Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 11 Aug 2024
Revised 07 Sep 2024
Accepted 26 Sep 2024

Natural Resources for Human Health 2024, Vol. 4 (4): 689-702

KEYWORDS:
teleradiology; remote reporting; low- and middle-income countries; quality assurance; medicolegal liability

Teleradiology and Remote Reporting Networks in Low- and Middle-Income Settings: Quality Assurance Models, Turnaround-Time Performance, and Medicolegal Considerations

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ABSTRACT: Teleradiology and remote reporting networks are increasingly proposed as pragmatic responses to the severe shortage of radiologists in low- and middle-income countries (LMICs). This narrative review synthesises literature published between 2017 and 2025 on network architectures, quality assurance (QA) models, turnaround-time (TAT) performance, and medicolegal considerations. Evidence indicates that hub-and-spoke and federated reporting models can extend specialist capacity, but published LMIC data on QA and TAT remain sparse, heterogeneous, and largely descriptive. Effective QA relies on learning-oriented peer feedback, structured reporting, and workload governance, increasingly supplemented by artificial intelligence (AI) triage. TAT depends on connectivity, prioritisation, and staffing rather than technology alone. Medicolegal frameworks are fragmented, with unresolved questions concerning licensure, liability, data protection, and consent. We propose a tiered framework and a research agenda to support safe, equitable, and accountable remote reporting in resource-constrained settings.

1. Introduction

Diagnostic imaging underpins modern clinical care, from the triage of trauma and the diagnosis of tuberculosis to cancer staging and obstetric safety. Yet access to imaging and, more importantly, to expert interpretation is profoundly unequal across the world. Global inventories of medical devices show marked disparities in the availability of imaging equipment between high-income and low-income settings (World Health Organization [WHO], 2017). Commissions on diagnostics and on medical

imaging have described a persistent "diagnostic divide" in which large populations have no timely access to imaging services, and, where equipment exists, may have no one qualified to interpret the images it produces (Fleming et al., 2021; Hricak et al., 2021). In many LMICs, a small number of radiologists are concentrated in capital cities and private hospitals, while district and rural facilities rely on general physicians, radiographers, or clinical officers to read their own examinations (Frija et al., 2021). The shortage is compounded by uneven subspecialty training; a review of radiology in Africa, for example, documented limited and geographically concentrated subspecialty expertise (Iyawe et al., 2021).

Teleradiology, defined as the electronic transmission of radiological images from the site of acquisition to a remote location for interpretation and consultation, has long been presented as a means of closing part of this gap. In its simplest form, images acquired at a peripheral facility are sent, by store-and-forward transmission or through a cloud-based picture archiving and communication system (PACS), to a radiologist elsewhere, who returns a report. In high-income systems, teleradiology has matured into a diverse ecosystem encompassing after-hours coverage, subspecialty second opinions, cross-border outsourcing, and enterprise reading networks, and it has generated its own literature on practice patterns, professional attitudes, and operational challenges (Hanna et al., 2020; Hanna et al., 2019). In LMICs, by contrast, teleradiology has grown through a patchwork of donor-funded projects, national telemedicine programmes, academic partnerships, and commercial vendors, often with limited standardisation and sparse published evaluation (Mollura et al., 2020).

Two features of the contemporary landscape complicate the assumption that remote reporting can simply "import" radiological capacity. First, the radiologist shortage is not confined to LMICs. National workforce analyses in the United Kingdom, for example, describe sustained gaps between imaging demand and reporting capacity (Kalidindi & Gandhi, 2023; Rose et al., 2022). Remote capacity in high-income settings is therefore also scarce and contested, and LMIC networks must be designed to be sustainable rather than dependent on surplus goodwill. Second, evidence on the safety of imaging interpretation is clear that error is inevitable and that its frequency is shaped by workload, fatigue, communication, and system design (Brady, 2017; Waite et al., 2017). Removing the radiologist from the point of care introduces additional opportunities for failure, including incomplete clinical information, poor-quality images, delayed communication of critical findings, and ambiguity about who is accountable for the final interpretation.

These considerations make three questions central to the safe expansion of remote reporting in resource-constrained settings. How should quality be assured when readers, referrers, and patients are separated by distance, institutions, and sometimes national borders? What turnaround times can realistically be achieved and what determines them? And what legal and ethical frameworks govern liability, licensure, consent, and data protection when images and reports cross jurisdictional lines? The present review addresses these questions through a narrative synthesis of literature published between 2017 and 2025. It begins by describing the principal network models, then examines QA approaches, TAT performance, and medicolegal issues, and concludes with an integrative framework and an agenda for research and policy.

2. Review Approach

This article is a narrative review rather than a systematic review. The narrative format was chosen because the relevant evidence is conceptually diverse, spanning operational reports, programme descriptions, professional guidance, legal instruments, and primary research from both LMIC and high-income settings, and because it does not lend itself to quantitative pooling. Literature was identified through iterative, purposive searching of PubMed, Scopus, and Google Scholar, supplemented by guidance documents from WHO and professional radiological societies, and by the reference lists of key articles. Search concepts combined teleradiology, remote reporting, telemedicine, and radiology networks with quality assurance, peer review, discrepancy, turnaround time, artificial intelligence, liability, data protection, and low- and middle-income or low-resource settings. Publications from 2017 to 2025 were prioritised so as to reflect the contemporary regulatory, technological, and workforce environment. Because quality and liability literature specific to LMIC teleradiology is thin, evidence from high-income radiology was used where it addresses mechanisms that are likely to be transferable, and its provenance is flagged in the text.

3. Remote Reporting Networks in LMICs: Context and Architectures

3.1 The capacity problem and the case for remote reporting

The rationale for remote reporting rests on a simple asymmetry: image acquisition is becoming cheaper and more widely distributed, whereas interpretive expertise remains scarce and slow to train. Digital radiography, portable and point-of-care

ultrasound, and increasingly affordable computed tomography (CT) have extended imaging capability into district hospitals and, in some cases, primary care. The interpretive workforce has not kept pace (Frija et al., 2021; Hricak et al., 2021). Teleradiology offers a way of decoupling acquisition from interpretation so that a limited pool of radiologists can serve a larger geographical footprint, can concentrate subspecialty expertise, and can provide out-of-hours cover that individual facilities cannot sustain.

3.2 Principal network models

The literature describes several recurring architectures, which are summarised in Table 1 and illustrated in Figure 1. The most common is the hub-and-spoke model, in which a central hub, typically a tertiary or teaching hospital, a national imaging centre, or a university department, receives images from multiple peripheral facilities, reports them, and returns results through a PACS, a web portal, or messaging platforms (Mollura et al., 2020). Hub-and-spoke networks benefit from centralised governance, shared protocols, and straightforward audit, but they are vulnerable to single-point failures in connectivity or staffing and may encounter bottlenecks as spoke volumes grow.

Table 1. Principal teleradiology network models in LMIC settings: features, strengths, and limitations

Model	Description	Typical LMIC application	Principal strengths	Principal limitations
Hub-and-spoke	Central hub reports for multiple peripheral sites via PACS or web portal	National or regional programmes; teaching-hospital outreach	Centralised governance; shared protocols; easier audit	Single-point failure; reader bottlenecks; dependence on hub funding
Federated / peer-to-peer	Multiple radiology departments share a common worklist and reporting load	Networks among university or referral hospitals	Resilience; pooling of subspecialty expertise	Interoperability demands; governance complexity; variable standards
Commercial / outsourced	Contracted providers, often external to the country, report on a fee-for-service basis	Private hospital groups; after-hours cover; subspecialty reads	Rapid scalability; 24-hour availability	Licensure and liability uncertainty; data transfer risk; limited local clinical context
Hybrid with AI triage	AI flags urgent or abnormal studies within any of the above	Chest radiography for tuberculosis; emergency and fracture triage	Prioritisation of workload; potential reduction in delay	Need for local validation; accountability for AI output; automation bias
Store-and-forward vs. real-time	Asynchronous image transfer versus live consultation or tele-ultrasound guidance	Routine reporting (asynchronous); guided acquisition (synchronous)	Asynchronous model tolerates low bandwidth	Real-time model needs stable connectivity; asynchronous model adds delay

Natural Resources for Human Health
eISSN: 2583-1194

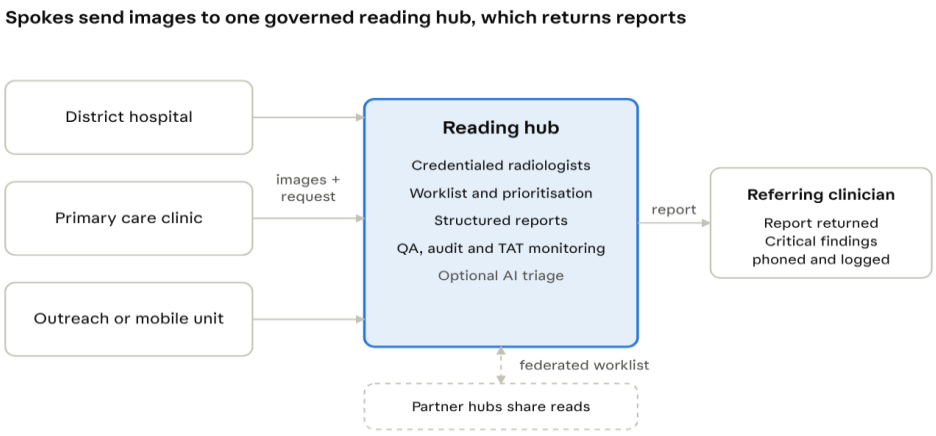

Figure 1. Conceptual architecture of a hub-and-spoke remote reporting network with optional federated partner hubs and AI triage.

3.3 Infrastructure and workflow determinants

Whatever the architecture, remote reporting depends on a chain of technical and human links, and a failure at any link will degrade quality or timeliness. At the acquisition end, image quality depends on equipment maintenance, radiographer training, appropriate protocols, and accurate patient identification. The WHO inventory of medical devices highlights that equipment is often non-functional or poorly maintained in low-resource settings, which directly reduces the diagnostic yield of whatever is transmitted (WHO, 2017). At the transmission end, bandwidth, electricity, and cybersecurity determine whether studies reach the reader quickly, completely, and securely. Many LMIC networks mitigate bandwidth constraints through image compression, asynchronous transfer, and offline-first applications, but compression and incomplete transmission can themselves introduce diagnostic risk if not governed by explicit protocols.

At the reading end, the reader requires adequate clinical information, prior imaging where available, appropriate display, and a reporting environment that supports structured, actionable reports. Clinical context is frequently the weakest link: request forms in peripheral facilities are often brief or illegible, and radiologists who are remote from the patient cannot examine the patient or readily clarify the question. Structured request templates and reporting templates have been advocated as pragmatic countermeasures, as they standardise the information needed for interpretation and make reports more consistent and easier to audit (European Society of Radiology [ESR], 2018). The final link is the return of the report to the clinician who will act on it, and especially the communication of critical or unexpected findings. In networks where results are returned only to a central portal that the referring clinician seldom checks, even an accurate and prompt report may fail to change patient management.

3.4 Artificial intelligence as an emerging component

AI-based decision support has attracted particular interest in LMICs because it promises to extend capability where human readers are absent. The most mature use case is the detection of tuberculosis on chest radiographs. Deep learning systems have achieved performance comparable to that of human readers in multi-site evaluations (Qin et al., 2019), and one widely deployed system was found to perform at least as well as certified readers on a large set of chest radiographs (Murphy et al., 2020). A systematic review nonetheless judged the evidence base promising but limited, noting heterogeneity and a shortage of prospective studies in real-world settings (Harris et al., 2019). WHO now recommends computer-aided detection as an alternative to human reading for chest radiograph screening for tuberculosis in individuals aged 15 years and above (WHO, 2021). Algorithms developed for general chest radiograph interpretation have also reported radiologist-level performance for pneumonia on benchmark datasets (Rajpurkar et al., 2018), and a meta-analysis of fracture detection found that AI accuracy was comparable to that of clinicians (Kuo et al., 2022).

These results should be interpreted cautiously. Systematic evaluation of radiology AI research has repeatedly documented methodological weaknesses, limited external validation, and concerns about generalisability to populations and equipment that differ from the training data (Kelly et al., 2022). For LMIC networks, local validation on locally acquired images is essential, as

is attention to the way AI outputs are integrated into workflows and who bears responsibility for them (Daye et al., 2022; Recht et al., 2020). Practical guidance on implementing machine learning emphasises governance, monitoring, and integration into existing workflows as much as algorithm performance (Kohli et al., 2017), and commentary on the field has stressed that AI is better conceived as augmenting radiologists than replacing them (Dreyer & Geis, 2017). Ranschaert et al. (2021) similarly describe AI as a workflow optimisation tool, with triage, prioritisation, and quality control as realistic near-term benefits. This framing is especially relevant to remote reporting networks, where prioritisation of limited reader time may deliver greater benefit than attempts to fully automate interpretation.

4. Quality Assurance Models for Remote Reporting

4.1 Conceptual foundations

Quality assurance in radiology is commonly understood as a system of structures, processes, and outcome measures designed to ensure that imaging is appropriate, technically adequate, accurately interpreted, and effectively communicated. In teleradiology these elements are distributed across organisations and geography, which makes explicit governance more, not less, important. The error literature offers a starting point. Interpretive error in radiology is a persistent and well-characterised phenomenon, with commonly cited rates of discrepancy in the low single-digit percentages across daily practice, reflecting a mixture of perceptual errors (missed findings), cognitive errors (misinterpretation), and system-related factors (Brady, 2017; Waite et al., 2017). Itri et al. (2018) describe how diagnostic errors arise from a combination of cognitive biases, workload, communication failures, and inadequate information, and emphasise that systems rather than individuals are the appropriate target of improvement.

4.2 Core QA components in remote networks

Synthesising the literature, the following elements recur as the building blocks of QA in remote reporting networks. They are summarised in Figure 2 as a continuous cycle.

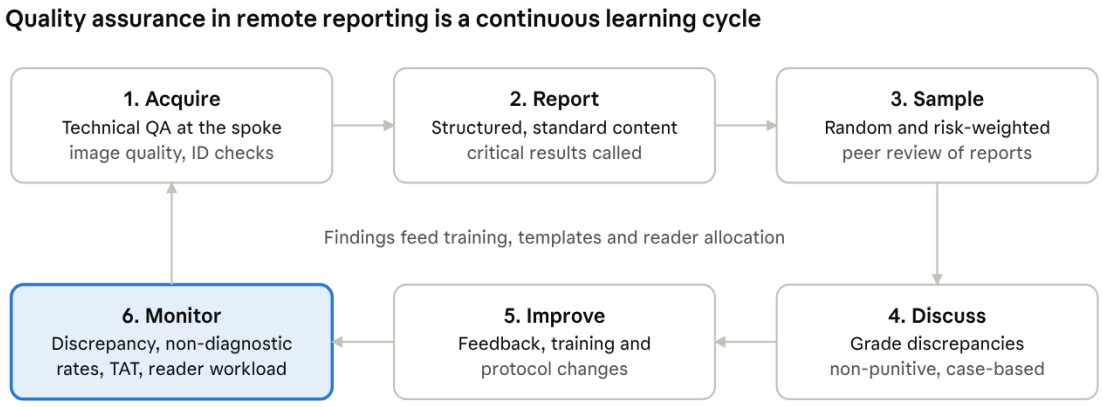

Figure 2. Proposed continuous quality assurance cycle for remote reporting networks, synthesised from the sources cited in Section 4.

Image acquisition and technical quality

Because the remote reader cannot repeat an unsatisfactory radiograph, upstream QA at the acquisition site is critical. Programmes commonly specify minimum technical standards, provide radiographer training, require identification checks, and provide feedback on rejected or non-diagnostic studies. Automated quality checks at upload, for example for laterality markers, exposure, or completeness of series, can reduce downstream rework. Boland (2019) have described how imaging quality control can be reconceived in the AI era, with automated tools supporting monitoring of image quality and process indicators on a continuing basis.

Reporting standards and structured reporting

Professional standards specify the minimum content of radiology reports, the communication of urgent findings, and the responsibilities of reporting radiologists (RCR, 2018). Structured reporting, which uses standardised templates and terminology, has been promoted as a means of improving completeness, consistency, and the ease of audit (ESR, 2018). In remote networks, structured templates also help compensate for limited clinical information by prompting the radiologist to comment on specific questions and by providing a consistent format for referrers with varying levels of experience.

Peer review and discrepancy management

Peer review, in which a sample of reports is re-read by a second radiologist and discrepancies are graded and discussed, is the most widely used formal QA mechanism. Its value depends on design: random sampling, clear definitions of clinically significant discrepancy, protected time, and a non-punitive culture (Larson et al., 2017). In LMIC networks with few radiologists, peer review may be difficult to staff, and pragmatic alternatives include reciprocal review between partner institutions, review of a risk-weighted sample (for instance, all studies read by non-radiologist readers, or all examinations with a critical finding), and the use of consensus case conferences supported by video links.

Workload governance and reader wellbeing

Evidence from high-income practice indicates that fatigue and workload influence interpretive performance. Overnight shift work has been associated with changes in search patterns and diagnostic performance (Hanna et al., 2018a), and analyses of very large volumes of examinations have examined how shift, schedule, and volume relate to interpretive accuracy (Hanna et al., 2018b). Alexander et al. (2022) have called for explicit limits on workload, duty hours, and reading speed to protect patients and radiologists. These findings suggest that network operators should monitor reads per reader per day, shift length, and reading rates as safety indicators, particularly where a small number of readers serve large catchment populations.

4.3 Models of QA organisation

The literature suggests three broad organisational approaches to QA in LMIC remote reporting, which can be combined. In a centralised model, the hub operates a formal QA programme, covering sampling, discrepancy review, audit, and feedback, and applies it uniformly across spokes. This model offers consistency and economies of scale but depends on hub capacity. In a federated model, partner institutions undertake reciprocal peer review and share discrepancy learning, which spreads workload and strengthens ownership but needs common definitions and data-sharing agreements. In an externally accredited model, networks adhere to recognised professional standards, with periodic external audit or accreditation. External oversight provides credibility and a benchmark for commercial providers but may be difficult to resource.

5. Turnaround-Time Performance

5.1 Defining and decomposing turnaround time

Turnaround time is the interval between a defined starting event and the availability of a report to the clinician who will act on it, and its meaning depends heavily on where the clock starts and stops. In remote reporting networks, the total interval can be decomposed into several segments: the time from patient arrival or request to image acquisition; the time from acquisition to successful upload; the queue time before a reader opens the study; the reading and dictation or structured-reporting time; the verification or sign-off interval; and the time from final report to receipt by the referring clinician (Figure 3). Reports that cite a single "TAT" without specifying these boundaries are difficult to compare, and in LMIC settings the segments outside the reader's control, particularly upload delays and communication of results, often account for much of the total delay.

The clinical importance of TAT varies by indication. For trauma, stroke, suspected pneumothorax, obstetric emergencies, and acute abdomen, delays of hours may alter outcomes; for tuberculosis screening or routine follow-up imaging, timeliness is more a matter of programme efficiency and patient retention in the care pathway. This heterogeneity argues for priority-specific targets, rather than a single network-wide figure, and is consistent with the emphasis on value-based radiology, which treats timeliness as one dimension of the value that imaging delivers (Brady et al., 2020).

Natural Resources for Human Health
eISSN: 2583-1194

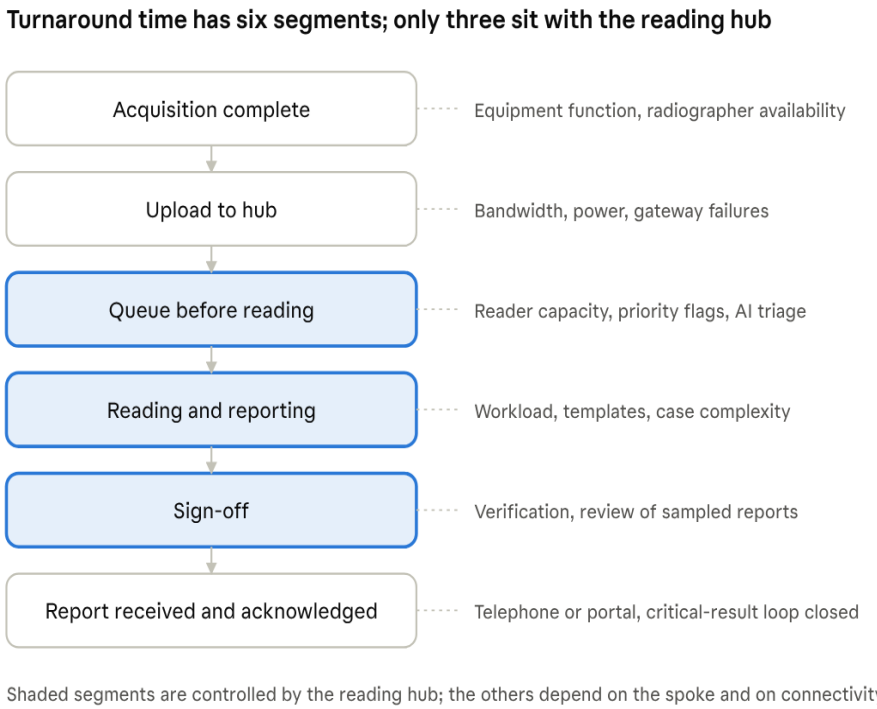

Figure 3. Segments of the remote reporting pathway at which turnaround time accrues, and the main influences on each.

5.2 What the evidence shows

Published, systematically collected TAT data from LMIC teleradiology networks are scarce. Much of what is reported appears in programme descriptions, conference reports, and grey literature, and tends to emphasise volumes and coverage rather than distributions of TAT by priority category (Mollura et al., 2020). Reviews of imaging access in LMICs repeatedly note that outcomes and process measures are inadequately reported, which limits benchmarking and learning across programmes (Frija et al., 2021; Hricak et al., 2021). In high-income settings, teleradiology is widely used precisely because it can provide rapid out-of-hours reporting and can balance workload across sites, but even here survey evidence indicates that practices, expectations, and challenges vary markedly between organisations (Hanna et al., 2020; Hanna et al., 2019). This review therefore does not present pooled TAT estimates; instead, it identifies the determinants that the literature suggests are most influential and proposes indicative targets for network design.

5.3 Determinants of turnaround time

Connectivity and transmission

In many LMIC facilities, unreliable electricity and limited bandwidth lengthen the interval between acquisition and availability for reading. Asynchronous, store-and-forward architectures tolerate intermittent connectivity, but at the cost of unpredictable delays; compressed image transfer and offline-capable gateways can reduce but not eliminate this variability (WHO, 2019). Because the delay occurs before the study enters the reader's worklist, it is invisible to reader-level performance metrics unless upload timestamps are captured.

Reader capacity and workload

The number of available readers, their working hours, and reading rates are primary determinants of queue time. Sustained high volumes can shorten TAT in the short term but at the expense of accuracy, as evidence on workload, speed, and fatigue indicates (Alexander et al., 2022; Hanna et al., 2018a). The trade-off between speed and safety is central: a network that achieves excellent TAT by pushing readers beyond safe limits is likely to exchange delay for diagnostic error (Brady, 2017; Waite et al., 2017). TAT targets should therefore be set alongside workload ceilings and discrepancy monitoring, not in isolation.

Prioritisation and triage

In the absence of explicit prioritisation, studies are typically read in order of arrival, so urgent cases wait behind routine ones. Simple clinician-assigned priority flags, supported by clear criteria, can substantially improve the handling of urgent cases, although their reliability depends on the referrer's training. AI-based triage offers a complementary approach by automatically flagging studies with probable critical findings, or, for tuberculosis screening, those with a high probability of disease, for earlier review (Qin et al., 2019; Murphy et al., 2020; Ranschaert et al., 2021). These approaches have been shown to be technically feasible, but evidence that AI triage improves clinical outcomes in LMIC remote reporting networks remains limited and should be treated as a research question, not an assumption (Harris et al., 2019; Kelly et al., 2022).

Communication and closing the loop

Even a rapid report is of limited value if it does not reach the treating clinician. Professional standards stress that urgent and unexpected findings require direct, documented communication, not passive availability in an electronic system (RCR, 2018). In many LMIC contexts, mobile messaging platforms and telephone calls are the most reliable routes, but they raise privacy and documentation concerns. Defining and auditing the interval from final report to acknowledgement by the clinician is therefore as important as measuring reading time.

5.4 Indicative targets and monitoring

Because no universally accepted TAT standards exist for LMIC remote reporting, targets must be locally negotiated and tied to clinical need. As a starting point for discussion, we propose a three-tier approach, which should be regarded as an indicative proposal derived from the literature and not a validated standard. For emergency studies, such as trauma, suspected stroke, or acute chest presentations, networks might aim for a preliminary report within roughly one hour of successful upload, with telephone communication of critical findings. For urgent inpatient or same-day outpatient studies, a target of a few hours may be realistic where reader coverage is continuous. For routine studies, reporting within 24 to 48 hours is a pragmatic goal, with tuberculosis screening and elective follow-up examinations handled in batches. Where a country has too few radiologists to meet these targets continuously, task-sharing with trained non-radiologist readers for preliminary reads, followed by radiologist review of a defined sample, may allow time-critical decisions to proceed while preserving oversight (Frija et al., 2021).

6. Medicolegal Considerations

6.1 Why medicolegal clarity matters

The separation of the reader from the patient, and frequently from the jurisdiction in which care is delivered, is the defining medicolegal feature of teleradiology. A radiologist's report is a medical opinion on which clinical decisions are based; where it is wrong, late, or not communicated, the harm falls on a patient who has typically never met the reader. In many LMICs, the legal frameworks governing telemedicine are incomplete, are in transition, or are silent about teleradiology specifically, so that practitioners and institutions operate with considerable uncertainty. WHO guidance on digital health stresses the need for enabling legal and regulatory environments, including clear provisions on accountability, privacy, and the protection of patients, as preconditions for safe digital health services (WHO, 2019, 2022). The principal issues are summarised in Table 2 and discussed below. This section is intended as an overview of recurrent issues and is not legal advice; requirements differ by country and should be confirmed with qualified local counsel.

Table 2. Principal medicolegal issues in remote reporting networks and suggested mitigations

Domain	Key issue	Typical risk	Suggested mitigation
Licensure and jurisdiction	Whether the remote reader must be registered where the patient is, where the reader is, or both	Unlicensed practice; invalid reports; regulatory sanction	Verify registration requirements; contractual warranty of licensure; maintain a register of credentialed readers
Standard of care and liability	Who is accountable for an error: reader, referring facility, network operator, or vendor	Unclear allocation of responsibility; uninsured claims	Written service agreements allocating responsibility; professional indemnity cover that explicitly includes remote and cross-border work

Clinical information and communication	Incomplete requests; delayed or undocumented communication of critical findings	Missed or delayed diagnosis; disputes over whether a finding was communicated	Mandatory request fields; documented critical-result communication with time stamps; defined escalation pathways
Consent and patient information	Whether patients know their images may be reported remotely or abroad	Complaints; invalid consent; loss of trust	Plain-language notices in local languages; consent or notification embedded in intake processes
Data protection and cross-border transfer	Transfer, storage, and processing of identifiable health data outside the originating facility or country	Breach of data protection law; security incidents	De-identification where feasible; data processing agreements; encryption; compliance with national data protection statutes
Records and retention	Retention of images, reports, and audit trails; access by patients and regulators	Inability to reconstruct events; evidentiary weakness	Defined retention periods; immutable audit logs; clear ownership of records
Artificial intelligence	Responsibility for AI-influenced reads; transparency to clinicians and patients	Liability ambiguity; automation bias	Human-in-the-loop sign-off; local validation; documentation of AI role in the report

Note. Compiled by the authors from Daye et al. (2022), Geis et al. (2019), Mezrich (2022), WHO (2022), and the data protection statutes cited in the text; the table is illustrative and does not constitute legal advice.

6.2 Licensure, credentialing, and jurisdiction

In principle, a remote reader may need to hold registration in the jurisdiction in which the patient is treated, the jurisdiction in which the reader practises, or both, and national regimes differ on which applies. Surveys of teleradiology practice in high-income settings show that licensure and credentialing are recurrent administrative burdens, and these burdens are magnified when reporting crosses national borders (Hanna et al., 2020; Hanna et al., 2019). In LMICs, regulators may lack specific provisions for remote practice by foreign radiologists, and facilities may inadvertently rely on providers whose registration status is uncertain. Networks should therefore verify and document the credentials of every reader, ensure that readers' qualifications are appropriate for the modality and population, and obtain regulatory clarification before commencing cross-border arrangements. Professional standards on the interpretation and reporting of imaging provide a useful baseline for defining reader competence and responsibilities irrespective of location (RCR, 2018).

6.3 Standard of care and allocation of liability

A central question is what standard of care applies to remote reporting, and who bears responsibility when it is not met. The general principle that the reporting radiologist is accountable for the interpretation provided is widely accepted, but responsibility in a network is shared among several parties: the referring clinician who determines the indication and supplies clinical information, the radiographer who acquires the images, the network or hub that assigns studies and governs QA, and any commercial intermediary. Because interpretive error is inevitable even in optimal conditions (Brady, 2017; Waite et al., 2017), the legally relevant question is typically whether the process met the standard expected of a reasonably competent practitioner in the circumstances, including the information and image quality available. Itri et al. (2018) emphasise that diagnostic error commonly arises from system factors, which supports the view that network-level governance, not only individual reader performance, is relevant to accountability.

6.4 Clinical information, communication, and consent

Many malpractice claims in radiology arise not from perceptual error alone but from failures of communication, including incomplete information on the request, unreported incidental findings, and unacknowledged urgent results. Remote reporting amplifies these risks because the reader cannot clarify the question informally. Structured requests that mandate key clinical fields, and structured reports that explicitly state limitations, recommendations, and follow-up needs, strengthen both clinical communication and medicolegal defensibility (ESR, 2018; RCR, 2018). Reports should record any limitations related to image

quality or missing information, and the audit trail should demonstrate when and how critical findings were communicated and to whom.

6.5 Data protection and cross-border data flows

Remote reporting necessarily entails the transmission and storage of identifiable health data, which are among the most sensitive categories of personal information. A growing number of LMICs have enacted comprehensive data protection legislation that addresses health data, and these laws increasingly regulate cross-border transfers. Kenya's Data Protection Act (2019), Nigeria's Data Protection Act (2023), and India's Digital Personal Data Protection Act (2023) are illustrative examples; each establishes obligations on those who process personal data, including requirements concerning lawful processing, security safeguards, and the circumstances under which data may be transferred abroad. The detailed conditions differ, and compliance obligations may vary depending on the nature of the data, the destination country, and the role of the parties as controllers or processors. Networks that use offshore readers or cloud servers located abroad should therefore seek specific legal advice, establish data processing agreements, and apply technical safeguards such as encryption, access controls, and, where feasible, de-identification of images and metadata before transmission.

6.6 Records, auditability, and the role of AI

Reliable records are the foundation of any medicolegal defence. Networks should retain images, reports, order information, time stamps, and communication logs for defined periods consistent with national requirements, with immutable audit trails that allow reconstruction of who accessed or amended a study and when. Where AI is used, records should show what the algorithm output was, how it was presented, and how the reader responded.

AI introduces unresolved questions of accountability. Legal analyses highlight that existing liability frameworks were not designed for algorithmic decision-support and that responsibility may be distributed among developers, deploying institutions, and clinicians in ways that remain uncertain, which constrains the autonomy that can safely be granted to AI systems (Mezrich, 2022). Multisociety guidance on the ethics of AI in radiology stresses transparency, accountability, fairness, and the need to ensure that the benefits and risks of AI are distributed equitably (Geis et al., 2019), and further ethical analysis highlights risks related to data bias, privacy, and the possible erosion of clinical expertise (Brady & Neri, 2020). European professional guidance similarly emphasises that radiologists should understand the strengths and limitations of AI tools and maintain responsibility for clinical decisions (ESR, 2019). For LMIC networks, three practical principles follow: AI output should be advisory, with a named human accountable for the final report; algorithms should be validated on local data before use and monitored afterwards (Daye et al., 2022; Recht et al., 2020); and patients and clinicians should be informed when AI has contributed to an interpretation.

7. Integrative Framework and Research Agenda

Taken together, the literature suggests that quality, timeliness, and legal defensibility are interdependent properties of the network as a whole and are not attributes of individual readers or technologies. A network that is fast but unaudited, or compliant but understaffed, will not be safe. We therefore propose a tiered approach in which requirements scale with risk and capacity. At a minimum, every network should have written service agreements, credentialed readers, structured requests and reports, documented critical-result communication, time-stamped TAT monitoring, and a data protection arrangement compliant with national law. Networks with more capacity should add a formal peer-review sample, workload ceilings, reciprocal review among partner institutions, and local validation and monitoring of any AI tools. The most mature networks should add external accreditation, outcome correlation, and public reporting of performance.

Several priorities for research and policy emerge. First, prospective, multi-site studies in LMIC networks should report discrepancy rates, non-diagnostic image rates, segment-specific TAT distributions, and patient-level outcomes using common definitions, so that performance can be benchmarked. Second, trials or pragmatic evaluations are needed to determine whether AI triage and AI-assisted second reading improve timeliness and outcomes in real-world remote reporting, and at what cost (Kelly et al., 2022). Third, comparative legal analysis of telemedicine and data protection regimes across LMICs would help networks navigate licensure, liability, and cross-border transfer. Fourth, models of task-sharing, in which trained radiographers and clinicians provide preliminary interpretation under radiologist supervision, require rigorous evaluation of safety and cost-effectiveness. Finally, health system financing models that sustain networks beyond donor funding deserve attention, since discontinuation of reporting services is itself a patient safety risk.

8. Limitations

This review has several limitations. As a narrative synthesis, it did not follow a pre-registered protocol, did not systematically enumerate or appraise the records screened, and may be affected by selection bias. The evidence base specific to LMIC teleradiology quality, turnaround time, and liability is thin, so conclusions draw substantially on high-income literature and on guidance documents whose transferability is uncertain. The proposed TAT tiers and the tiered framework are interpretive proposals and have not been empirically validated. Legal observations are general, reflect only a small number of jurisdictions, and may become outdated as legislation evolves; they should not be taken as legal advice. Finally, the review is restricted to publications from 2017 to 2025 and may omit earlier foundational work.

9. Conclusion

Teleradiology and remote reporting networks offer a credible route to extending specialist interpretation to settings where radiologists are scarce, and recent technological and policy developments, including AI and digital health strategies, have widened the options available. Their safe expansion, however, depends less on technology than on governance: learning-oriented quality assurance with sustainable indicators, priority-specific and transparently monitored turnaround times, and clear contractual and regulatory arrangements for liability, consent, and data protection. Evidence from LMIC networks remains limited, and building it should be treated as integral to service delivery rather than an afterthought. By embedding audit, workload governance, and legal clarity from the outset, networks can expand access to imaging expertise while protecting patients and the clinicians who serve them.

REFERENCES

[1] Alexander, R., Waite, S., Bruno, M. A., Krupinski, E. A., Berlin, L., Macknik, S., & Martinez-Conde, S. (2022). Mandating limits on workload, duty, and speed in radiology. Radiology, 304(2), 274-282. https://doi.org/10.1148/radiol.212631

[2] Boland, M. G. W. (2019). Imaging quality control in the era of artificial intelligence. Journal of the American College of Radiology, 16(9), 1259-1266. https://doi.org/10.1016/j.jacr.2019.05.048

[3] Brady, A. P. (2017). Error and discrepancy in radiology: inevitable or avoidable?. Insights into imaging, 8(1), 171-182. https://doi.org/10.1007/s13244-016-0534-1

[4] Brady, A., Brink, J., & Slavotinek, J. (2020). Radiology and value-based health care. Jama, 324(13), 1286-1287. https://doi.org/10.1001/jama.2020.14930

[5] Brady, A. P., & Neri, E. (2020). Artificial intelligence in radiology—ethical considerations. Diagnostics, 10(4), 231. https://doi.org/10.3390/diagnostics10040231

[6] Daye, D., Wiggins, W. F., Lungren, M. P., Alkasab, T., Kottler, N., Allen, B., ... & Langlotz, C. P. (2022). Implementation of clinical artificial intelligence in radiology: who decides and how?. Radiology, 305(3), 555-563. https://doi.org/10.1148/radiol.212151

[7] Dreyer, K. J., & Geis, J. R. (2017). When machines think: radiology's next frontier. Radiology, 285(3), 713-718. https://doi.org/10.1148/radiol.2017171183

[8] European Society of Radiology (ESR) communications@ myesr. org. (2018). ESR paper on structured reporting in radiology. Insights into imaging, 9(1), 1-7. https://doi.org/10.1007/s13244-017-0588-8

[9] European Society of Radiology (ESR) communications@ myesr. org Neri Emanuele de Souza Nandita Brady Adrian Bayarri Angel Alberich Becker Christoph D. Coppola Francesca Visser Jacob. (2019). What the radiologist should know about artificial intelligence–an ESR white paper. Insights into imaging, 10(1), 44. https://doi.org/10.1186/s13244-019-0738-2

[10] Fleming, K. A., Horton, S., Wilson, M. L., Atun, R., DeStigter, K., Flanigan, J., ... & Walia, K. (2021). The Lancet Commission on diagnostics: transforming access to diagnostics. The Lancet, 398(10315), 1997-2050. https://doi.org/10.1016/S0140-6736(21)00673-5

[11] Frija, G., Blažić, I., Frush, D. P., Hierath, M., Kawooya, M., Donoso-Bach, L., & Brkljačić, B. (2021). How to improve access to medical imaging in low-and middle-income countries?. EClinicalMedicine, 38. https://doi.org/10.1016/j.eclinm.2021.101034

[12] Geis, J. R., Brady, A. P., Wu, C. C., Spencer, J., Ranschaert, E., Jaremko, J. L., ... & Kohli, M. (2019). Ethics of artificial intelligence in radiology: summary of the joint European and North American multisociety statement. Radiology, 293(2), 436-440. https://doi.org/10.1148/radiol.2019191586

[13] Hanna, T. N., Lamoureux, C., Krupinski, E. A., Weber, S., & Johnson, J. O. (2018a). Effect of shift, schedule, and volume on interpretive accuracy: a retrospective analysis of 2.9 million radiologic examinations. Radiology, 287(1), 205-212. https://doi.org/10.1148/radiol.2017170555

[14] Hanna, T. N., Zygmont, M. E., Peterson, R., Theriot, D., Shekhani, H., Johnson, J. O., & Krupinski, E. A. (2018b). The effects of fatigue from overnight shifts on radiology search patterns and diagnostic performance. Journal of the American College of Radiology, 15(12), 1709-1716. https://doi.org/10.1016/j.jacr.2017.12.019

[15] Hanna, T. N., Steenburg, S. D., Rosenkrantz, A. B., Pyatt Jr, R. S., Duszak Jr, R., & Friedberg, E. B. (2020). Emerging challenges and opportunities in the evolution of teleradiology. American Journal of Roentgenology, 215(6), 1411-1416. https://doi.org/10.2214/AJR.19.22681

[16] Hanna, M. T. N., Steenburg, M. S. D., Tarrant, M. M. J., Pyatt, M. R. S., & Friedberg, M. E. B. (2019). The current state of teleradiology across the United States: a national survey of radiologists' habits, attitudes, and perceptions on teleradiology practice. Journal of the American College of Radiology, 16(12), 1677-1687. https://doi.org/10.1016/j.jacr.2019.05.053

[17] Harris, M., Qi, A., Jeagal, L., Torabi, N., Menzies, D., Korobitsyn, A., ... & Ahmad Khan, F. (2019). A systematic review of the diagnostic accuracy of artificial intelligence-based computer programs to analyze chest x-rays for pulmonary tuberculosis. PloS one, 14(9), e0221339. https://doi.org/10.1371/journal.pone.0221339

[18] Hricak, H., Abdel-Wahab, M., Atun, R., Lette, M. M., Paez, D., Brink, J. A., ... & Scott, A. M. (2021). Medical imaging and nuclear medicine: a Lancet Oncology Commission. The Lancet Oncology, 22(4), e136-e172. https://doi.org/10.1016/S1470-2045(20)30751-8

[19] India, Digital Personal Data Protection Act, No. 22 of 2023. https://www.meity.gov.in/static/uploads/2024/06/2bf1f0e9f04e6fb4f8fef35e82c42aa5.pdf

[20] Itri, J. N., Tappouni, R. R., McEachern, R. O., Pesch, A. J., & Patel, S. H. (2018). Fundamentals of diagnostic error in imaging. Radiographics, 38(6), 1845-1865. https://doi.org/10.1148/rg.2018180021

[21] Iyawe, E. P., Idowu, B. M., & Omoleye, O. J. (2021). Radiology subspecialisation in Africa: A review of the current status. SA Journal of Radiology, 25(1), 1-7. https://doi.org/10.4102/sajr.v25i1.2168

[22] Kalidindi, S., & Gandhi, S. (2023). Workforce crisis in radiology in the UK and the strategies to deal with it: is artificial intelligence the saviour?. Cureus, 15(8). https://doi.org/10.3390/epidemiologia4020023

[23] Kelly, B. S., Judge, C., Bollard, S. M., Clifford, S. M., Healy, G. M., Aziz, A., ... & Killeen, R. P. (2022). Radiology artificial intelligence: a systematic review and evaluation of methods (RAISE). European radiology, 32(11), 7998-8007. https://doi.org/10.1007/s00330-022-08784-6

[24] Kenya, Data Protection Act, No. 24 of 2019. https://kenyalaw.org/akn/ke/act/2019/24/eng@2022-12-31

[25] Kohli, M., Prevedello, L. M., Filice, R. W., & Geis, J. R. (2017). Implementing machine learning in radiology practice and research. American journal of roentgenology, 208(4), 754-760. https://doi.org/10.2214/AJR.16.17224

[26] Kuo, R. Y., Harrison, C., Curran, T. A., Jones, B., Freethy, A., Cussons, D., ... & Furniss, D. (2022). Artificial intelligence in fracture detection: a systematic review and meta-analysis. Radiology, 304(1), 50-62. https://doi.org/10.1148/radiol.211785

[27] Larson, D. B., Donnelly, L. F., Podberesky, D. J., Merrow, A. C., Sharpe Jr, R. E., & Kruskal, J. B. (2017). Peer feedback, learning, and improvement: answering the call of the institute of medicine report on diagnostic error. Radiology, 283(1), 231-241. https://doi.org/10.1148/radiol.2016161254

[28] Mezrich, J. L. (2022). Is artificial intelligence (AI) a pipe dream? Why legal issues present significant hurdles to AI autonomy. American Journal of Roentgenology, 219(1), 152-156. https://doi.org/10.2214/AJR.21.26777

[29] Mollura, D. J., Culp, M. P., Pollack, E., Battino, G., Scheel, J. R., Mango, V. L., ... & Dako, F. (2020). Artificial intelligence in low-and middle-income countries: innovating global health radiology. Radiology, 297(3), 513-520. https://doi.org/10.1148/radiol.2020201434

[30] Murphy, K., Habib, S. S., Zaidi, S. M. A., Khowaja, S., Khan, A., Melendez, J., ... & van Ginneken, B. (2020). Computer aided detection of tuberculosis on chest radiographs: An evaluation of the CAD4TB v6 system. Scientific reports, 10(1), 5492. https://doi.org/10.1038/s41598-020-62148-y

[31] Nigeria, Data Protection Act, 2023. https://placng.org/i/wp-content/uploads/2023/06/Nigeria-Data-Protection-Act-2023.pdf

[32] Qin, Z. Z., Sander, M. S., Rai, B., Titahong, C. N., Sudrungrot, S., Laah, S. N., ... & Creswell, J. (2019). Using artificial intelligence to read chest radiographs for tuberculosis detection: A multi-site evaluation of the diagnostic accuracy of three deep learning systems. Scientific reports, 9(1), 15000. https://doi.org/10.1038/s41598-019-51503-3
[33] Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., ... & Lungren, M. P. (2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS medicine, 15(11), e1002686. https://doi.org/10.1371/journal.pmed.1002686
[34] Ranschaert, E., Topff, L., & Pianykh, O. (2021). Optimization of radiology workflow with artificial intelligence. Radiologic Clinics, 59(6), 955-966. https://doi.org/10.1016/j.rcl.2021.06.006
[35] Recht, M. P., Dewey, M., Dreyer, K., Langlotz, C., Niessen, W., Prainsack, B., & Smith, J. J. (2020). Integrating artificial intelligence into the clinical practice of radiology: challenges and recommendations. European radiology, 30(6), 3576-3584. https://doi.org/10.1007/s00330-020-06672-5
[36] Royal College of Radiologists. (2018). Standards for interpretation and reporting of imaging investigations.
[37] Royal College of Radiologists. (2023). Clinical radiology workforce census 2022.
[38] Rose, S. D., Jordan, D. W., Bevins, N. B., Dave, J. K., Hintenlang, D. E., Lofton, B. K., & Patel, P. (2022). Estimated size of the clinical medical imaging physics workforce in the United States. Journal of applied clinical medical physics, 23(7), e13664. https://doi.org/10.1002/acm2.13664
[39] Wahl, B., Cossy-Gantner, A., Germann, S., & Schwalbe, N. R. (2018). Artificial intelligence (AI) and global health: how can AI contribute to health in resource-poor settings?. BMJ global health, 3(4), e000798. https://doi.org/10.1136/bmjgh-2018-000798
[40] Waite, S., Scott, J., Gale, B., Fuchs, T., Kolla, S., & Reede, D. (2017). Interpretive error in radiology. American Journal of Roentgenology, 208(4), 739-749. https://doi.org/10.2214/AJR.16.16963
[41] World Health Organization. (2017). Global atlas of medical devices.
[42] World Health Organization. (2019). WHO guideline: Recommendations on digital interventions for health system strengthening.
[43] World Health Organization. (2021). WHO consolidated guidelines on tuberculosis. Module 2: screening-systematic screening for tuberculosis disease. World Health Organization.
[44] World Health Organization. (2022). Monitoring the implementation of digital health: an overview of selected national and international methodologies.

التصوير الشعاعي عن بُعد وشبكات الإبلاغ عن بُعد في البيئات منخفضة ومتوسطة الدخل: نماذج ضمان الجودة، وأداء زمن الاستجابة، والاعتبارات القانونية الطبية

الملخص

يُقترح التصوير الشعاعي عن بُعد وشبكات الإبلاغ عن بُعد بشكل متزايد كاستجابات عملية للنقص الحاد في أخصائيي الأشعة في البلدان منخفضة ومتوسطة الدخل (LMICs). تُجمّع هذه المراجعة السردية الأدبيات المنشورة بين عامي 2017 و2025 حول بنى الشبكات، ونماذج ضمان الجودة(QA) ، وأداء زمن الاستجابة(TAT) ، والاعتبارات القانونية الطبية. وتشير الأدلة إلى أنّ نماذج الإبلاغ المحورية (hub-and-spoke) والاتحادية يمكن أن توسّع قدرة المتخصصين، غير أنّ البيانات المنشورة في البلدان منخفضة ومتوسطة الدخل حول ضمان الجودة وزمن الاستجابة تظل شحيحة وغير متجانسة ووصفية إلى حد كبير. ويعتمد ضمان الجودة الفعّال على التغذية الراجعة من الأقران الموجّهة نحو التعلّم، والإبلاغ المنظّم، وحوكمة عبء العمل، مع تعزيز متزايد بالفرز بمساعدة الذكاء

Natural Resources for Human Health
eISSN: 2583-1194

الاصطناعي .(AI) ويعتمد زمن الاستجابة على الاتصال والأولوية والكوادر وليس على التكنولوجيا وحدها. والأطر القانونية الطبية مجزّأة، مع أسئلة لم تُحل بعد تتعلق بالترخيص والمسؤولية القانونية وحماية البيانات والموافقة. ونقترح إطاراً متدرّجاً وأجندة بحثية لدعم الإبلاغ عن بُعد الآمن والمنصف والخاضع للمساءلة في البيئات محدودة الموارد.

الكلمات المفتاحية: التصوير الشعاعي عن بُعد؛ الإبلاغ عن بُعد؛ البلدان منخفضة ومتوسطة الدخل؛ ضمان الجودة؛ المسؤولية القانونية