

## The computational and technological vanguard: A review of transformative frontiers in modern radiology

Bharvi Joshi<sup>1\*</sup>, Pratik Virat<sup>2</sup>, Sandeep Kumar<sup>3</sup>

<sup>1</sup> Assistant Professor, College of Paramedical Sciences, COER University, Roorkee, Uttarakhand, India

<sup>2</sup> Assistant Professor, Sharda School of Allied Health Sciences, Sharda University, Noida, Uttar Pradesh, India

<sup>3</sup> Assistant Professor, Department of Radiological Imaging Techniques, GD Goenka Healthcare, Amhat, Ghazipur, Uttar Pradesh, India

### Abstract

Radiology stands at an inflection point, transitioning from a discipline primarily focused on qualitative image interpretation to a data-driven science underpinning precision medicine. This review article synthesizes the high-impact technological and computational advancements that define this new era, often termed "Radiology 2.0." The convergence of Artificial Intelligence (AI), revolutionary hardware modalities such as Ultra-High-Field Magnetic Resonance Imaging (UHF-MRI) and Photon-Counting Computed Tomography (PCCT), and the fusion of diagnostics with therapeutics through Theranostics, fundamentally alters clinical practice. AI, encompassing deep learning and Natural Language Processing (NLP), is optimizing workflow efficiency and pioneering non-invasive prediction models through radiogenomics. Simultaneously, advanced hardware provides unprecedented anatomical and functional fidelity, with 7T MRI enhancing neurosurgical planning and PCCT enabling reduced radiation dose and superior spectral quantification. However, the successful integration of these innovations is contingent upon navigating systemic challenges, including the imperative for Explainable AI (XAI), the mitigation of algorithmic bias through diverse data governance, and the establishment of robust, harmonized regulatory frameworks. This review concludes that the radiologist's role is evolving into a critical diagnostic and therapeutic consultant, demanding proficiency in both clinical expertise and complex data synthesis to ensure equitable and precise patient care.

**Keywords:** Precision medicine, diagnostic transformation, Artificial Intelligence (AI), deep learning, Natural Language Processing (NLP)

### Introduction

#### Defining the Modern Paradigm of Radiology

Radiology's historical trajectory is intrinsically linked to technological innovation, tracing its origins to Wilhelm Conrad Röntgen's discovery of X-rays in 1895. Subsequent breakthroughs, including the clinical introduction of Ultrasound in the 1950s, Computed Tomography (CT) in the 1970s, and Magnetic Resonance Imaging (MRI) in the 1980s, progressively enhanced the ability to visualize the human interior with increasing clarity and detail. These foundational modalities established the radiologist as the gatekeeper of internal anatomical information [1].

The current epoch, however, is defined not merely by image acquisition but by the exponential growth of digital image data and corresponding computational power. This necessitates a fundamental conceptual evolution a shift from the trained physician's traditional qualitative visual assessment to a quantitative, data-driven approach [2]. This transformation, referred to as the dawn of Radiology 2.0, represents a profound metamorphosis that redefines traditional workflows and elevates the radiologist's role.

The contemporary practice of radiology faces escalating pressures, including managing an overwhelming volume of imaging data, the persistent need to improve diagnostic precision to support truly personalized medicine, and the optimization of increasingly complex clinical workflows [3]. Addressing these constraints has catalyzed innovation across three interconnected pillars: computational intelligence (Artificial Intelligence and Radiomics), the evolution of diagnostic hardware (UHF MRI and PCCT), and the fusion of diagnostics with therapeutics (Interventional Radiology and Theranostics).

This review outlines the current frontiers of radiology by examining these transformative elements. It first investigates how AI is restructuring the entire value chain, from triage to prognostic modeling. Secondly, it analyzes how next-generation imaging hardware achieves superior fidelity, enabling new clinical applications [4]. Thirdly, it details the integration of image guidance with molecular therapy. Finally, it critically assesses the ethical, regulatory, and systemic challenges that must be addressed to ensure the safe, transparent, and equitable translation of these advancements into routine clinical practice.

#### Artificial Intelligence: The Computational Engine of Radiology 2.0

Artificial Intelligence (AI), particularly its sub-disciplines Machine Learning (ML) and Deep Learning (DL), represents the most profound change agent in modern radiology [5]. DL, based on neural network structures inspired by the human brain, excels at automatically recognizing complex patterns in large imaging datasets, providing quantitative rather than merely qualitative assessments of radiographic characteristics.

#### 1. AI in Workflow Optimization and Clinical Decision Support (CDS)

The integration of ML is demonstrating tangible benefits by optimizing multiple steps throughout the radiology workflow, including optimizing order scheduling, intelligent triage, dose estimation, quality control, and automating aspects of reporting. This widespread application across the value chain addresses systemic inefficiencies.

A significant challenge in continuity of care, particularly when patients switch healthcare systems, involves the

processing and archiving of external DICOM studies. AI frameworks, such as those employing deep learning, are achieving superior performance in automatically classifying and mapping these external DICOM studies for Picture Archiving and Communication Systems (PACS). This capability to identify up to 76 medical study types across seven modalities (including CT, MRI, ultrasound, and mammograms) with high accuracy significantly outperforms commercial products, indicating a substantial boost in predictive power [6]. The implementation of this automation directly targets critical workflow bottlenecks, accelerating the crucial administrative tasks handled by medical-technical personnel and enabling faster access to complete patient history.

Furthermore, AI is instrumental in bridging the gap between qualitative human interpretation and structured, computable data [7]. Natural Language Processing (NLP) engines are now being used to extract findings, organ measurements, and critical recommendations from narrative radiology reports. This process is vital because, traditionally, unstructured text reports are challenging for machines to analyze directly. NLP converts these qualitative descriptions into structured data, which then feeds back into downstream machine learning applications that require quantitative medical data. This integration creates a closed-loop system, enabling advanced analytics for quality improvement and, critically, tracking radiologists' follow-up recommendations, thereby reducing communication disconnects and safeguarding against missed critical care junctures. The utility of AI, therefore, extends beyond image analysis to encompass the entire data ecosystem surrounding the diagnostic process [8].

## 2. Quantitative Imaging: Radiomics and Radiogenomics for Precision Medicine

The shift toward quantification underpins the vision of personalized medicine. Radiomics leverages high-throughput quantitative analysis to extract subtle digital features related to texture, shape, and intensity embedded within medical images. These features, often occult to the human eye, are reflective of tissue histology, biological activity, and genetic expression, effectively serving as an "imaging phenotype" of malignancy [9]. Radiogenomics represents the next evolutionary step, integrating these complex quantitative radiomic features with underlying genomic, transcriptomic, and proteomic data. This cross-scale integration holds immense promise as a catalyst for digital precision medicine and enhanced cancer decoding.

Radiogenomic models are demonstrating clinical applicability by providing non-invasive predictions of patient outcomes that traditionally require invasive molecular sampling [10]. In Glioblastoma (GBM), for example, multiparametric radiogenomic models incorporating MRI texture features, patient age, and MGMT methylation status have demonstrated an ability to predict long-term survival (months) with an accuracy of up to 89.3% in external validation cohorts. Similarly, in Ovarian Cancer (OC), AI methods based on imaging have been shown to accurately differentiate between benign and malignant tumors, classify their subtypes, and reliably forecast survival rates, treatment outcomes, metastasis risk, and recurrence.

This capability is transformative because it fundamentally addresses two major limitations of traditional molecular

biomarker guidance: the invasiveness associated with tissue biopsies and the inherent sampling errors resulting from high intra-tumor heterogeneity. By non-invasively characterizing the entire tumor mass and its microenvironment through the imaging phenotype, radiogenomics provides a global molecular portrait of the disease, moving beyond the localized information provided by a single biopsy sample [11].

## 3. Multimodal Learning Architectures

The most sophisticated clinical decision-making relies on synthesizing disparate data sources—not just imaging. The future of computer-assisted diagnostics requires intelligent systems capable of processing a variety of data simultaneously, mirroring the comprehensive approach utilized by human clinicians who examine radiographic images, histopathology, laboratory results, and electronic health records (EHR) [12]. Multimodal Machine Learning (MMML) aims to achieve this by extracting novel characteristics from diverse medical data sources. This approach enhances the flexibility and reliability of AI algorithms, mitigating the inherent risks associated with models trained solely on a single modality. When an algorithm is only exposed to imaging data, its generalizability can be compromised when deployed in a complex clinical setting where non-imaging factors (e.g., comorbidities, medications) significantly influence patient presentation and outcomes. By integrating multiple modalities, MMML ensures that diagnostic predictions are more robust and applicable across diverse clinical settings, solidifying AI's role as a comprehensive diagnostic partner [13].

## Advancements in Next-Generation Diagnostic Imaging Modalities

While computational intelligence dominates the discussion of "Radiology 2.0," foundational breakthroughs in imaging hardware continue to push the boundaries of achievable diagnostic fidelity, providing the high-quality source data necessary for subsequent AI processing.

### 1. Ultra-High-Field Magnetic Resonance Imaging (UHF-MRI)

UHF-MRI, typically represented by 7 Tesla (7T) systems, provides a major leap forward in magnetic field strength compared to the clinical workhorses (1.5T and 3T). This increased field strength directly translates to a higher Signal-to-Noise Ratio (SNR) and enhanced susceptibility effects, which allows for improved visualization of highly fine anatomical substructures and micro-pathologies.

The clinical application of 7T systems is proving particularly transformative in neuroimaging. In the evaluation of epilepsy, the increased resolution at 7T enables a more precise delineation of the gray–white matter interface. This enhancement improves the sensitivity for identifying subtle epileptic lesions, such as Focal Cortical Dysplasias (FCD), hippocampal sclerosis, and amygdala abnormalities, facilitating more accurate surgical planning and improving patient outcomes. A pooled analysis of existing literature reports a 31% diagnostic gain with 7T MRI over conventional field strengths in detecting these subtle lesions [14].

The enhanced susceptibility effects at 7T also significantly improve the detection of cerebral microbleeds—small round

or ovoid foci of blood products which are often subtle on lower field strengths. For patients with Alzheimer’s Disease (AD) and mild cognitive impairment (MCI), 7T MRI has been shown to increase the detected prevalence of microbleeds from 33% to 78% compared to 3T. This heightened sensitivity is crucial as the detection of microbleeds can substantially influence treatment decisions, particularly regarding the use of antithrombotic therapies. Furthermore, 7T MRI allows for superior spatial resolution and smaller voxels, enhancing the characterization of white matter pathology, notably in Multiple Sclerosis (MS). Lesions that appear confluent on 3T images frequently resolve into multiple smaller, discrete lesions on 7T

systems, offering superior understanding of disease burden [15].

The precision offered by UHF-MRI is also critical for image-guided therapeutic procedures. For Deep Brain Stimulation (DBS) in conditions like essential tremor, studies confirm that 7T MRI provides greater precision in electrode placement than 3T systems, achieved through highly accurate direct targeting of subcortical structures, which correlates directly with improved patient outcomes. This specialized superiority cements 7T MRI’s role as a niche clinical specialist modality, justified for high-value applications where the detection of subtle lesions or improved targeting precision significantly impacts patient management.

**Table 1:** Comparative Advantages of Next-Generation Imaging Hardware

Modality	Core Technical Advancement	Clinical Translational Benefit	Comparative Advantage Cited
Ultra-High-Field (7T) MRI	Increased Signal-to-Noise Ratio (SNR); enhanced susceptibility contrast; higher spatial resolution.	Superior visualization of fine anatomical substructures; 31% diagnostic gain in epilepsy (FCD); enhanced detection of microbleeds (33% to 78% prevalence).	Improved precision for neurosurgical procedures like Deep Brain Stimulation (DBS) targeting, directly impacting patient outcomes.
Photon-Counting CT (PCCT)	Direct photon energy measurement; high spectral/spatial resolution; noise reduction.	Allows for significant radiation dose reduction and reduced contrast media volume (up to 40%) while maintaining/improving image fidelity (high CNR).	Superior spectral contrast, k-edge differentiation, and improved Coronary Artery Calcium Scoring (CACS) accuracy compared to conventional Dual-Energy CT (DECT).

**2. Photon-Counting Detector Computed Tomography (PCCT)**

The evolution of CT technology has culminated in the clinical introduction of Photon-Counting Detector CT (PCCT), which fundamentally changes the way X-ray data is captured. Unlike conventional energy-integrating detectors (EIDs), PCCT systems measure and quantify the energy of individual photons, enabling the generation of a wide range of spectral reconstructions alongside inherent improvements in spatial resolution and noise reduction [16].

PCCT provides spectral contrast that is superior to conventional Dual-Energy CT (DECT). Crucially, PCCT’s ability to capture multi-energy information, often utilizing three or more energy bins, is essential for the simultaneous differentiation of K-edge agents and iodine contrast. This technological improvement redefines CT by making quantitative spectral imaging a standard feature, rather than a specialized acquisition mode. The ability to accurately quantify materials, such as iodine, across various exposures while simultaneously visualizing high-resolution features, dramatically improves diagnostic performance in oncological and cardiovascular domains.

Clinically, the superiority of PCCT is manifested in two crucial areas: patient safety and diagnostic accuracy. The improved image quality and noise characteristics enable a substantial reduction in contrast media volume (e.g., up to 40% in certain studies). Furthermore, PCCT facilitates significant radiation dose optimization, aligning perfectly with the As Low as Reasonably Achievable (ALARA) principle. For cardiovascular imaging, PCCT yields advantages in cardiac, vascular, thoracic, and musculoskeletal applications. Specifically, it improves the accuracy of Coronary Artery Calcium Scoring (CACS) at lower radiation doses and enhances the detectability of coronary lumen pathologies due to superior spatial resolution and noise characteristics compared with DE-EID systems.

**Interventional Radiology and the Integration of Theranostics**

The role of radiology has expanded significantly beyond diagnosis into therapy, primarily through the maturation of Interventional Radiology (IR) and the development of the Theranostics paradigm.

**1. High-Precision Image-Guided Procedures and AI**

Interventional Radiology has evolved into a sophisticated clinical discipline dedicated to performing minimally invasive, high-precision procedures under real-time image guidance. The modern IR suite utilizes a hybrid arsenal of imaging modalities, including X-ray fluoroscopy, CT, MRI, Ultrasound, and molecular imaging, often combined through image fusion technology.

Advanced techniques, such as the volumetric fusion of MRI, CT, and cone-beam CT digital subtraction angiography data, are overlaid on real-time fluoroscopy to guide complex interventions, such as the ablation of spinal metastases or detailed preoperative mapping of vascular structures. This sophisticated integration ensures that the therapeutic delivery system is precisely aligned with the target anatomy identified during diagnostic workup [17].

Artificial intelligence is becoming integral to augmenting IR procedures throughout the care continuum. Before the procedure, AI improves patient selection for specific treatments, aligning with the concept of precision medicine. During the procedure, AI systems can accelerate computationally intensive or manual tasks, such as correcting translational motion via pixel shifting in angiography, and enhance accuracy in challenging maneuvers like needle placement and catheter manipulation. AI’s role also extends to integrating and managing the technical complexity arising from fusing multiple imaging modalities, ensuring that the necessary precision is translated reliably to therapeutic delivery. While fully autonomous AI-guided robotic systems have not yet reached

clinical practice, the current integration represents a clear trajectory toward highly standardized, efficient, and precise interventional procedures. Following treatment, AI aids in measuring response and predicting prognosis, completing the end-to-end care loop.

## 2. The Theranostics Model: Molecular Imaging and Targeted Therapy

Theranostics, a portmanteau of "therapeutics" and "diagnostics," embodies the pinnacle of integrated radiological care. It utilizes a radioactive drug to identify (diagnose) disease, followed by a second radioactive drug or the same drug delivered in a therapeutic dose to specifically target and treat the localized pathology. The procedures for delivering these agents, such as radioembolization, frequently occur within the hybrid IR suite, highlighting the professional convergence between interventional and nuclear medicine specialists [18].

One established application is Yttrium-90 (<sup>90</sup>Y) radioembolization, which uses microscopic spheres tagged with to deliver high-dose radiation selectively to tumors, particularly Hepatocellular Carcinoma (HCC). Clinical studies demonstrate favorable outcomes, with patients exhibiting preserved liver function (Child-Pugh A) achieving a median Overall Survival (OS) of 17 months from the date of treatment. This therapy also proves effective in achieving downstaging of HCC patients to within Milan criteria, enabling eligibility for curative liver transplantation.

A highly prominent emerging application is Lutetium-177 (<sup>177</sup>Lu) PSMA radioligand therapy, primarily targeting metastatic castration-resistant prostate cancer (mCRPC). The therapeutic agent targets Prostate-Specific Membrane Antigen (PSMA), which is highly expressed in many prostate cancer cells. Beyond prostate cancer, pioneering systematic reviews indicate that <sup>177</sup>Lu-PSMA can be used to treat specific non-prostatic cancers that also express PSMA, exhibiting relatively low toxicity and promising outcomes.

The diagnostic component of radiotheranostics, exemplified by PSMA-PET imaging, provides exceptional molecular sensitivity, enabling the detection and precise localization of metastatic disease that might be missed by conventional imaging modalities. This molecular specificity is now being leveraged to guide local thermal ablation procedures. By clearly identifying oligometastatic prostate cancer deposits, PSMA-PET allows interventional radiologists to accurately target these lesions for cryoablation or stereotactic radiotherapy, facilitating earlier intervention and potentially superior long-term outcomes.

## Systemic Challenges: Ethical, Regulatory, and Implementation Barriers

The rapid pace of technological innovation in radiology is constrained by complex ethical, regulatory, and technical hurdles that must be overcome for safe and equitable deployment.

### 1. The Imperative for Explainable AI and Mitigating Bias

The clinical utility of deep learning models is frequently hampered by the "black box" dilemma the inherent complexity and opacity of the algorithms prevent clinicians from understanding *how* a specific diagnostic decision was reached. This lack of transparency undermines clinical trust,

complicates the process of regulatory approval, and makes legal accountability difficult when an AI system fails.

Explainable Artificial Intelligence (XAI) addresses this by providing techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM) and Integrated Gradients, that enhance interpretability and provide visual cues as to which features in the image drove the decision. XAI is central to building effective AI-driven diagnostic tools that align with the practical demands of modern healthcare [19].

Beyond algorithmic transparency, there is a pervasive risk of automation bias, where human decision-making is compromised by undue reliance on AI outputs. In high-pressure environments, radiologists may rely on AI-generated results as a shortcut, potentially overlooking crucial information or committing diagnostic errors. To counteract this, future AI systems must evolve beyond simply providing static explanations. They must be flexible, context-dependent, and capable of engaging in a genuine dialogue with the human user, effectively becoming a collaborative participant in complex medical reasoning. Robust ethical AI frameworks specific to radiology are essential to integrate fairness, privacy, and accountability into the design and deployment of these systems.

### 2. Ethical Governance, Algorithmic Bias, and Global Equity

A primary ethical concern in AI deployment is algorithmic bias. These models are trained on datasets, and if that data lacks diversity across critical parameters ethnicity, gender, or socioeconomic background—the resulting algorithms will exhibit unfair performance, potentially failing disproportionately among unrepresented populations. This risk is widespread, including known concerns about algorithmic bias in breast and chest imaging datasets.

To ensure equitable predictions across demographic groups, mitigation strategies require comprehensive efforts, including the compilation of diverse, multi-institutional datasets for training. Furthermore, rigorous fairness testing and counterfactual analysis must be employed to evaluate and proactively address biases before clinical deployment.

Data privacy and ownership present continuous legal and ethical challenges. The massive quantities of patient data required for training deep learning models must be protected against misuse, such as leveraging medical history for financial gain (e.g., insurance decisions or adverse financial decisions) or potential extortion. Developers and users are ethically mandated to protect patient privacy throughout development and ongoing clinical use.

The disparity in access to advanced imaging technologies compounds these ethical concerns. Advanced, resource-intensive modalities (MRI, PET/CT) and cutting-edge AI are generally less available in hospitals serving vulnerable populations and Low- and Middle-Income Countries (LMICs). LMICs often have sparse equipment (e.g., fewer than one CT scanner per million inhabitants, compared to 40 per million in high-income countries) due to high costs, maintenance challenges, and infrastructure deficiencies. Radiology inadvertently perpetuates health disparities not only through limited equipment access but also through the inadequate performance of algorithms trained on biased datasets. Efforts to mitigate this gap must prioritize portable, "fit for purpose" modalities like ultrasound in low-resource settings and advocate for policy changes that support universal health coverage goals through imaging investment [20].

**Table 2:** Emerging Ethical and Implementation Challenges in AI Deployment

Challenge Domain	Root Cause/Mechanism	Clinical Implication/Risk	Mitigation Strategy/Regulation
Algorithmic Bias	Non-diverse training datasets (ethnicity, geography, SES); lack of representation.	Inequitable diagnostic performance; model failure in diverse real-world settings.	Fairness testing; counterfactual analysis; regulatory emphasis on data diversity (FDA, EU AI Act).
Opacity/Trust (Black Box)	Complexity of deep learning algorithms (CNNs).	Hindered clinical trust; difficulty in legal/ethical accountability; reluctance for widespread adoption.	Development of Explainable AI (XAI) techniques (Grad-CAM); moving toward genuine AI-human dialogue.
Interoperability/Deployment	Data silos; limitations in DICOM standard Query/Retrieve models; system fragmentation.	Non-scalable data extraction for research; high barrier to translating academic models into clinical PACS integration.	Standardization efforts (DICOM, HL7, FHIR translation layers); Institutional governance and collaboration.
Automation Bias	Over-reliance on AI recommendations, especially in high-pressure settings.	Clinician error (overlooking findings); degradation of fundamental diagnostic skills.	Robust ethical AI frameworks; mandatory human oversight; clinician education.

**3. Interoperability, Standardization, and Regulation**

The practical adoption of AI is heavily constrained by technical standardization and interoperability issues. Different imaging systems utilize varying data formats, protocols, and coding systems, creating "data silos" that limit the accessibility of the diverse patient datasets critical for training generalizable AI models. In fact, a significant proportion of radiologists cite interoperability issues as a major barrier to AI adoption in their practice.

Furthermore, the existing DICOM standard for Query/Retrieve Information Models, while sufficient for daily workflow, is often inappropriate for the massive bulk data extraction required for deep learning research and audit [21]. The limitations in available DICOM metadata tags mean that retrieving complete data for a research cohort often requires retrieving the full image, including pixel data, making the process non-scalable. The solution involves leveraging platforms that act as translation layers, supporting standards like DICOM, HL7, and FHIR, to facilitate seamless data exchange between legacy systems and modern AI tools.

In response to the rapid influx of AI-enabled medical devices, regulatory frameworks are rapidly adapting. Regulatory bodies, including the US Food and Drug Administration (FDA) and the European Union (EU), recognize that traditional regulations designed for static, rule-based software are insufficient for devices that exhibit adaptive learning. The FDA encourages innovation while maintaining a focus on safety and effectiveness through the Total Product Life Cycle (TPLC) approach. The EU has adopted stringent postmarket monitoring frameworks under evolving regulations like the EU AI Act, particularly for high-risk AI systems [22].

This increased regulatory rigor, while necessary to identify and mitigate risks such as bias and ensuring clinical meaning, imposes a substantial compliance burden. This tension may slow the transition of novel academic AI tools to the commercial clinical market, but the additional scrutiny is vital to ensure patient trust and robust evidence supporting device efficacy.

**Conclusion and Future Outlook**

Radiology is undergoing a fundamental transformation characterized by the convergence of computational intelligence, advanced physical hardware, and integrated therapeutic options. The evidence reviewed demonstrates that AI is restructuring the clinical value chain, moving beyond image detection to integrate quantitative data derived from imaging, genomics, and clinical records via multimodal radiogenomics. Concurrently, hardware

breakthroughs such as 7T MRI and PCCT are establishing new benchmarks for image fidelity and safety, enabling non-invasive quantitative analysis and reduced exposure to radiation and contrast agents. This diagnostic depth is increasingly fused with therapeutic delivery through Theranostics, exemplified by radioembolization and -PSMA therapy, cementing radiology's critical role in oncological management [23].

The radiologist of the future will operate as a high-level diagnostic and therapeutic consultant, managing complex data streams, verifying prognostic models, and providing crucial therapeutic guidance. This requires less focus on routine detection, which is increasingly automated, and more on interpreting the aggregated output of AI systems and ensuring appropriate clinical context.

Navigating the transition successfully mandates sustained focus on systemic challenges. The imperative for developing Explainable AI (XAI) is non-negotiable for achieving clinical trust and medico-legal accountability. Proactive efforts in data governance are required to mitigate algorithmic bias through the use of diverse datasets and the implementation of robust fairness testing. Furthermore, regulatory bodies and the academic community must collaborate to harmonize standards and overcome interoperability hurdles, ensuring that technological advancements benefit all patient populations equitably, including addressing global disparities in access. The sustained innovation, dynamic partnerships, and commitment to ethical responsibility will ultimately determine the success of Radiology 2.0.

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