Call to Action: Accelerating AI-Driven Transformation in Medical Imaging and the Broader Health Care System

This International Society for Strategic Studies in Radiology (IS3R) consensus statement recommends that AI should be used to redesign radiology around faster workflows, better data integration, and value-based care, with radiology positioned as a central driver of digital transformation in health systems. It also stresses that AI must be trustworthy, continuously monitored, and paired with real workflow replacement to deliver measurable value. The IS3R is a non-political, not-for-profit organization of radiology leaders focused on strategic, scientific, and economic issues shaping medical imaging.

The statement is a response to rising imaging demand, workforce shortages, expanding indications for imaging, and pressure to cut costs while improving access. These forces are pushing radiology toward more automated, digitally integrated care models rather than traditional volume-based practice. The IS3R's recommendations and strategies to adopt AI into clinical practice reflect expert consensus from the 2025 biennial meeting in Dublin.

The statement summarizes how AI can improve efficiency across the imaging pathway by shortening exams, accelerating acquisition, prioritizing urgent cases, and helping radiologists focus on higher-value work. The IS3R also highlights patient-facing gains, including better communication, smoother follow-up, and more understandable automated reports.

The consensus panel urges that radiologists should not just adopt AI passively but use it to recover value and justify continued investment through measurable productivity gains and downstream savings. The authors suggest that showing these benefits will matter for payer engagement and for sustaining AI deployment at scale.

Four action areas

The white paper organizes its recommendations into four domains: image interpretation, capacity building, data governance, and systemic digital transformation. In image interpretation, it encourages AI that can recognize normal exams, identify stable or non-actionable disease, and support trustworthy reporting with explainability and uncertainty quantification.

For capacity building, it emphasizes using AI to increase appointment availability, reduce low-value imaging, and improve scan efficiency through focused protocols and faster acquisition. It also proposes more advanced tools such as ambient AI, agentic AI, and vision-language models to shift radiologists from first-draft authors to expert editors.

The statement gives major weight to data quality, standardization, and interoperability because AI performance depends on broad, reliable, and well-governed datasets. It calls for large-scale data-sharing networks, global standards for fairness and bias surveillance, and secure international reference datasets for post-market monitoring.

It also recommends collaborative governance models and policy support for interoperability so that AI tools can move across systems more safely and efficiently. In this view, data governance is not a side issue; it is a prerequisite for dependable AI in clinical practice.

The report's broader claim is that AI will help sustain health care transformation by improving efficiency, reducing burnout, integrating health data, and supporting better outcomes. It argues radiology is especially well placed to lead because imaging sits at the entry point of diagnosis and can act as a hub for multimodal data integration.

The IS3R also envisions radiologists evolving into integrative diagnosticians who use predictive analytics for chronic disease monitoring, opportunistic screening, and proactive management. That shift would move the specialty further into care coordination and away from purely transactional image reading.

Bottom line

Overall, the IS3R statement is a strategic call for radiology to lead digital transformation rather than merely adapt to it. Its core message is that AI should be adopted not for novelty, but for trustworthy automation, better resource use, and alignment with health system priorities.

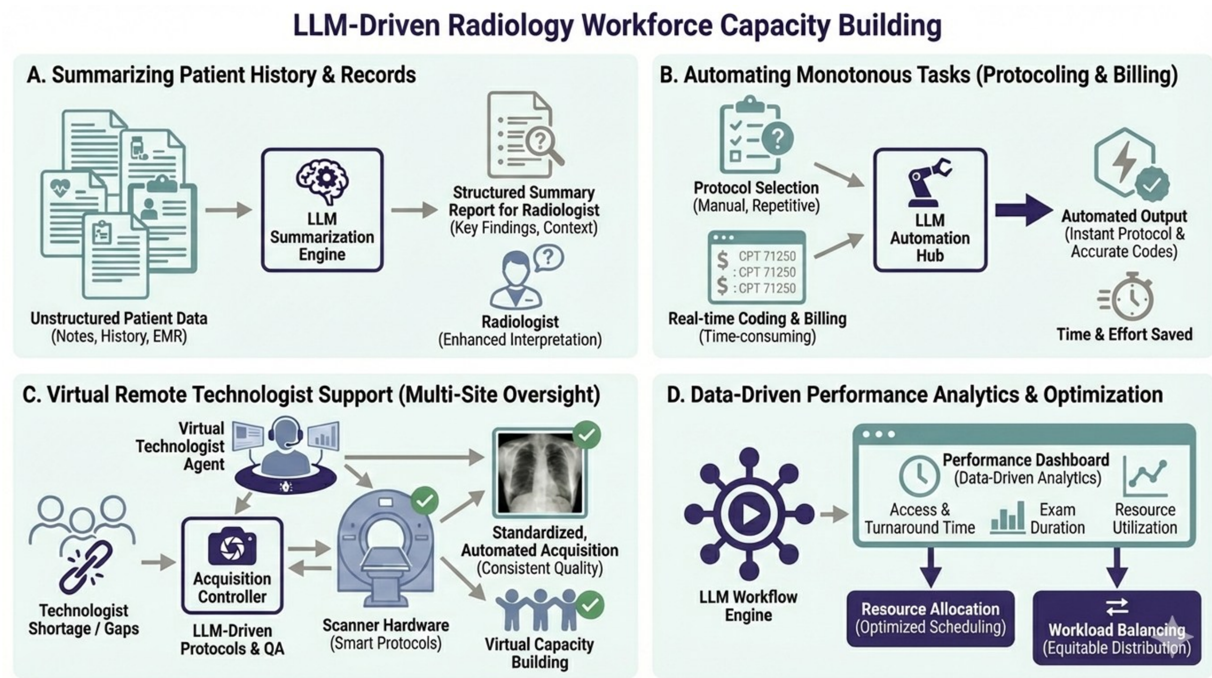

Figure 1 | Examples of LLM-Driven Radiology Workforce Capacity Building. Conceptual schematic illustrating the multifaceted roles of Large Language Models (LLMs) in enhancing operational efficiency and clinical throughput within a radiology department. **(A) Summarizing Patient History & Records:** LLMs can ingest unstructured data from Electronic Medical Records (EMRs), including clinical notes and provided study history/indication, to generate concise, structured summaries. This can provide radiologists with immediate context, reducing the cognitive load required for image interpretation. **(B) Automating Monotonous Tasks:** LLMs can streamline administrative and technical overhead by automating protocol selection and real-time coding for billing. This shift can reduce manual entry errors and allows staff to focus on higher-value clinical activities. **(C) Automated Image Acquisition Support:** In response to radiology technologist shortages, LLMs can assist in the acquisition phase by guiding scanner hardware through "smart protocols." This can ensure standardized image quality and expands virtual capacity. **(D) Workflow Orchestration & Performance Monitoring:** The LLM workflow engine can dynamically manage departmental resources, optimizing scheduling and case prioritization based on clinical urgency. Simultaneously, the system can monitor real-time performance metrics to provide continuous feedback and ensure equitable workload distribution. <u>This figure was generated using Google Gemini and Nano Banana Pro.</u>

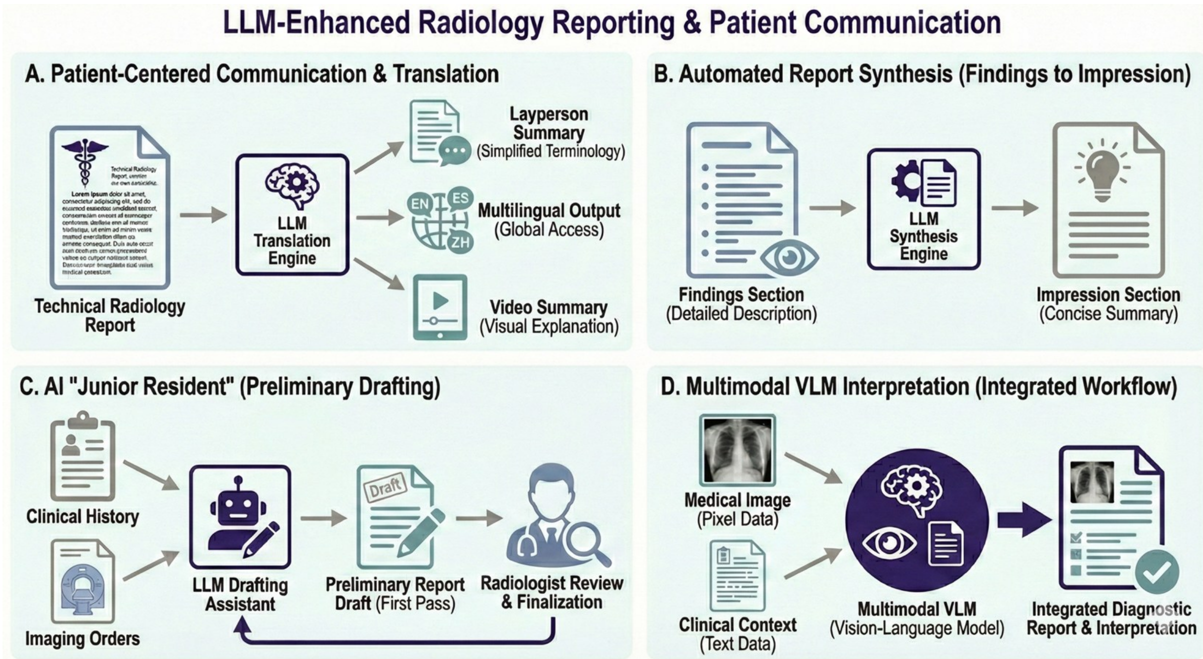

Figure 2 | LLM-Enhanced Radiology Reporting and Patient Communication. Conceptual schematic illustrating the potential roles of Large Language Models (LLMs) for enhancing radiology reporting and patient communication. **(A) Patient-Centered Communication:** LLMs can serve as a translation layer, converting dense, technical radiology reports into "patient-friendly" formats. This includes simplified lay terminology, multi-language support for non-native speakers, and automated video summaries to improve health literacy and patient engagement. **(B) Automated Report Synthesis:** Illustrates the "Findings-to-Impression" pipeline in which the LLM analyzes the detailed descriptive Findings section to synthesize a concise, actionable Impression, reducing the time spent on manual summarization. **(C) The AI 'Junior Resident':** LLMs can act as a preliminary drafter by integrating clinical history and imaging orders to generate a "first pass" report. This draft serves as a starting point for the radiologist, who then reviews and finalizes the document, mirroring the resident-attending workflow. **(D) Multimodal VLM Interpretation:** Represents the frontier of Vision Language Models (VLMs). These systems process both pixel data (images) and text (clinical context) simultaneously to provide integrated diagnostic interpretations and comprehensive report generation in a single step. <u>This figure was generated using Google Gemini and Nano Banana Pro.</u>

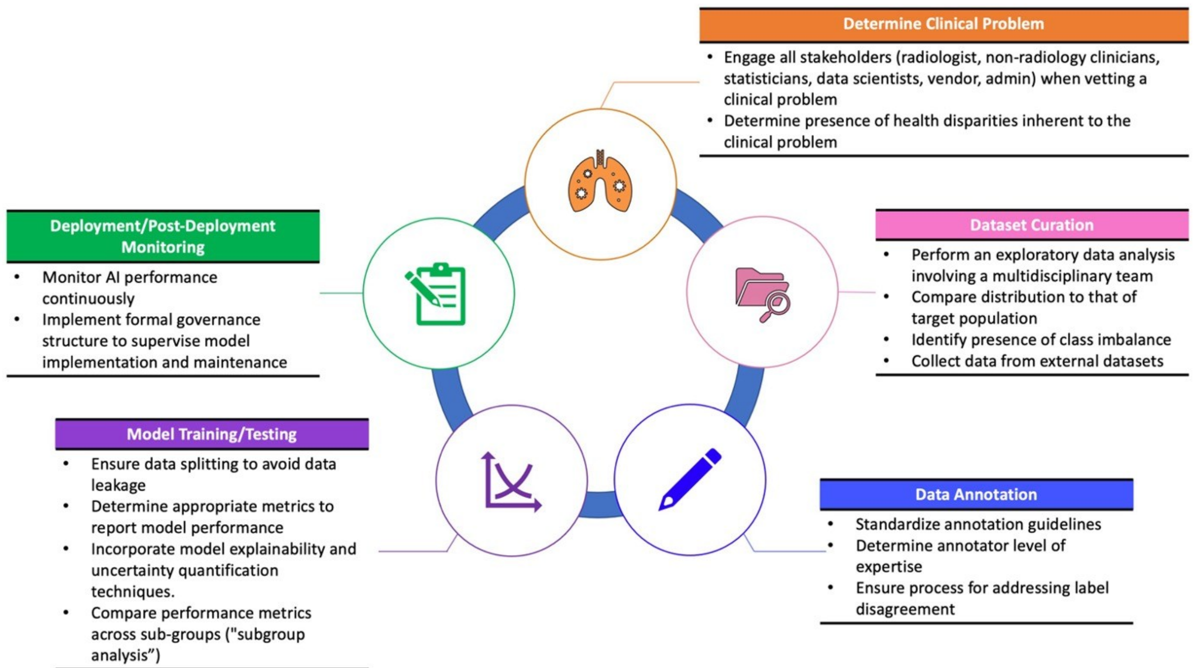

Figure 3 Proposed recommendations addressing sources of bias during AI development and after deployment. A strategic ap-proach to mitigating bias focuses on adopting checkpoints along the ML life cycle to prospectively address potential sources of bias From Tejani AS, Ng YS, Xi Y, Rayan JC. Understanding and mitigating bias in imaging artificial intelligence. RadioGraphics 2024;44(5). doi:10.1148/rg.230067

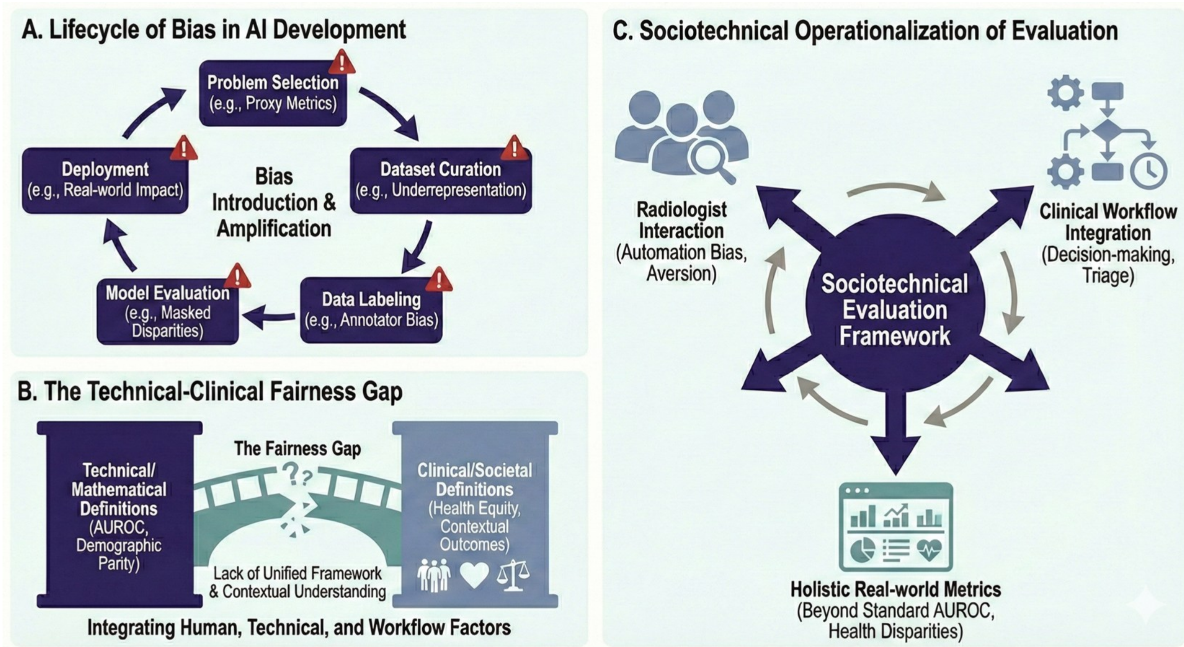

Figure 4 | The Lifecycle of Bias and Sociotechnical Evaluation Frameworks for AI in Radiology. (A) The Lifecycle of Algorithmic Bias: Bias is not a single point of failure but is introduced and amplified at every stage of development, from the initial **Problem Selection** (choosing the wrong proxy metrics) to **Dataset Curation** (underrepresentation of demographic groups), **Labeling** (human annotator bias), and eventually **Deployment**. **(B) The Fairness Gap:** This panel illustrates the conceptual gap between **Technical Definitions** (mathematical fairness and AUROC) and **Clinical Definitions** (real-world health equity and patient-centered outcomes), which often lack a unified framework. (C) **Sociotechnical Operationalization:** A proposed framework for real-world setting evaluation. It moves beyond standard technical metrics to incorporate **Sociotechnical Assessments**, integrating the interaction between **Radiologists** (e.g., automation bias), **Clinical Workflows**, and model outputs to ensure equitable healthcare delivery. <u>This figure was generated using Google Gemini and Nano Banana Pro.</u>

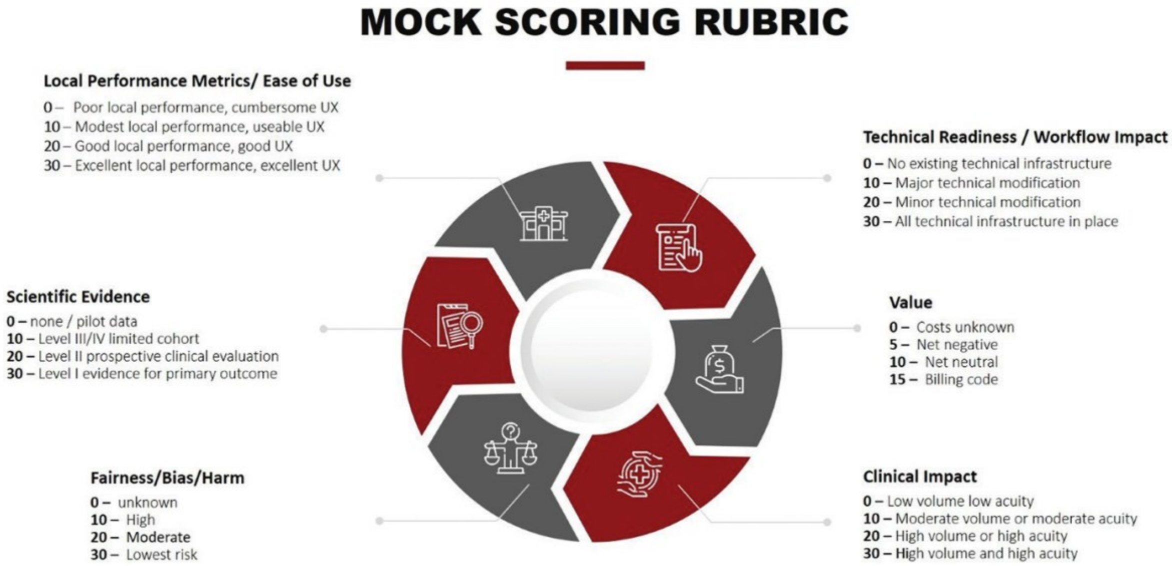

Figure 5: Artificial intelligence (AI) algorithm evaluation for clinical implementation mock scoring rubric. When evaluating an AI solution for clinical implementation, a number of areas should be assessed and scored. These include data security risk, clinical readiness, technical readiness, available evidence for validation and performance metrics, and clinical value the tool will bring. UX = user experience. From Daye Radiology 2022; 305:555–563 • https://doi.org/10.1148/radiol.212151 •

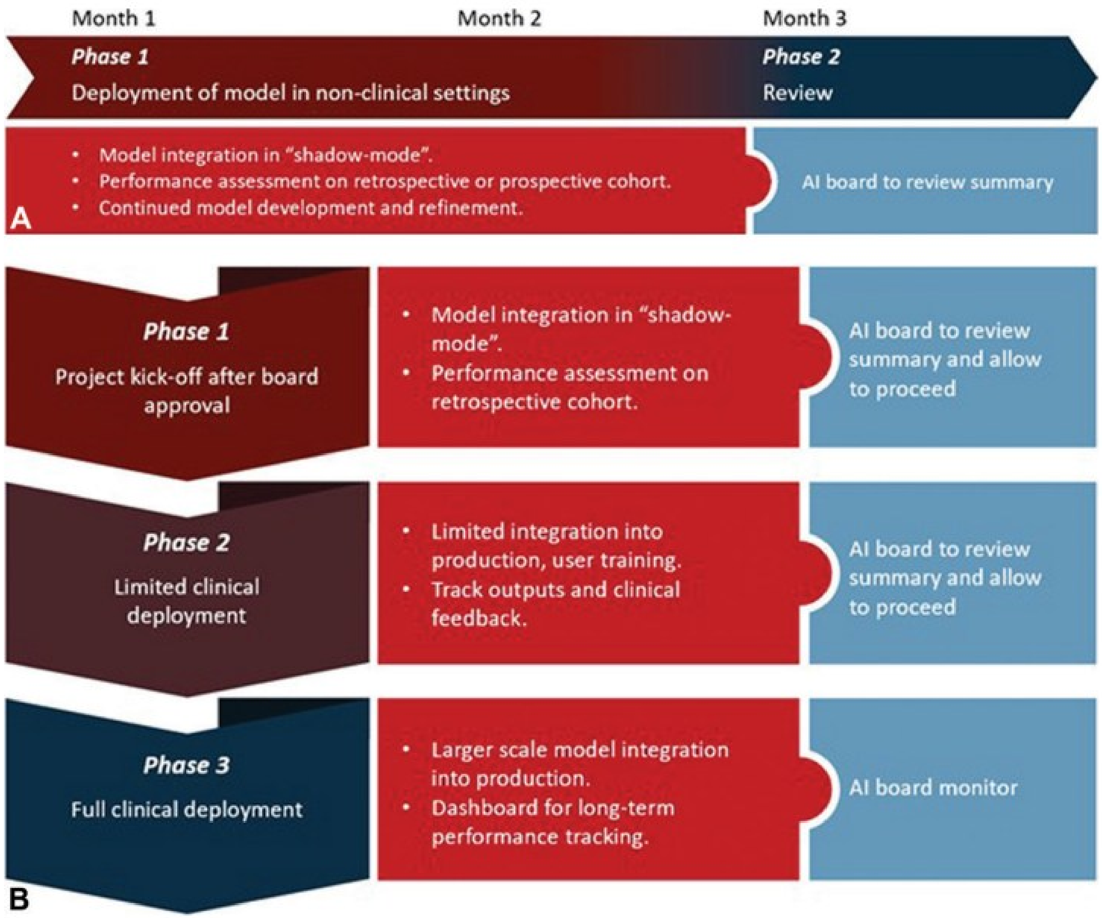

Figure 6: Modes of artificial intelligence (AI) implementation and integration in clinical practice. Two modes of clinical implementation are typically pursued by AI governance structures: shadow mode and canary clinical mode. (A) In shadow mode, tools are first implemented in the background with no impact on clinical decision-making. During this time, algorithms are being tested and refined prior to live clinical implementation. (B) In model integration into production, or canary mode implementation, tools are released in the live clinical environment using a phased approach while undergoing rigorous oversight by the AI governance structure. From Daye Radiology 2022; 305:555–563 • https://doi.org/10.1148/radiol.212151 •

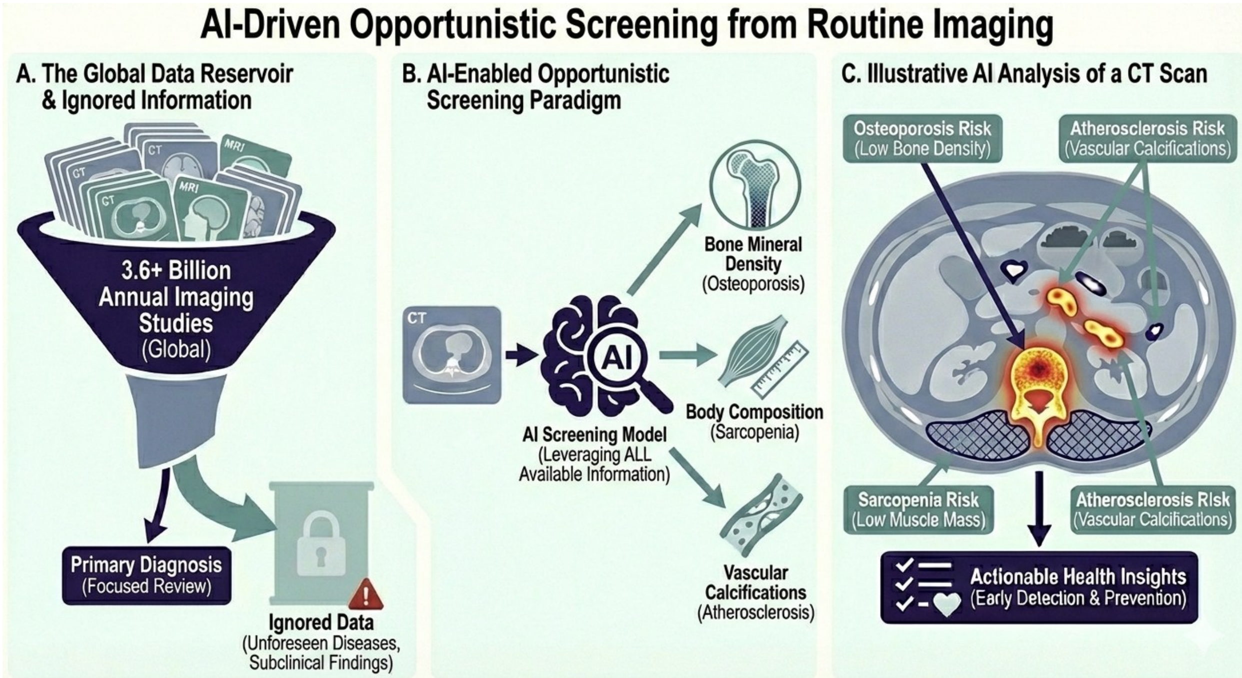

Figure 7 | AI-Driven Opportunistic Screening from Routine Imaging. This schematic illustrates the paradigm shift from traditional, focused diagnostic reviews to comprehensive, AI-enabled opportunistic screening of global imaging data. **(A) The Global Data Reservoir & Ignored Information:** Currently, over 3.6 billion imaging studies are performed annually worldwide. A significant volume of data within these studies remains "ignored" as radiologists typically focus on the primary clinical indication. AI allows for the extraction of unforeseen diseases and subclinical findings from this massive data reservoir. (B) **AI-Enabled Opportunistic Screening Paradigm:** This panel shows the AI screening model's ability to leverage "all available information" from a single CT or MRI scan. By processing routine clinical data, the model can simultaneously assess multiple biomarkers including **Bone Mineral Density** (for osteoporosis), **Body Composition** (for sarcopenia/muscle mass), and **Vascular Calcifications** (for atherosclerosis). **(C) Illustrative AI Analysis of a CT Scan:** A representative abdominal CT scan demonstrating the practical application of opportunistic screening for osteoporosis, sarcopenia, and atherosclerosis. <u>This figure was generated using Google Gemini and Nano Banana Pro.</u>