).

The idea of AI augmented radiology is consistent with this approach. AI can provide additional information and support workload management, while the clinician remains responsible for integrating the information into patient care.

4. AI Augmented Radiology in Resource Constrained Settings

The strongest case for AI in resource constrained radiology may not be in the hospitals with the most advanced technology. It may be in places where the gap between the need for diagnostic services and the availability of specialist expertise is greatest.

This changes the question. Instead of asking only whether AI can interpret an image, we can ask whether AI can help a health system make better use of the expertise and infrastructure it already has.

4.1 Extending Existing Diagnostic Capacity

AI could potentially help radiology services manage larger numbers of examinations by assisting with case sorting, preliminary analysis and identification of findings that deserve closer attention.

For a facility with limited specialist capacity, this could allow radiologists to use their time differently.

The important point is that AI does not create new radiologists. It may, however, help the available specialists support more patients.

4.2 Bringing Specialist Support Closer to Rural Patients

For people living far from major hospitals, geographical distance can become part of the diagnostic problem.

Teleradiology already provides one way of reducing this barrier. The patient can receive imaging locally while the images are interpreted remotely. The experience reported by Char et al. (2010) provides a concrete Indian example of this model.

AI could potentially strengthen such networks by helping organise cases or identify examinations that may require urgent specialist attention.

The patient does not necessarily have to travel simply because the specialist is somewhere else.

4.3 Helping to Identify Urgent Cases

Limited specialist capacity makes prioritisation particularly important. AI may assist by identifying examinations that appear to contain potentially serious findings. This could be valuable in emergency imaging where delays can have immediate consequences.

The purpose, however, should be to support prioritisation rather than to allow an algorithm to determine clinical urgency without professional oversight.

4.4 Reducing Delays in the Diagnostic Process

Sometimes the problem is not access to imaging. The examination has already been completed, but the report is delayed.

This can happen when imaging volumes are high and specialist capacity is limited. AI supported workflow and reporting tools may help reduce some routine workload. Even modest improvements in workflow could create additional time for radiologists to focus on complex cases.

Speed, however, should not become the only measure of success. A fast report has little value if it is inaccurate or clinically unhelpful.

4.5 Supporting Rather Than Replacing Professionals

The idea that AI will simply replace radiologists is not especially useful when the underlying problem is already a shortage of specialists.

A more practical approach is to use AI to support the professionals who are available. AI may highlight an area of concern or help organise a large workload. The radiologist can then combine this information with clinical knowledge and professional experience.

This recognises that diagnosis involves communication and responsibility, not simply image recognition (Topol, 2019).

4.6 Making Expertise Less Dependent on Location

Perhaps the most important possibility is that AI and teleradiology together could change the relationship between geography and specialist expertise.

A rural facility does not necessarily need every specialist physically present if it can connect reliably with a wider network. Local staff can acquire images. Digital systems can transmit them. AI can provide selected forms of support. Radiologists elsewhere can provide specialist interpretation.

The result could be a more connected diagnostic system in which expertise is shared rather than concentrated in a small number of urban centres.

4.7 The Question of Cost

Cost may determine whether AI reduces inequality or creates another form of inequality.

If advanced systems are affordable only to major private hospitals and academic centres, their contribution to underserved communities may be limited.

Cost also goes beyond purchasing software. Healthcare institutions need to consider infrastructure, maintenance, software updates, cybersecurity, training, data storage and ongoing evaluation.

A relatively simple system that solves a clearly defined problem may therefore be more useful in a district hospital than a sophisticated system that requires infrastructure the facility cannot maintain.

4.8 Using Data That Reflect Indian Patients

The quality and representativeness of data are central to AI performance.

An algorithm may perform well on the population represented in its development dataset but behave differently in another population or healthcare environment.

This is particularly relevant to India because of its geographical, demographic and healthcare diversity.

External testing is therefore important. Kelly et al. (2019) highlighted dataset shift, discriminatory bias and generalisation to new populations as important challenges for clinical AI. The use of representative Indian datasets is therefore not simply a technical issue. It is also an issue of fairness.

4.9 AI Needs a Health System Around It

It is tempting to think of AI as something that can simply be installed in a hospital.

In reality, its usefulness depends on everything around it.

A functioning AI augmented radiology service requires appropriate imaging equipment, trained personnel, reliable connectivity, secure information systems, specialist expertise, referral arrangements and mechanisms for monitoring performance.

If one of these elements is weak, the expected benefit may not be achieved.

This is why AI should be understood as part of a diagnostic ecosystem rather than a standalone intervention (Kelly et al., 2019).

5. Challenges and Risks

5.1 Infrastructure and Connectivity

AI assisted radiology depends on reliable infrastructure. Images need to be acquired at appropriate quality, stored securely and, in many applications, transmitted between locations. This requires electricity, computing resources, connectivity and information systems.

A technology that works well in a major urban hospital may be difficult to operate consistently in a facility where internet connectivity is unreliable or technical support is limited.

Investment in AI therefore needs to be considered alongside investment in basic digital and imaging infrastructure.

5.2 Cost and Sustainability

AI systems can involve substantial costs beyond the initial purchase. Software, hardware, integration, data storage, cybersecurity, staff training and system updates all require resources.

A pilot may appear successful but become unsustainable when the initial funding ends. The appropriate question is therefore not simply whether AI is affordable. It is whether a particular AI application provides sufficient value for the patients and healthcare system in which it is being introduced.

5.3 Quality of Data and Algorithmic Bias

AI systems learn from data, and the quality of those data matters. If particular populations or clinical conditions are poorly represented, performance may differ between groups.

Obermeyer et al. (2019) demonstrated how an algorithm used in healthcare could produce significant racial bias because the system used healthcare cost as a proxy for health need. The lesson for radiology is broader than race alone. AI systems need to be evaluated across populations and clinical environments rather than judged solely by overall accuracy.

The WHO has similarly emphasised the importance of equity, inclusiveness and appropriate data governance in health AI (WHO, 2021).

5.4 Accuracy Does Not Equal Clinical Safety

High diagnostic accuracy is important, but it does not automatically guarantee safe clinical use.

A model may perform well on a defined dataset and encounter difficulties in everyday clinical practice. Patients may have multiple conditions, unusual presentations or images that differ from the data used to develop the system.

Systematic reviews have highlighted substantial variation in AI study design and concerns about limited external testing (Aggarwal et al., 2021; Liu et al., 2019).

This is why local and external testing should be treated as an important part of responsible implementation.

5.5 Accountability

The use of AI raises a difficult question: who is responsible when something goes wrong?

If an AI system fails to identify an abnormality, responsibility cannot simply be assigned to the algorithm.

There need to be clear arrangements defining the responsibilities of the radiologist, clinician, healthcare institution and technology provider.

This becomes even more important in connected systems where image acquisition, AI processing, specialist interpretation and clinical management may occur at different locations.

The WHO and the FUTURE AI consensus framework both emphasise accountability, traceability and human oversight in trustworthy healthcare AI (Lekadir et al., 2025; WHO, 2021).

5.6 Privacy and Patient Information

Medical images are sensitive health information.

As radiology becomes more digital and connected, patient privacy becomes increasingly important.

Images may be stored locally, transferred between institutions or processed through external systems. Each stage creates potential privacy and security concerns.

The use of patient data for AI development and testing also requires appropriate governance.

Responsible AI therefore requires attention not only to what a system can learn from patient data but also to how that data are collected, protected, shared and used (WHO, 2021).

5.7 Professional Acceptance and Trust

Even a technically strong system may have limited impact if professionals do not trust or understand it.

Radiologists need to understand what an AI system is designed to do, where it can fail and how its outputs should be interpreted.

Trust cannot be created simply by reporting a high accuracy figure. It develops through evidence, transparency, experience and appropriate evaluation.

This is one reason why reporting standards such as CLAIM have become important in medical imaging AI research. The CLAIM 2024 update emphasises transparency and reproducibility so that AI studies can be interpreted more reliably (Tejani et al., 2024).

5.8 Training and Changing Professional Roles

AI will change the skills required within radiology.

Radiologists may increasingly need to understand AI outputs, recognise their limitations and identify circumstances in which the system should not be trusted.

Other healthcare workers will also require training if AI is introduced into lower level facilities.

Training should therefore be treated as part of implementation rather than something added after the technology has been purchased.

5.9 The Risk of Creating a New Digital Divide

Perhaps the most important concern is that AI could unintentionally increase the inequality it is intended to address.

Advanced technology is often introduced first in hospitals that already have stronger infrastructure and financial resources.

If that pattern continues, the benefits of AI may remain concentrated in urban and private healthcare settings.

Equity therefore needs to be considered at the beginning of planning. Underserved communities should not be an afterthought.

5.10 Avoiding Technology Driven Healthcare

Healthcare technology should begin with a clearly identified problem rather than with the assumption that a new technology must be used because it exists.

In radiology, planners should first ask what the actual problem is. Is it a shortage of radiologists? Is it delayed reporting? Is it limited access to imaging? Is it difficulty transferring images? Is it poor emergency prioritisation?

Different problems may require different solutions. AI may be appropriate for some of them, but not all.

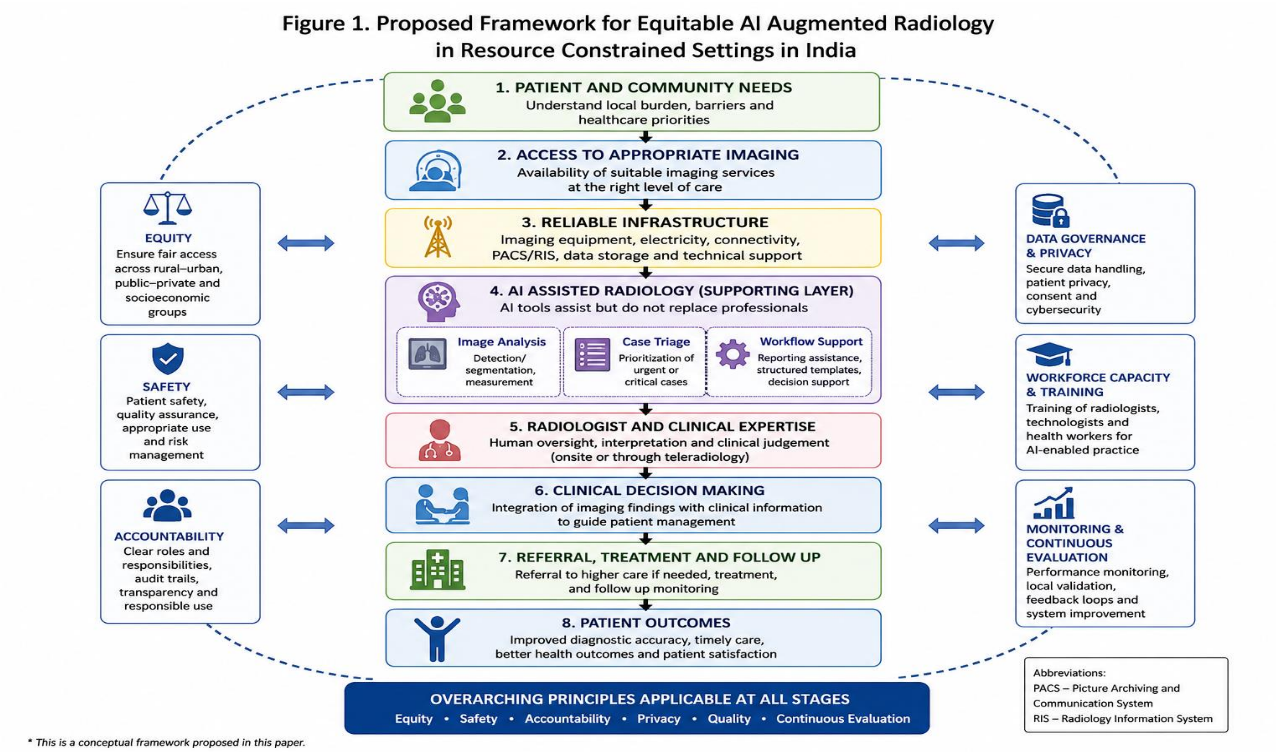
6. A Framework for Equitable AI Augmented Radiology in India

The preceding discussion suggests that the usefulness of AI in radiology depends on more than algorithmic performance.

For this reason, this paper proposes a conceptual framework for equitable AI augmented radiology in India.

The framework places the patient and the health system at the centre and treats AI as one component of a wider diagnostic pathway. The proposed relationships between access, infrastructure, AI assistance, professional expertise, clinical decision making and patient outcomes are presented in Figure 1.

Figure 1. Proposed Framework for Equitable AI Augmented Radiology in Resource Constrained Settings in India



Across every stage: Equity • Safety • Privacy • Accountability • Continuous evaluation

6.1 Access to Appropriate Imaging

The first operational component is access to appropriate imaging. AI cannot improve diagnosis if patients cannot obtain the examination they need. Different facilities can have different roles within a connected diagnostic network. The important issue is that patients have a realistic route into the diagnostic system.

6.2 Reliable Infrastructure

The second component is infrastructure. Digital imaging and AI assisted radiology depend on functioning equipment, electricity, connectivity, data storage and technical support. This is why infrastructure appears before AI in Figure 1. Technology should strengthen an existing diagnostic pathway rather than be expected to create one where basic services are absent.

6.3 AI as a Supporting Layer

The third component is AI assistance. AI may support image analysis, case prioritisation, workflow management or other defined functions. The appropriate use depends on the problem being addressed. AI should therefore follow the clinical need rather than the other way around.

6.4 Radiologist and Clinical Expertise

The fourth component is human expertise. As Figure 1 illustrates, AI assistance leads into professional review rather than replacing it. The radiologist can consider AI outputs alongside the images, clinical history and other information. The purpose of AI should be to make limited specialist expertise more effective and more widely available.

6.5 Clinical Decision Making

Radiological interpretation has value when it contributes to a clinical decision. As shown in Figure 1, AI assistance and specialist interpretation ultimately feed into patient management. This may result in treatment, additional investigation, referral or follow up.

6.6 Referral, Treatment and Follow Up

A patient may begin care at a local facility, undergo imaging at a district hospital and require specialist treatment elsewhere. Better imaging does not automatically produce better outcomes. Patients also need access to the services required to act on the findings. This is why Figure 1 continues beyond diagnosis to referral, treatment and follow up.

6.7 Equity as an Overarching Principle

Equity surrounds the entire framework because it should influence every stage of implementation. A technically accurate system is not necessarily equitable. The important questions are who can access it, where it works, for whom it works and who might be left behind.

6.8 Local Testing and Continuous Evaluation

AI systems need to be evaluated in the environments where they will actually be used. Differences in patients, equipment, disease patterns and workflows can affect performance. Local testing should therefore form part of implementation. Evaluation should also look beyond diagnostic accuracy and ask whether the technology improves access, reduces delays, supports professionals and provides sufficient value for the resources invested (Tejani et al., 2024; Lekadir et al., 2025).

6.9 Governance and Accountability

AI systems used in clinical care require clear responsibilities. Professionals should know when AI is advisory and when specialist review is required. There should also be procedures for dealing with disagreement between AI outputs and professional judgement. Patient information needs protection throughout acquisition, storage, transmission and use. These principles are consistent with WHO guidance and the FUTURE AI framework (Lekadir et al., 2025; WHO, 2021).

6.10 From Technology Adoption to Health System Design

The framework suggests a different way of approaching technology adoption. Instead of beginning by asking which AI product should be purchased, healthcare planners should begin by asking where the diagnostic pathway is weakest.

If specialist interpretation is the main problem, teleradiology may be the priority. If large numbers of examinations are waiting for review, AI assisted triage may be useful. If reporting workload is the main constraint, workflow or reporting support may be appropriate. If connectivity is poor, infrastructure should be strengthened first.

This makes technology a means rather than an end.

7. Discussion

The central argument of this paper is that AI could contribute to reducing inequalities in access to radiological services, but only when introduced as part of a functioning healthcare system.

India provides an important setting for this discussion because it already has experience with teleradiology. Char et al. (2010) demonstrated that a rural hospital could connect with radiologists located more than 3,000 kilometres away. Chandramohan et al. (2024) later showed that teleradiology and other technologies were being explored across multiple Indian states to improve access to imaging.

These experiences provide a useful foundation for thinking about AI.

Teleradiology addresses geographical distribution of specialist expertise. AI may assist with some of the workload associated with image interpretation and workflow. Their combination could therefore provide a way of strengthening existing networks rather than creating entirely new systems.

The proposed framework in Figure 1 reflects this relationship. AI is positioned as a supporting layer between imaging infrastructure and professional expertise. This is intentional.

The strongest use of AI in resource constrained settings may come from combining technological assistance with human expertise rather than attempting to remove the human element from diagnosis.

7.1 Starting With the Patient

AI adoption should begin with patient and community needs.

If a community lacks basic imaging, an advanced AI interpretation system may not be the most urgent intervention.

If images are already being produced but reports are delayed because of a shortage of radiologists, AI supported triage or workflow assistance may have greater value.

This distinction is important because technology can easily become the focus of healthcare planning. The framework therefore begins with the patient rather than the algorithm.

7.2 Equity Must Be Considered From the Beginning

AI will not automatically reduce inequality. If advanced systems are concentrated in major urban hospitals, they may simply strengthen services that are already comparatively strong.

The objective should be to improve the parts of the healthcare system where patients face the greatest barriers. This is consistent with WHO guidance on inclusiveness and equity in health AI (WHO, 2021). Equity therefore needs to be treated as an outcome, not merely an ethical statement.

7.3 AI Cannot Compensate for a Weak Health System

A health facility still needs functioning equipment, trained staff, connectivity and appropriate referral services. AI cannot replace these foundations.

This is why the framework does not place AI at the centre of the system. It places AI within the system. The broader literature on implementation similarly shows that the gap between technical performance and clinical impact can be substantial (Kelly et al., 2019).

7.4 The Human Role Remains Central

The concept of augmentation is particularly relevant. AI can identify patterns, organise information and support workflow, but radiologists remain responsible for interpreting findings in context.

Topol (2019) has argued for a model in which human and artificial intelligence complement each other rather than one simply replacing the other. For resource constrained settings, this may be especially important because the immediate challenge is often insufficient specialist capacity.

7.5 India Requires Local Evidence

India is too diverse for assumptions based entirely on evidence from other settings to be sufficient.

Differences in populations, imaging equipment, disease patterns and clinical workflows may affect AI performance.

Research should therefore include Indian clinical environments and, importantly, lower level facilities. The need for external testing is supported by systematic reviews showing substantial variation in AI study design and limited external testing (Aggarwal et al., 2021; Liu et al., 2019).

7.6 Measuring Success Differently

Accuracy remains important. But accuracy alone does not tell us whether AI has reduced imaging inequality.

A broader evaluation should ask whether access to specialist interpretation has improved, reporting delays have decreased, rural facilities can use the system reliably, radiologists can manage larger workloads, unnecessary referrals have decreased, patients reach appropriate care sooner and the technology can be sustained financially.

These measures move AI evaluation from the laboratory to the health system.

7.7 What the Proposed Framework Adds

The contribution of Figure 1 is not the claim that AI can analyse medical images. That is already well established.

The contribution is the way the problem is framed.

Instead of asking only, "How can AI improve radiology?", the framework asks, "How can AI be used within the health system to make radiological expertise more accessible to people who currently have limited access to it?"

That shift changes the outcome of interest. The goal becomes improved access, appropriate diagnosis and better patient care rather than simply higher algorithmic performance.

7.8 Relevance Beyond India

Although this paper focuses on India, the argument may also be relevant to other resource constrained settings. Many countries face similar challenges involving rural healthcare, uneven specialist distribution and limited diagnostic capacity.

However, solutions should not simply be transferred from one country to another. The infrastructure, disease burden, workforce and regulatory environment differ between countries.

The broader lesson is therefore not that every country should adopt the same model. It is that AI should be designed around actual gaps in care.

8. Implications for Policy and Practice

8.1 Link AI Policy to Diagnostic Need

Policy should begin by identifying where diagnostic gaps are greatest. This includes areas with long reporting delays, limited specialist availability and difficulty reaching referral centres. AI should then be considered as one possible response rather than the automatic response.

8.2 Strengthen Rural Diagnostic Networks

Rural healthcare should be central to any equity focused AI strategy. Rather than attempting to reproduce the full diagnostic capacity of tertiary hospitals everywhere, policymakers could support connected networks. Local facilities could provide appropriate imaging while regional or tertiary centres provide specialist interpretation. AI could support selected parts of this network.

8.3 Invest in Foundations Before Technology

Reliable imaging equipment, electricity, connectivity, data systems and maintenance are prerequisites. In some facilities, strengthening these foundations may provide greater benefit than immediately introducing an advanced AI system.

8.4 Develop an AI Ready Workforce

Radiologists and other healthcare workers need practical knowledge of AI. Training should include the purpose of AI systems, their limitations, common sources of error and situations in which outputs should be questioned. This does not mean every radiologist needs to become a programmer. It means professionals need sufficient understanding to use AI responsibly.

8.5 Establish Clear Responsibility

Healthcare institutions should define who is responsible for reviewing AI outputs, how disagreements are handled and when human review is mandatory. This is especially important when image acquisition, AI processing, radiological interpretation and clinical management occur at different locations.

8.6 Strengthen Data Governance

Medical images and associated clinical information require appropriate protection. Institutions should establish clear arrangements for data storage, access, transfer, security and secondary use. Patient trust should be treated as part of successful implementation (WHO, 2021).

8.7 Require Local Testing

AI systems intended for Indian healthcare should be tested in representative Indian clinical environments. Testing should consider technical performance as well as workflow, infrastructure and usability. Pilot implementation followed by careful evaluation may be more appropriate than immediate large scale deployment.

8.8 Encourage Responsible Partnerships

Technology developers, hospitals, universities, researchers, policymakers and communities need to work together. Developers understand technology. Clinicians understand clinical needs. Researchers can evaluate effectiveness. Health institutions understand implementation. Policymakers provide governance. Patients and communities provide another essential perspective.

8.9 Measure Equity as an Outcome

AI evaluation should include equity indicators. The important question is not only whether the system works, but whether it reaches people who need it most. Access, waiting time, specialist availability, referral patterns, affordability and patient outcomes should therefore be considered alongside diagnostic accuracy.

8.10 Support Appropriate Rather Than Excessive Innovation

Innovation does not always mean using the most sophisticated technology. A relatively simple system that solves an important problem may be more valuable than a complex system that requires infrastructure a facility cannot maintain.

The practical question should therefore be: Does this technology solve a meaningful problem for patients and healthcare workers in this setting?

8.11 Implications for Developers

Developers should understand the environments in which their systems will operate. Systems designed for highly resourced hospitals should not automatically be assumed to be suitable for lower level facilities. Developers should communicate intended use, limitations and performance clearly. Affordable models and flexible infrastructure requirements may make a greater contribution to health equity than highly complex systems designed only for major hospitals.

8.12 Implications for Researchers

Future research should move beyond controlled datasets. Studies should examine how AI performs in real clinical environments, including rural and district hospitals. Research should also consider cost, workforce experience, patient acceptance, workflow, equity and long term sustainability. The most useful research will connect technical performance with actual changes in patient care.

9. Future Directions and Research Priorities

Several areas deserve particular attention.

First, more real world research is needed. The literature remains heavily influenced by retrospective studies, and external testing is still limited in many areas of medical imaging AI (Aggarwal et al., 2021; Liu et al., 2019).

Second, more research should be conducted in rural and district hospitals. If AI is intended to reduce inequality, evidence needs to come from settings where that inequality is most visible.

Third, researchers should examine AI and teleradiology together. India already has experience with teleradiology, creating an opportunity to study whether AI can strengthen these networks.

Fourth, representative Indian datasets are needed. Data should reflect differences in geography, patient populations, disease patterns, imaging equipment and levels of healthcare delivery.

Fifth, research should examine performance across different populations and healthcare environments rather than relying only on overall accuracy.

Sixth, economic evaluation is essential. Healthcare systems need to know whether the benefits of AI justify the costs of software, infrastructure, training, maintenance and monitoring.

Seventh, the perspectives of professionals and patients should be studied. Technical performance alone cannot determine whether a system will succeed.

Finally, AI systems require long term monitoring. A system should not be regarded as permanently reliable simply because it performed well during initial testing.

The FUTURE AI framework similarly emphasises that trustworthy AI requires attention across the entire lifecycle, from design and development through testing, deployment and monitoring (Lekadir et al., 2025).

10. Conclusion

Artificial intelligence is likely to become an increasingly important part of radiology. The question for India is not whether this development should simply be embraced or resisted. The more important question is how AI can be used in a way that responds to the country's very different healthcare realities.

This paper has argued that AI could contribute to reducing inequalities in access to radiological expertise, particularly when combined with digital connectivity and teleradiology.

India already has experience showing that geographical distance does not necessarily have to prevent access to specialist radiological interpretation. The development of teleradiology provides an important foundation on which carefully implemented AI supported services could build.

However, AI is not a substitute for a functioning healthcare system.

Patients still need access to appropriate imaging. Facilities need reliable equipment and connectivity. Healthcare workers need training. Radiologists need to remain involved in appropriate professional decision making. Patient information needs protection. Technologies need to be tested in the settings where they will be used.

The framework proposed in Figure 1 therefore places AI within a broader diagnostic pathway. The pathway begins with patient and community needs, moves through access to imaging and reliable infrastructure, uses AI as a supporting layer, connects that technology with radiologist and clinical expertise, and ultimately leads towards clinical decisions, referral, treatment and follow up.

Equity, safety, accountability, privacy and continuous evaluation operate across the entire pathway.

This way of thinking changes the central question from whether AI can perform radiological tasks to whether it can help healthcare systems deliver radiological expertise to people who currently have limited access to it.

The future of AI augmented radiology should therefore not be measured only by the sophistication of algorithms or their performance in controlled studies. It should also be measured by whether patients receive timely and appropriate diagnostic care, whether healthcare professionals are supported rather than displaced, and whether the benefits of innovation reach communities that have historically had the least access to specialist services.

For India, the opportunity is significant. But the opportunity will be realised only if AI is introduced thoughtfully, locally tested, responsibly governed and connected to the wider health system.

AI should not simply make already well resourced radiology departments more technologically advanced.

Its greater promise may lie in helping make radiological expertise more accessible, more connected and more equitable.

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