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REVIEW

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Artificial intelligence-driven change redefining radiology through interdisciplinary innovation

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Abstract

Artificial intelligence (AI) is rapidly advancing, yet its applications in radiology remain relatively nascent. From a spatiotemporal perspective, this review examines the forces driving AI development and its integration with medicine and radiology, with a particular focus on advancements addressing major diseases that significantly threaten human health. Temporally, the advent of foundational model architectures, combined with the underlying drivers of AI development, is accelerating the progress of AI interventions and their practical applications. Spatially, the discussion explores the potential of evolving AI methodologies to strengthen interdisciplinary applications within

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medicine, emphasizing the integration of AI with the four critical points of the imaging process, as well as its application in disease management, including the emergence of commercial AI products. Additionally, the current utilization of deep learning is reviewed, and future advancements through multimodal foundation models and Generative Pre-trained Transformer are anticipated.

KEYWORDS
artificial intelligence, deep learning, interdisciplinary application, radiology

1 | INTRODUCTION

In recent years, the artificial intelligence (AI) wave has not only transformed sectors across various fields but also profoundly impacted research and practice in medicine, Figure 1. The traditional work structures and frameworks of human society are being transformed by AI-driven investments and technological innovations.[1–3] Several new AI-related journals have been established within the academic realm to reflect the widespread application and penetration of AI in medicine. The interdisciplinary paradigm of radiology has evolved with the integration of AI.[4–6] Consequently, it is highly relevant to examine the impact of AI on medicine and its subdisciplines over a temporal continuum.

Currently, radiology plays an irreplaceable role in the clinical diagnosis and management of major diseases that threaten human health, such as cardiovascular diseases, cancer, and chronic respiratory diseases.[7–12] Radiology predominantly encompasses imaging modalities such as X-rays, computed tomography (CT), magnetic resonance imaging (MRI), and digital subtraction angiography, accompanied by detailed reports that provide clinicians with critical, evidence-based insights to inform diagnostic and therapeutic decisions.[13,14] As a digital medical discipline, radiology is distinguished by its use of the digital imaging and communications in medicine (DICOM) standard for image storage, and picture archiving and communication systems (PACS) for efficient image management and retrieval. This structured, standardized data architecture positions radiology as an optimal field for the integration of AI, offering significant potential to enhance diagnostic precision and improve clinical decision-making processes. Within this context, the comprehensive workflow includes four critical points: image acquisition, post-processing, diagnostic interpretation, and quality control, collectively forming a closed-loop structure. Each point plays a significant role in influencing the final diagnosis, treatment outcomes, and efficacy evaluation of patients.[14–17] Therefore, it will be beneficial to investigate the relationship between AI and imaging workflow from a holistic spatial perspective.

It is true that significant progress has been made in the application of AI to radiology. However, there is still a lack of exploration in the academic community regarding the philosophical principles that govern the development of AI. Further, there are no comprehensive reviews of AI's spatiotemporal impact on medicine and radiology or its potential directions following the development of interdisciplinary medicine. In this review, we focus on the potential and challenges of AI in radiology from a spatiotemporal perspective.

2 | THE PHILOSOPHICAL FOUNDATIONS, PIONEERS, AND MILESTONES IN AI DEVELOPMENT

Overall, we fully agree with the summary of AI development and its current objective limitations presented in the sister review, which notes that AI has been developed since the 1950s[18] AI began to make a significant impact on medicine only in the past few years as a result of explosive growth in data and advances in computational power.[18] There was, however, no discussion of the philosophical questions that underlie this data-driven and computation-driven development. According to our systematic analysis, in the 1980s, there was a significant divergence between the two major schools of thought in AI, Symbolicism and Connectionism, Figure 1.[19] Symbolicism, which dominated initially, was based on logical reasoning and symbolic processing, whereas Connectionism attempted to mimic the brain's neural network structure through deep learning (DL).[19] In addition to being known as the “Godfather of AI”, *Geoffrey Hinton* [*]also introduced and popularized the theory of backpropagation, which greatly contributed to the development of DL.[20] In contrast, the philosophical principles and methodologies of Symbolicism once dominated early radiomics research.[21,22] In clinical practice, we have found that the combination of radiomics and

[*]Who won the Nobel Prize in Physics in 2024.

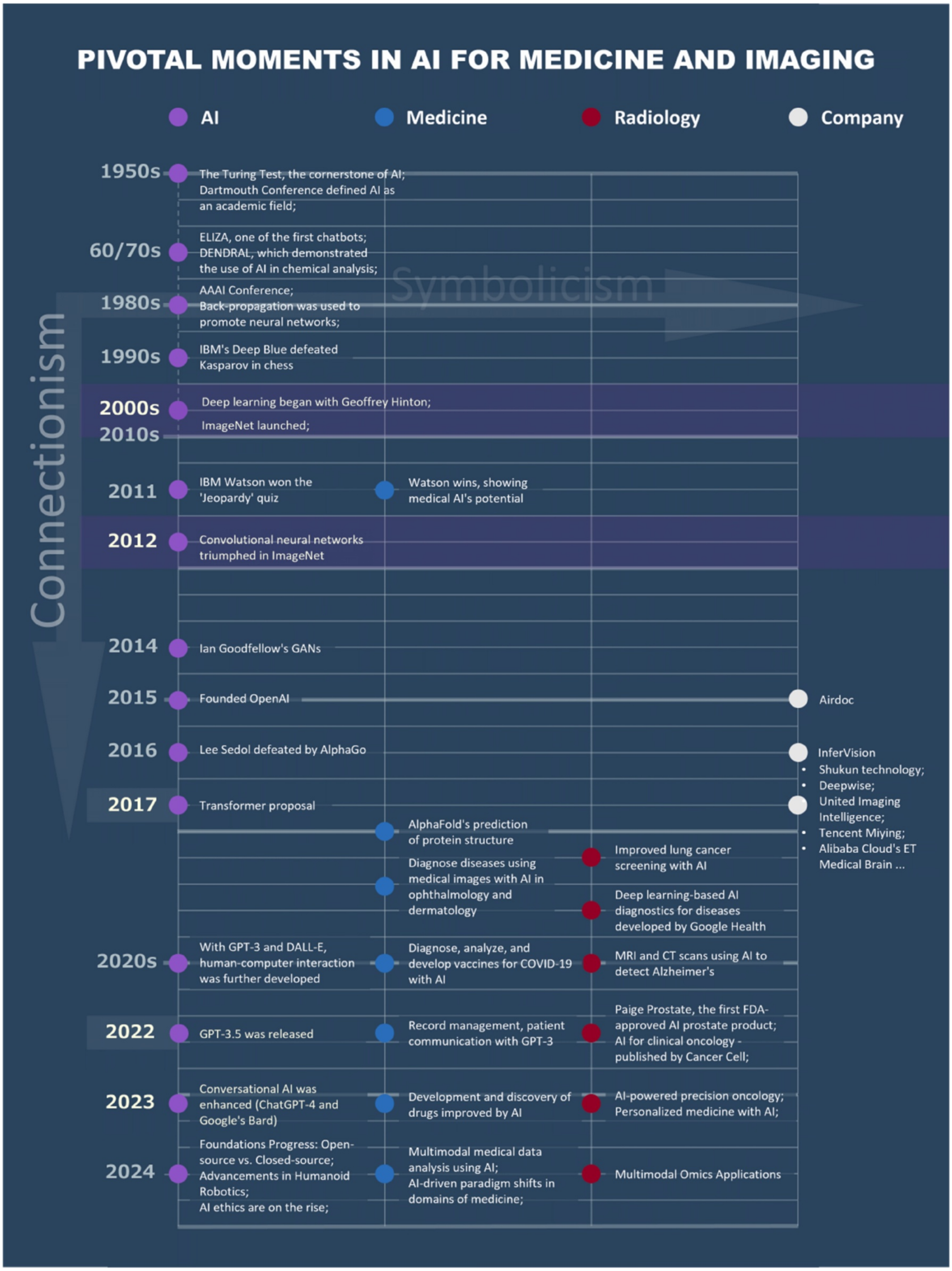

FIGURE 1 Spatiotemporal progress in AI development for medicine and radiology. The clinical applicability of AI has been the result of cumulative scientific advancements and the contributions of pivotal contributors and events. A significant philosophical divergence in AI occurred during the 1980s, establishing the differentiation between symbolism and connectionism. The development trajectory of AI has been predominantly shaped by the principles of the Connectionism school, as indicated by the directional distinctions of the light gray arrows. The first decade of the 21st century (highlighted in light purple) represents a pivotal period in AI advancement, directly facilitating its integration into clinical medicine and radiology. The substantial expansion of AI in these domains, concentrated around 2017–2018, was driven by developments in CNNs. This transformer was developed based on the multi-head attention mechanism proposed in 2017 (highlighted in gray). Notably, by the end of 2022 (highlighted in gray), a new phase of evolution was initiated, marked by the emergence of LLMs, Multimodal Omics, and robotics, as exemplified by GPT. AI, artificial intelligence; CNNs, convolutional neural networks; LLMs, large language models.

symbolicism provides poor robustness. This may be due to the reliance on rules and symbols, which results in poor model generalization and hinders its wider clinical application. In contrast, Connectionism-driven AI, particularly DL, has led to significant improvements in AI performance and model generalization through its biologically inspired foundation.[19] As a supplement to the sister review, we focus on the relationships between AI, machine learning (ML), and DL.[18]

Furthermore, there is another point mentioned in the review with which we disagree: "with the advent of big data and cloud computing, AI has seen significant breakthroughs and has become increasingly integrated into our daily lives." In this description, there seems to be a superficial nature.[18] By searching for "artificial intelligence" in PubMed, we can clearly observe an explosive growth in significant AI-related events and publications starting around 2017, forming the "6" shape trend in AI development, as shown in Figure 1. As a general rule, major advances in human history are often driven by pioneers or significant events rather than just the accumulation of technological conditions. There are three highly representative historical turning points that highlight these pivotal individuals and events as the true driving forces behind development. The first key figure and event is the introduction of DL into the mainstream by Professor *Geoffrey Hinton*, which marks the beginning of a new era in the development of AI. A pioneer in neural networks and backpropagation algorithms, *Hinton* is not only one of the inventors of the backpropagation algorithm but also a major proponent of the Contrastive Divergence algorithm, which played an important role in the advancement of DL and made it feasible.[23] It was these works that paved the way for the development of many modern AI technologies and subsequent breakthroughs in the field. Another key figure is Professor *Fei-Fei Li*, often referred to as the "Mother of AI" who initiated the ImageNet project, laying the groundwork for the development of large-scale visual recognition systems with a dataset containing over 14 million labeled images, which became a critical resource for training deep neural networks. This initiative significantly advanced the development of convolutional neural networks (CNNs). The third pivotal event occurred in 2012 when *Hinton*'s team achieved a groundbreaking victory in the ImageNet competition, which significantly advanced AI's capabilities in image recognition and catalyzed the widespread adoption of DL.[24,25] Known as the "Godfather of DL", Professor *Hinton* received the Turing Award in 2018 for his outstanding contributions to DL. The emergence of these 'Godfather' and 'Mother' figures, along with their remarkable contributions, undoubtedly spurred the rapid development of AI. However, it is important to recognize that while these key events were critical milestones, the evolution of AI has also been significantly propelled by advancements in equipment upgrades and improvements in core computing power.[26–29] Together, these factors have driven the field forward at an accelerated pace. In the period preceding their emergence, AI development was in a dormant phase, as illustrated in Figure 1. After these pioneers, AI has experienced explosive growth, forming a distinctive "6" shape in its development trajectory. Our curiosity also drove us to search for literature related to the integration of AI and medicine to explore its progress and trends.

3 | AI's GENERALIZATION IN MEDICINE AND ITS POTENTIAL IN IMAGING WORKFLOWS

The integration of AI in medicine exemplifies an interdisciplinary research convergence. By reviewing recent studies published in top-tier journals over the past five years, we observe both common focuses and distinct differences in how these journals address the application of AI in medicine. A recurring theme across these publications is the emphasis on AI's role in enhancing diagnostic accuracy, optimizing clinical decision-making, and enabling personalized treatment. For instance, *NEJM* expands the discussion to include AI's role in medical statistics, infectious disease monitoring, and the integration of electronic health records and multi-omics data to support personalized treatment, particularly in global health surveillance systems. Notably, a review in *NEJM* further elaborated on these topics by outlining six critical areas: AI's potential in medicine, the breadth of AI applications, limitations and challenges, publication and regulatory hurdles, ethical and regulatory considerations, and future directions—emphasizing often-overlooked issues that are crucial for clinicians to consider.[2,30–34] *Nature Medicine* emphasizes the application of AI in surgical procedures, highlighting improvements in both success rates and patient safety.[35] Similarly, *Nature* leans towards innovative uses of AI in surgery and pathology.[36,37] On the other hand, *The Lancet* focuses on the use of AI in radiology, particularly in enhancing the sensitivity of lung cancer screening, and emphasizes multicenter clinical validation in imaging and public health.[38,39] These multidimensional data integration techniques have also been applied in precision oncology treatments as reported in *Cancer Cell*.[40] However, each journal demonstrates distinct preferences in AI applications. The distinct focal points across these journals highlight the diverse ways AI is transforming healthcare, from data integration and personalized treatment in *NEJM*, to surgical advancements in *Nature Medicine*, innovations in surgery and pathology in *Nature*, and radiological applications in *The Lancet*. Together, these perspectives underscore the wide-ranging impact of AI in medicine, each reflecting the unique priorities and evolving needs of their respective readerships. It is noteworthy that Moor et al. introduced the concept of 'generalist medical AI (GMAI)' in *Nature*, signaling a paradigm shift from task-specific models to multi-task generalist models, thereby advancing the generalizability and multi-modality of AI in healthcare, Figure 2.[41] This signifies the beginning of AI transition towards generalization in medicine.

We, as radiologists, continue to explore the integration and evolution of AI in radiology. Imaging departments play a pivotal role in clinical diagnosis and treatment. For instance, the journal *CA: A Cancer Journal for Clinicians* provides a comprehensive overview of the patient journey in oncology, emphasizing a workflow from "Radiographic Imaging—Clinical Judgment - Decision Making" (Figure 3A).[42] However, Linda's team overlooked the significant role AI plays within radiology. Addressing this gap, our team incorporated four critical points into the imaging workflow based on a 2024 study published in *Radiology* and tailored to the characteristics of the mainland China healthcare system.[43] These points include (1) image acquisition, (2) image reconstruction and post-processing, (3) Imaging Diagnosis, and ④ Quality Control Feedback. These nodes form a linear loop structure that constitutes the core and workflow of radiology. By focusing on these key nodes as observation points, AI can offer a new perspective on integration with the entire imaging workflow (Figure 3B).[43] This review will provide a detailed explanation of these four key nodes.

As a result of our study of the literature, we found that the majority of current research is focused primarily on two of these points, that is, (2) Image Reconstruction and Post-Processing, as well as (3) Imaging Diagnosis, Figure 3B: red light. The former is predominantly led by experts in biomedical engineering, who aim to enhance imaging speed, clarity, and information richness. *Medical Image Analysis* represents a leading journal in this field. In contrast, Imaging Diagnosis is the focal point for radiologists, with *Radiology* being the top journal. A PubMed search of "AI" articles in *Radiology* and its sub-journals yielded 512 articles, with significant growth starting around 2016–2017, aligning with the trend shown in our time-series analysis, Figure 1. Similarly, a search for "DL" articles yielded 231 results, with a noticeable increase after 2017. This trend suggests that the term "AI" was widely used in radiology until 2016, after which "DL" gained broader acceptance. Conversely, (1) Image Acquisition

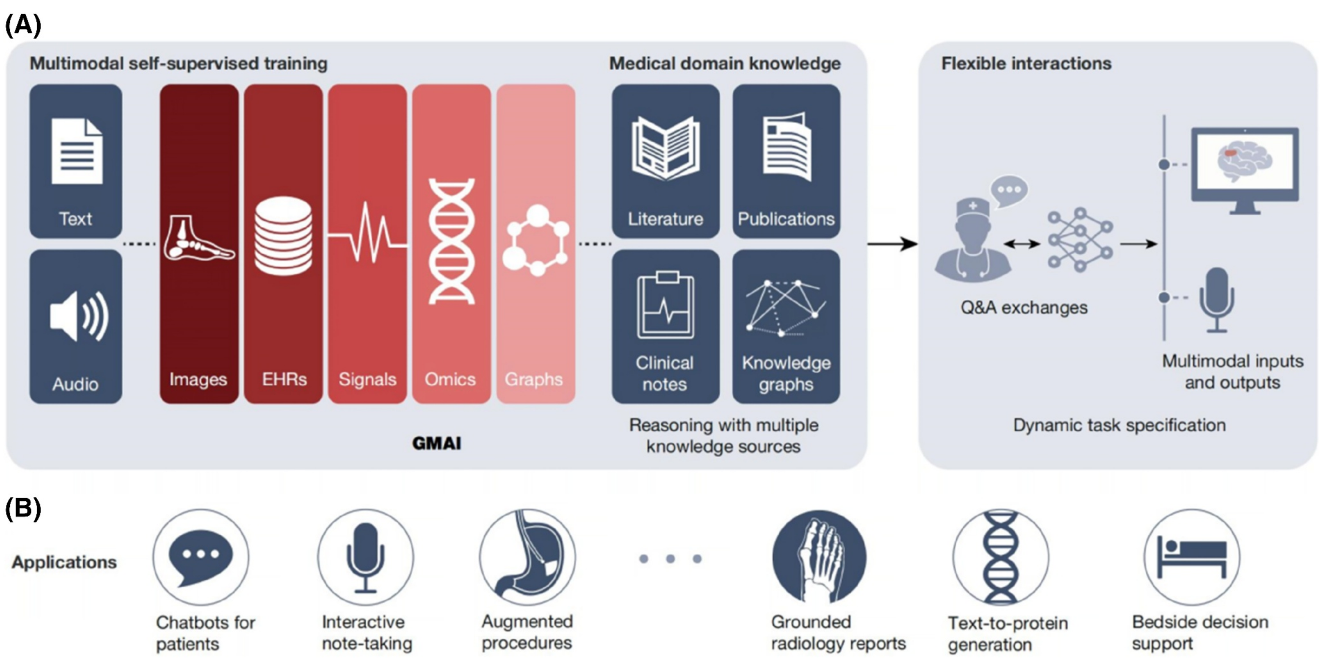

FIGURE 2 AI ubiquity in medicine from an overhead spatial perspective. Some renowned experts have begun to assert that generalist medical AI (GMAI) is both necessary and imminent. The rapid advancement of GMAI models, which are capable of executing a wide range of medical tasks with minimal task-specific data through self-supervision on large and diverse datasets, is poised to revolutionize medicine by integrating multiple modalities and generating sophisticated outputs such as free-text explanations. (A) The GMAI model is trained on diverse medical data using self-supervised learning, enabling real-time task execution by accessing medical knowledge and contextual information. (B) The GMAI model underpins various clinical applications, each requiring rigorous validation and regulatory assessment. Reproduced with permission.[41] Copyright 2023, Nature Publishing Group. AI, artificial intelligence; GMAI, generalist medical AI.

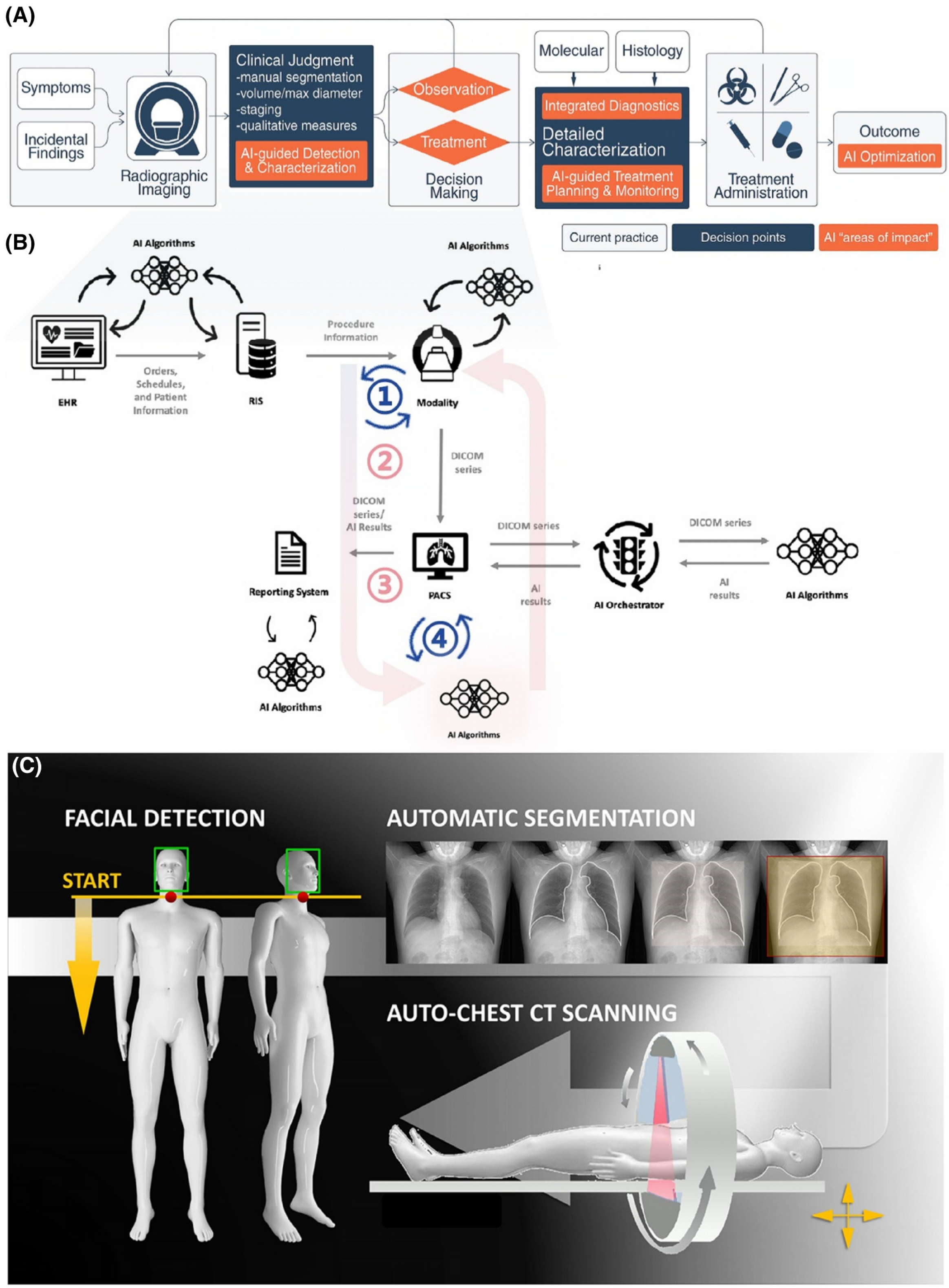

FIGURE 3 Legend on next page.

node receives relatively little attention, as evidenced by only 10 articles found in *Radiology* and its sister journals when searching for "DL" and "acquisition." However, a search for "DL" in *Medical Image Analysis* returned 682 articles, highlighting the research intensity in the Image Reconstruction and Post-Processing domain. For the (4) Quality Control Feedback node, a search of "Quality Control" in *Radiology* yielded 39 articles. However, combining "Quality Control" with "DL" resulted in no articles, indicating a clear research gap in the fields of image acquisition and quality control feedback, which warrants further exploration. By delving into these areas, we can expand the depth of research and ultimately complete the imaging chain.

Our analysis of these four key nodes reveals that (2) Image Reconstruction and Post-Processing, along with (3) Imaging Diagnosis, are current research hotspots. However, the (1) Image Acquisition and (4) Quality Control Feedback nodes are relatively neglected and require further investigation, Figure 3B: blue. The importance of studying these two key points cannot be overstated. Specifically, the former underpins image quality, while the latter ensures the reliability and consistency of acquired images for subsequent processing and diagnosis. Failure to achieve standardized, high-quality image acquisition directly impacts imaging decisions and clinical accuracy. Without proper quality control, data variability can lead to diagnostic discrepancies, affecting AI model training and hindering AI clinical application. Thus, advancing both image acquisition and quality control is essential. This is similar to the development of full self-driving (FSD) capabilities in the electric vehicle market. Although the environment faced by FSD is more complex and requires real-time responses, the trend toward automation is accelerating commercialization. Similarly, we can anticipate that full self-imaging in imaging acquisition will become feasible, aligning with AI development toward the robotics era Figure 1. Therefore, exploring this area is critically important. Our team has made some progress in ① Image Acquisition by conducting relevant research and applying for a series of patents to lay the foundation for future development in this field.[44–46]

4 | CLINICAL APPLICATIONS OF AI IN RADIOLOGY FOR MAJOR DISEASES

Radiologists have traditionally served as a bridge between imaging data and textual reports, relying solely on their expertise to identify critical lesions from images. However, with the advent of CNNs making breakthroughs in 2D image analysis, the previously exclusive domain of human cognitive tasks is being disrupted. Then, CNN-based models such as DeepLab, U-Net, GANs, etc., as well as transformers are proposed for the field of medical image analysis, leading to a growing interest in automated processing of 2D image or 3D volume data in radiology (Table 1). It has been demonstrated that the use of AI technology in radiology not only improves the ability to process and analyze vast amounts of information but also enhances the diagnostic efficiency and accuracy of risk prediction.[60–62] Clinical applications of AI in radiology are gradually expanding and are on the verge of commercialization (Figure 1). Additionally, the rise of multimodal omics that handle multidimensional information and large language models (LLMs) that process unidimensional data are infusing new vitality into the field of radiology, potentially revolutionizing traditional workflows.[63,64] The purpose of this section is to provide an overview of the current technological advancements in radiology for major diseases.

5 | AI-DRIVEN ADVANCEMENTS IN PROCESSING LARGE-SCALE MULTIMODAL DATA

The rapid development of AI in radiology has injected new momentum into image analysis, particularly in processing and analyzing large-scale complex data.[65–67] AI can perform imaging tasks that were previously

FIGURE 3 Identifying promising integration points in AI-enhanced imaging workflows from a spatial perspective. (A) AI-based interventions can enhance the traditional oncological workflow by augmenting diagnosis, decision-making, and outcome prediction at various stages, with continuous feedback and optimization potentially improving AI system performance. Reproduced with permission.[42] Copyright 2019, Wiley. (B) However, the initial segment of the traditional oncological workflow, as shown in Fig a, can be further refined into the more detailed processes and key-points illustrated in Fig b, which highlight the primary points in the radiology department. Radiology workflows in mainland China have been supplemented with AI involvement points from the original literature. Reproduced with permission.[43] Copyright 2024, Radiological Society of North America. (C) At point (1) in Fig. b, a schematic representation is provided, serving as an exemplar of our previous work and demonstrating a typical instance of AI integration in the image acquisition process. Reproduced with permission.[44] Copyright 2020, The Lancet Publishing Group. The AI-enhanced CT workflow involves facial detection and starting position determination, followed by automatic lung field segmentation using the V-Net algorithm and empirical boundary marking, culminating in auto-chest CT scanning with synchronized CT couch motion.

TABLE 1 An overview of recent radiology networks.

Models	Advantages	Disadvantages	Model relationships	Radiology applications
CNNs[47,48]	• Local feature extraction • Efficient processing of high-dimensional image data • Hierarchical feature learning	• Limited capability in handling long-range dependencies • Requirement for large-scale datasets	The basis for DeepLab, U-net, and other networks	Classification; detection; segmentation
DeepLab[49,50]	• Multi-scale feature extraction • Atrous spatial pyramid pooling	• Computational complexity • Limited segmentation performance for small objects	An extension of CNNs commonly applied to natural and medical image segmentation	Detection; segmentation
U-Net[51]	• Precise segmentation • Strong small-sample learning capability	• Requirement for annotated training data • Limited ability to handle complex backgrounds • Sensitivity to hyperparameters	An extension of CNNs mainly for 2D medical image segmentation tasks	Segmentation
V-Net[52]	• Robust segmentation of 3D volume data • Multimodal integration	• High computational cost and long training time • High model complexity and the risk of overfitting • Sensitivity to noise	Similar to U-net, V-net focuses on 3D medical image	3D segmentation
nnU-Net[53,54]	• Robust model with less overfitting • Adaptive framework without manual parameter tuning • Standardized medical image preprocessing workflow	• Complex network structure and high resource consumption • Requirement for annotated training data	An extension of U-net, adaptively handling 2D or 3D medical image data	Segmentation; multimodal image fusion segmentation
Faster R-CNN[54,55]	• High precision and robust performance • High flexibility	• Complex network architecture and slow inference speed • Limited adaptability to small and dense objects	An extension of CNNs mainly used for object detection in natural and medical images	Detection; localization; segmentation
GANs[56,57]	• Image enhancement and denoising capabilities • Unsupervised learning capabilities • Synthetic data generation	• Training instability and pattern collapse • Lack of clear evaluation metrics	Commonly combined with other networks (e.g., CNNs) as a data augmentation or generation tool for medical images	Enhancement; Generation; Denoising; Synthesis
Transformer[58,59]	• Global feature capturing ability • Capability in handling sequential data • Scalability	• High computational complexity and resource demand • Suboptimal performance on small datasets • Long training time and difficult hyperparameter	Increasingly combined with CNNs to form hybrid models for enhanced medical image processing capabilities	Classification; segmentation

Abbreviations: CNNs, convolutional neural networks; DeepLab, deep convolutional neural networks for Semantic image segmentation; Faster R-CNN, Faster Region-convolutional neural network; GANs, Generative Adversarial networks; nnU-Net, self-Adapting framework for U-net-based medical image segmentation; U-net, convolutional networks for biomedical image segmentation; V-net, fully convolutional neural networks for Volumetric medical image segmentation.

impossible with human labor alone. Traditional methods of interpreting images heavily rely on human experts, which is not only time-consuming and labor-intensive but also prone to subjective bias, increasing the risk of misdiagnosis. In contrast, AI technologies based on DL have automated and standardized the processes of image detection, segmentation, and classification through training on large datasets, significantly enhancing diagnostic efficiency and accuracy.[68,69] For example, in breast cancer screening, AI systems, after learning from tens of thousands of breast MR images, can effectively identify the HER2-E molecular subtype of HER2-positive breast cancer, achieving an AUC of 0.89 (95% CI 0.84–0.93), which is notably superior to traditional human interpretation methods.[70] Moreover, AI can integrate various imaging data, including MR, CT, and PET, resulting in a more comprehensive and accurate diagnosis.[71,72] Multimodal data integration not only improves the efficiency of multidimensional data processing but also transforms the traditional medical imaging diagnostic model and realizes interdisciplinary collaboration, contributing to the development of data-driven automated medical imaging.[73,74]

6 | AI-POWERED EARLY DIAGNOSIS SCREENING AND RISK PREDICTION

The application of AI in radiology has greatly enhanced the capability for early disease detection and risk prediction.[75,76] In lung cancer screening, for instance, low-dose CT (LDCT) has become the standard method for high-risk populations. Traditional methods, however, have a high false positive rate when detecting lung nodules smaller than 10 mm, resulting in increased anxiety for patients and unnecessary follow-ups. This situation has been improved by AI. An algorithm developed by Ardila et al. that predicts lung cancer risk using CT images achieved an AUC of 94.4% in a screening trial with 6716 cases and showed similar results in an independent validation set of 1139 cases. The model reduced the false-positive rate by 11% and the false-negative rate by 5%, outperforming six radiologists, indicating AI's significant potential in improving the accuracy and consistency of lung cancer screening.[65] Additionally, AI's ability to extract information from large datasets enables the identification of high-risk lesions with malignant transformation potential, increasing clinicians' confidence in treatment decisions.[45,77,78] Our clinical practice has demonstrated the value of this technology in collaboration with doctors, which is reflected in similar reports.[45] During our daily clinical work, we have observed that when a doctor issues a diagnostic report without the assistance of AI, they already feel hesitant and anxious.

7 | APPLICATIONS AND CHALLENGES OF AI-DRIVEN CLINICAL IMAGING DIAGNOSIS

AI has already been demonstrated to be useful in a wide range of applications, including respiratory imaging, breast imaging, neuroimaging, and cardiovascular imaging, which are among the most commonly used and active applications. The use of AI not only enhances diagnostic accuracy but also reduces diagnostic time.[44,45,79,80] In breast cancer screening, for instance, related AI products have been approved by the U.S. Food and Drug Administration (FDA) for diagnostic assistance.[81] For mammographic imaging, Kim et al. evaluated the feasibility of data-driven biomarkers based on weakly supervised learning. On the basis of 29,107 digital mammograms, DIB-MG achieved AUC of 0.906 and 0.903 in both test and validation sets, demonstrating its wide applicability.[82] This not only solidifies AI's important role in breast cancer screening but also provides a valuable reference for detecting other types of tumors. Despite significant progress in AI applications, its widespread clinical adoption still faces many challenges. In particular, the diagnosis of rare diseases and neurodegenerative diseases using AI is still in the exploratory stage, requiring more data and clinical trials to verify its effectiveness.[83] In this context, *Cell* introduced a groundbreaking paradigm by employing transfer learning strategies to fine-tune a pre-trained neural network on smaller datasets, thereby creating a highly efficient diagnostic tool for disease detection.[84] While AI applications in more common and threatening diseases, particularly those involving 2D images, have reached clinical maturity, continuous optimization of AI algorithms and the integration of multimodal data hold the promise of providing accurate and timely diagnostic support for rare and confusing cases.

8 | AI IN ONCOLOGY: LUNG CANCER

Cancer-related mortality from lung cancer is one of the highest in the world and is also one of the most common cancers in clinical practice. The early detection and screening of lung cancer is crucial to improving survival rates, and AI holds significant promise in this regard.[5] As depicted in Figure 1, the earliest AI companies have primarily focused on solving diagnostic needs related to lung cancer. For the diagnosis of lung cancer, there is now a growing trend towards integrating datasets from multiple modalities or multiple centers that go beyond traditional AI's reliance on imaging. A study by Karimzadeh et al. demonstrated the use of an AI-based platform for the early detection of non-small cell lung cancer (NSCLC). Based on the analysis of 64,379 specific oncRNAs in 540 serum samples and other data, a logistic regression model was developed to predict NSCLC. The model achieved an AUC of 0.95 in the training cohort and 0.98 in the validation cohort. At 95% specificity, the model's sensitivity for early-stage (I/II) NSCLC was 0.78 in the training cohort and 0.92 in the validation cohort.[85] The results of a multicenter study also showed that AI-assisted diagnosis had a high sensitivity and specificity for the diagnosis of lung cancer, and the missed diagnosis rate and misdiagnosis rate were both 13%, demonstrating its high accuracy and potential utility in early screenings.[86] Furthermore, Cellina et al. highlighted AI's applications in low-dose CT scans, which increased lung nodule detection sensitivity while maintaining image quality and reducing radiation exposure.[87] There is an increasing trend toward the integration of more clinical and imaging data into new paradigms, based on these studies.

9 | AI IN ONCOLOGY: BREAST CANCER

Breast cancer is the most common malignancy among women worldwide. With the application of AI in digital breast tomosynthesis (DBT), screening sensitivity and specificity have been significantly improved. In the Digital Mammography DREAM Challenge, AI based on CNNs demonstrated a sensitivity of 0.95 and an AUC of 0.85.[78,81] These results demonstrate that AI in DBT not only matches but may even surpass radiologists' performance, while effectively reducing false positives and improving overall screening accuracy. Moreover, in contrast-enhanced spectral mammography, the introduction of DL models based on attention mechanisms has significantly improved the ability to differentiate breast lesions. The best-performing CBAM-Xception model achieved an AUC of 0.970 on the ROC curve in an external test set, with a sensitivity of 0.848, specificity of 1.000, and accuracy of 0.891, significantly outperforming other CNN models, radiomics models, and two radiologists with breast imaging expertise.[61,88] In addition to assisting screening, AI can reduce unnecessary biopsies and follow-ups, increasing the early detection rate of cancer. It has been shown that AI-based DL screening for mammography improved radiologists' specificity from 93.5% to 94.2% ($p = 0.002$) in 66,661 cases while maintaining almost the same sensitivity as the original diagnosis (90.1% vs. 90.6%) and reducing the number of mammograms reviewed by approximately 19.3%.[89] As AI is gradually promoted, breast cancer screening accuracy continues to improve, misdiagnosis rates decline, and clinicians receive more reliable decision support.[81] By integrating genetic, pathological, and imaging data, AI is likely to provide more comprehensive breast cancer risk assessments and personalized treatment plans by integrating data from other cancers.

10 | AI IN ONCOLOGY: RECTAL CANCER

Rectal cancer, the third leading cause of cancer-related death, requires early diagnosis and accurate staging for effective treatment. The application of AI in this cancer primarily relates to lesion segmentation and recognition, particularly in the precise analysis of MRI. Zhang et al. proposed an improved U-Net network based on attention mechanisms by incorporating ResNeSt and shape modules into the traditional U-Net, significantly improving segmentation accuracy. In the validation of 3773 2D MRI datasets from 304 patients, this method achieved Dice, MPA, MioU, and FWIoU scores of 0.987, 0.946, 0.897, and 0.899, respectively, significantly outperforming existing methods.[90] Another study proposed an attention-based multimodal fusion module that integrates information from different MR images (T2, ADC, DWI) while suppressing redundancy. The experimental results showed that this method outperformed existing state-of-the-art image segmentation methods in the Dice coefficient, further demonstrating its potential in rectal cancer segmentation.[68] Another study used a U-net network to accurately segment tumors and related regions, showing good performance in T2/T3 staging sensitivity and overall accuracy.[91] In addition, AI enhances both segmentation accuracy and the precision of T and N staging by incorporating MRI radiomic features with tumor markers. In a study, combining MRI radiomics with markers such as CEA and tumor diameter effectively distinguished rectal cancer stages, achieving AUCs of 0.87 for T-stage and 0.84 for N-stage.[92] Moreover, AI can be used to evaluate rectal cancer patients prior to surgery. Artificial intelligence enables doctors to formulate more precise surgical plans by analyzing multimodal imaging data, improving tumor localization accuracy, and reducing surgical complications.[35,93,94] As an example, Qu et al. developed a radiomic model for predicting tumor budding grade in preoperative rectal cancer using MRI T2WI and multiple

ML algorithms. In the study, the support vector machine algorithm performed the best with an accuracy of 0.826 and a sensitivity of 0.949 in the training group.[95] By assessing tumor invasiveness non-invasively, this model enables personalized surgical planning, thereby improving outcomes. A multimodal omics approach is evidently one of the directions in which this cancer can be developed.

11 | AI IN CARDIOVASCULAR DISEASES

There is no doubt that cardiovascular diseases are among the leading causes of mortality worldwide. A number of clinical applications of AI in this area have been demonstrated, especially in cardiac imaging.[96] The use of AI-assisted automated workflows has significantly improved the efficiency of cardiac function parameter measurement. Based on an automated cardiac MRI (CMR) analysis using fully convolutional networks (FCNs), excellent segmentation performance was demonstrated on short-axis and long-axis cardiac images, with Dice coefficients of 0.94 for the LV cavity, 0.88 for the LV myocardium, and 0.90 for the RV cavity, with mean absolute differences between manual measurements ranging from 6.1 to 8.5 ml. The automated method achieved expert-level performance in analyzing CMR images and identifying clinically relevant parameters while significantly reducing diagnostic time.[97] In our own clinical experience, commercial cardiovascular AI products have greatly enhanced clinical diagnostic accuracy. Artificial intelligence also plays a crucial role in the early screening and treatment evaluation of vascular diseases. In contrast to conventional quantitative coronary angiography, AI-assisted quantitative coronary CT angiography (AI-QCT) is capable of rapidly and accurately detecting and excluding high-grade stenosis. Based on the analysis of data from 303 patients, AI-QCT exhibited a sensitivity of 94%, specificity of 68%, and accuracy of 84% for detecting ≥50% stenosis, and a sensitivity of 94%, specificity of 82%, and accuracy of 86% for detecting ≥70% stenosis. An average of 10.3 min was required for AI-QCT analysis, which significantly improved diagnostic efficiency.[98] In a study of 196 patients, AI-assisted readers achieved a sensitivity of 94% for detecting ≥50% stenosis, significantly higher than non-AI-assisted readers. Artificial intelligence also greatly improved inter-reader consistency, with Kappa values of 0.75 and 0.80 indicating good consistency among AI-assisted readers, whereas non-AI-assisted readers showed poor consistency.[99] The Lancet's sister journal recently published a report on clinical trials highlighting the excellent performance of AI models in coronary CT. Among over 1500 patients enrolled in this multicenter study, AI demonstrated a high detection sensitivity of 96.7% and a specificity of 92.3%, which illustrates its broad clinical applicability for detecting vascular lesions.[100]

12 | AI IN RESPIRATORY DISEASES

Respiratory diseases, particularly interstitial lung diseases (ILD) and COVID-19 pneumonia, pose a significant threat to the health of individuals. Clinical applications of AI have reached maturity, including automated image analysis and early lesion detection. Reports have shown AI's excellent performance in identifying and classifying ILD, with a model achieving an overall classification accuracy of 76.4% and a classification accuracy of 92.7% for common ILD types, significantly outperforming traditional imaging experts at 70.7% (IQR 65.3–74.7). In addition, the model demonstrated superior observer agreement ($W = 0.69$) compared to most experts ($W = 0{,}67$).[101] Further studies indicate that AI systems based on transformer models, using RadImageNet pre-trained and multimodal data, can effectively diagnose five types of ILD and predict 3-year survival rates for patients.[102] Clinical research has shown that AI can assist doctors in detecting respiratory lesions at an early stage.

A major public health event such as COVID-19 has proven the importance of AI in respiratory infectious diseases.[103,104] It is possible to accurately predict COVID-19 patient outcomes by combining AI with imaging. With AI-assisted models, prediction accuracy was 83.9%, sensitivity was 79.1%, and specificity was 88.6%. Artificial intelligence outperformed traditional radiologists in predicting critical cases, with a concordance coefficient of 0.88, $P < 0.001$.[104] In another study, AI was demonstrated to be extremely effective at predicting the progression of COVID-19 patients to critical conditions, with a C-index of 0.80, successfully categorizing patients into high/low-risk groups and significantly identifying patients with a higher risk of disease progression ($p < 0.0001$).[105] Additionally, AI has been used to assess lung damage in COVID-19 patients, with results demonstrating that AI can calculate the volume of lung damage and provide severity scores within seconds. It was found that AI performed better in predicting mortality than radiologists, with ROC AUCs of 0.813 and 0.741, respectively, demonstrating a significant advantage for AI.[106] Commercial clinical processes have incorporated AI tools that have been proven through practice.

13 | KEY TRENDS IN MULTIMODAL OMICS: CAUTION ON SAFETY

In the above analysis of various diseases, we are able to observe that multimodal omics is gradually emerging as an innovative direction for AI in radiology. There is tremendous potential for multimodal omics development, particularly in diagnosis, risk prediction, and personalized treatment.[107,108] In recent years, multi-omics integration has become essential for improving cancer diagnosis and personalized treatment. By combining genomics, transcriptomics, proteomics, and metabolomics data, researchers can better understand cancer mechanisms, while AI algorithms enhance early diagnosis and treatment outcomes. Notably, in breast, ovarian, and colorectal cancers, AI with multi-omics data has significantly improved disease classification and prognosis accuracy.[109–111] An article published in *Cancer Cell* in recent years described how AI could significantly improve tumor diagnosis accuracy and treatment outcomes through the integration of various modalities (such as imaging data, genomic information, pathology data, and clinical records). As noted in the review, AI can be used to analyze the tumor microenvironment comprehensively by combining data from MRI, CT, and PET imaging with whole-genome sequencing and RNA sequencing data. Using an integrative approach increases the accuracy of tumor staging and improves the ability to identify complex tumor subtypes. The review also proposed five classic paradigms of multimodal omics, providing a clear technical roadmap for cancer research, Figure 4.[73,112] Specifically, AI's integration of radiomics and genomics has enabled the identification of previously undetectable subtypes of breast cancer.[113,114] Furthermore, multimodal omics can help uncover the molecular mechanisms underlying tumor heterogeneity, offering new directions for the development of more effective targeted therapies.[73] The performance of the AI models has been significantly enhanced by the integration of multi-omics data, such as blood-derived metabolomics, epigenomics, and transcriptomics data.[115] As a result of using multimodal omics data to predict cardiovascular disease risk factors, the model outperforms single-omics data, particularly in predicting factors associated with high-risk or low-risk cardiovascular disease.[116]

The combination of AI and radiology has shown significant advantages, gradually revolutionizing traditional medical imaging diagnostics by integrating multimodal data and improving diagnostic and therapeutic precision. However, the widespread clinical application of AI still faces numerous overlooked issues, such as ethical concerns, data privacy, model interpretability, and adaptability in complex diseases. These issues are also closely monitored by *NEJM*.[2] While developing AI's powerful capabilities, it is essential to pay attention to safety and ethical considerations.

14 | GPT INTEGRATION REDEFINING RADIOLOGISTS' EXPERTISE

The processing of one-dimensional natural language has historically been more challenging than two-dimensional image processing. Among the reasons for this delay are the complex logical relationships within the context of linguistics, as well as the inherent limitations of nonlinear models, such as recurrent neural networks (RNNs), which are sequential in nature. However, the introduction of the Transformer model in 2017 marked a significant turning point in this field.[64] As opposed to traditional RNN models that process each element of a sequence in a step-by-step manner using a recurrent structure, Transformer models are capable of processing an entire input sequence in parallel because of their attention mechanism. This gives the transformer a significant efficiency advantage in long-sequence language processing.[64] The well-known generative pre-trained transformer (GPT) model leverages the attention mechanism in the transformer model to efficiently process one-dimensional linguistic data (Figure 5).

In radiology, GPT models have effectively bridged the gap in processing and interpreting free-text information that CNNs previously struggled to handle, thereby establishing GPT as a critical auxiliary tool in the field. Over the past two years, *Radiology* has published 16 articles on the integration of GPT with radiology, encompassing original comparative studies (12/16, 75%), opinion reviews (2/16, 12.5%), editorials (1/16, 6.25%), and errata (1/16, 6.25%). These publications span multiple subfields within the discipline. Research is primarily focused on the following areas: (a) structured conversion of free-text reports: GPT-4 has shown exceptional performance in converting free-text reports into structured formats, achieving a 100% accuracy rate in actual conversions. All free-text reports were successfully converted into valid JSON files without any errors.[117] (b) Error detection and correction in reports: GPT-4 has been used to detect and correct errors in radiology reports, significantly improving the report accuracy to 94%.[118] (c) generation and summarization of imaging reports: In generating clinical reports for glioblastoma patients, GPT-4's reports were consistent with expert assessments in 91% of cases. The accuracy of essential information reached 95%, and the accuracy of medical history summaries was 89%, providing high-quality case reviews to support clinical decision-making.[119] (d) BI-RADS Classification and Standardization Application:

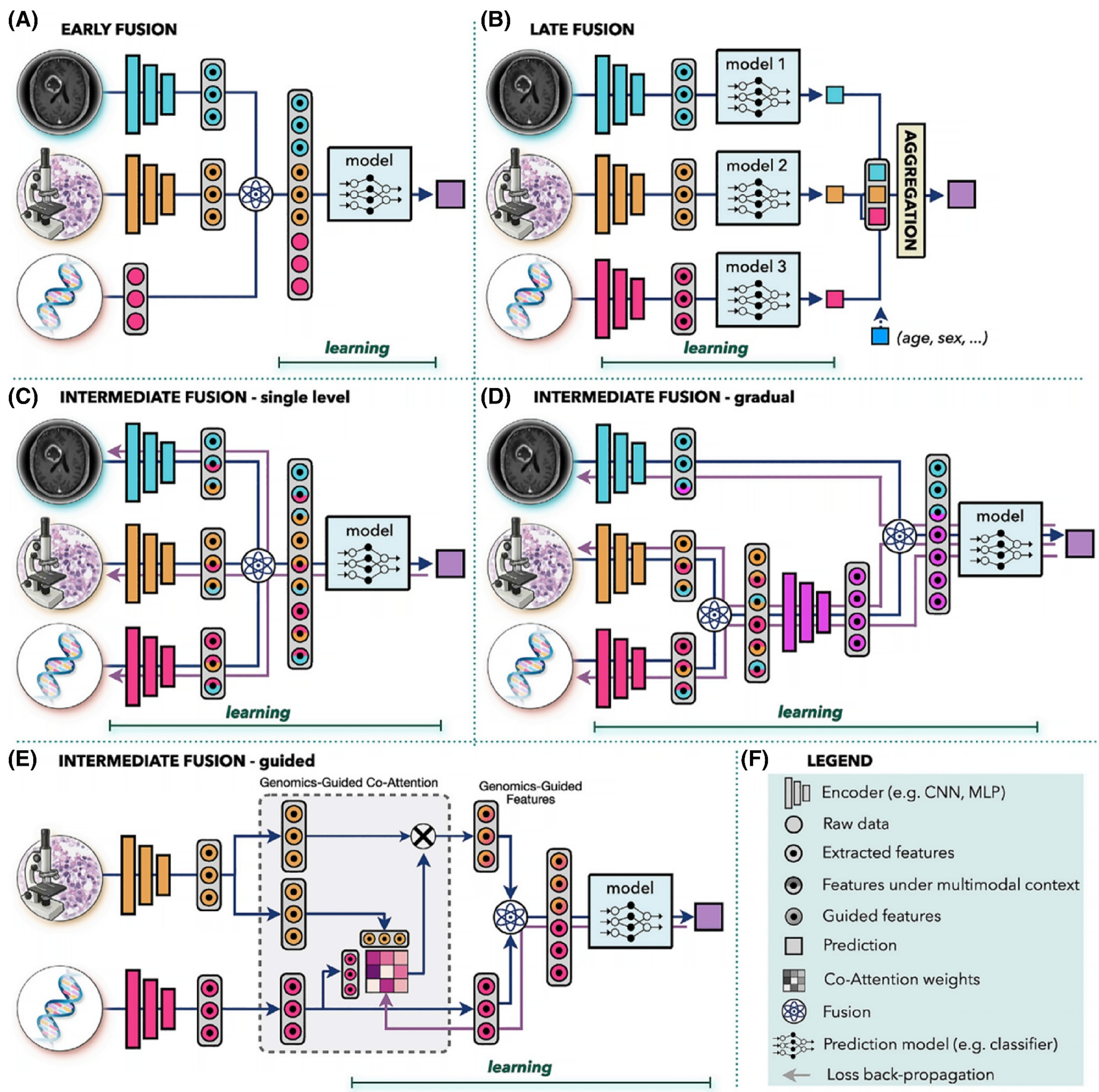

FIGURE 4 The five principal paradigms of multimodal data fusion are systematically summarized. (A) Early fusion constructs a unified representation from raw data or features at the input level before it is processed by the model. (B) Late fusion involves training separate models for each modality and then aggregating the predictions at the decision level. (C–E) Intermediate fusion propagates the prediction loss back to the feature extraction layer of each modality, allowing the iterative learning of enhanced feature representations within a multimodal context. The unimodal data can be fused (C) at a single level or (D) progressively across different layers. (E) Guided fusion enables the model to leverage information from one modality to inform and enhance feature extraction in another modality. (F) The key for the symbols used is provided. Reproduced with permission.[73] Copyright 2022, Cell Press.

GPT-4 achieved an 88% accuracy rate in assigning BI-RADS classifications in a multilingual environment, with an overall agreement rate of 70% compared to human readers. It is evident, despite some discrepancies, that GPT-4 is capable of performing BI-RADS classification tasks comparably to radiologists, demonstrating its practical utility.[120] (e) Automated Diagnostic Assistance: GPT-4 achieved a lesion detection accuracy of 90.5%, slightly lower than the typically over 95% accuracy of radiologists. However, in some cases, GPT-4 exhibited diagnostic capabilities comparable to those of radiologists, indicating its potential value in diagnostic assistance.[121] (f)

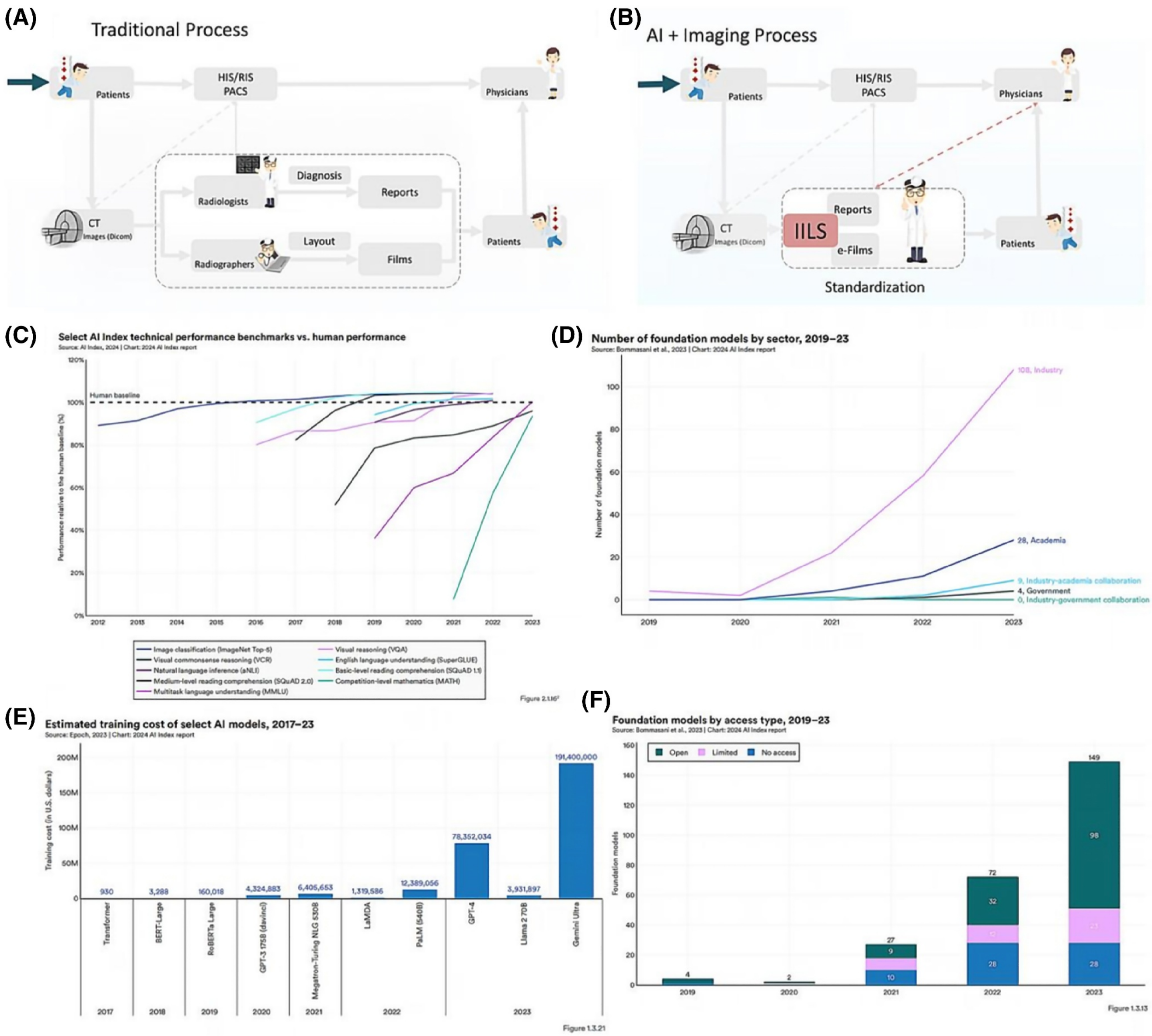

FIGURE 5 Comparison of traditional and AI-assisted clinical workflows in imaging, and global AI development trends. (A) In the traditional workflow, patients progress through registration, diagnosis, imaging acquisition, and reporting, with communication between radiologists and clinicians being time-consuming, particularly within the radiology department (gray dashed box); (B) The IILS intelligent system enhances diagnostic efficiency and accuracy, enabling automation and standardization. Reproduced with permission.[45] Copyright 2019, The Lancet Publishing Group. (C) According to Stanford University's Artificial Intelligence Index Report 2024, AI has reached or is approaching human-level performance in key benchmarks. Since 2015–2016, DL-driven machine vision systems have matched or exceeded human capabilities, particularly in visual question answering (VQA) and multi-task language understanding (MMLU); (D) The development and deployment of foundational model frameworks have been led predominantly by industry, with limited academic contributions; (E) Training costs for AI models have increased sharply over time; (F) Over the past 2–4 years, LLMs have been categorized into open-source, limited open-source, and fully closed-source, with a notable increase in open-source models. Reproduced with permission.[124] Copyright 2024, Stanford University. AI, artificial intelligence; CNNs, convolutional neural networks; LLMs, large language models; VQA, visual question answering.

Data Mining and Retrospective Analysis Capabilities: GPT-4 performed outstandingly in data mining from free-text CT reports, particularly in extracting lung cancer-related parameters, with a correct extraction accuracy of 94.0%, significantly outperforming GPT-3.5's 63.9%. It is apparent from this example that GPT-4 offers significant advantages in the processing of complex text data and in the extraction of key medical information from it.[122] (g) Clinical Research and Standardized Imaging Exam Performance: GPT-4 achieved an accuracy of 80.6%, 78.0%, and 76.7% in three tests, with significantly greater consistency than GPT-3 (76.7% vs. 61.3%). Furthermore, both GPT-4 and GPT-3.5 demonstrated high confidence in the majority of their initial answers (GPT-3.5 at 100%, GPT-4 at 94.0%), providing important references for the future application of AI in medical examinations.[123]

Based on the analyses of GPT applications in radiology and our practical experiences, we can conclude that GPT is reshaping traditional radiology's core workforce and partially altering the role of radiologists (Figure 6). Traditionally, radiologists primarily served as a bridge between image data and textual information, acting as 'image-to-text converters'. However, the integration of DL, which is based on the connectionist paradigm, has gradually dissolved the traditional boundaries between imaging and textual data, forcing a reevaluation of the role of the radiologist. It should be noted that this wave of AI not only replaces simple and repetitive tasks but also begins to encroach upon some of the radiologists' core responsibilities (Figure 6). The integration of GPT with radiology is likely to progress in the following directions: (a) Development and application of automated diagnostic assistance tools: It is intended that GPT will be used to develop more advanced diagnostic assistance systems as a means of improving diagnostic efficiency and accuracy, and reducing the workload of radiologists. (b) Real-time clinical decision support: With GPT, healthcare professionals can access clinical information in real time, enabling them to make more informed decisions. (c) Cross-disciplinary integration and personalized medicine: As a result of multidisciplinary collaboration, the GPT is expected to contribute to the development of new diagnostic and treatment models, thereby enabling patients with complex health conditions to receive more personalized treatment plans. Furthermore, these developments contribute to improving diagnostic and treatment standards in radiology as well as propelling healthcare towards greater intelligence and personalization.

In conclusion, drawing from extensive radiology experience and insights from Stanford University's 2024 AI Index report—their most comprehensive edition yet, released at a pivotal time of heightened AI impact on society—we present a forecast for the combination of AI and radiology (Figure 5).[124] Distilled from the 10 key points highlighted in the report are the following four main insights: (a) AI capabilities gradually surpassing human performance: The performance of AI on tasks such as image classification has reached or even exceeded that of

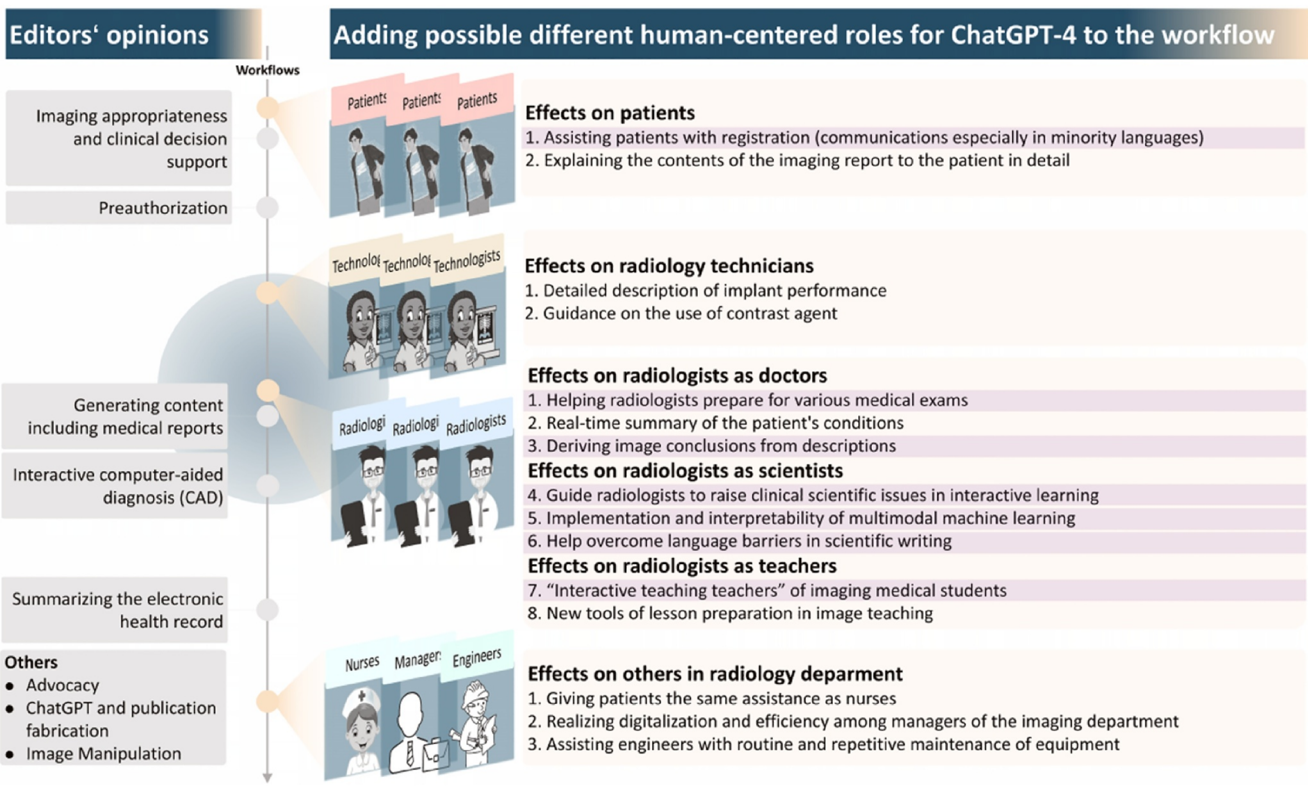

FIGURE 6 Benefits of upgrading to ChatGPT-4 in a human-centered clinical imaging workflow. Editors previously provided eight cases—five related to imaging and three to academic work and individual activities. Contrary to the editors' views, we found ChatGPT-4 to have the most significant impact on radiologists. Based on ChatGPT-4's capabilities, we identified eight potential benefits for doctors, two for technicians, two for patients, and three for others.

humans; however, in more complex tasks, such as competition level mathematics, AI still falls short. (b) The shift in leadership of AI from academia to industry: A total of 51 AI models were launched by the industry in 2023, whereas only 15 models were developed by academia. 21 models were produced through the collaboration between academia and industry, indicating that the driving force behind AI research is shifting from academic innovation to commercial applications. (c) Significant Increase in the Cost of Cutting-Edge Models: Training costs for advanced AI models have risen sharply, with the development of Google Gemini Ultra and GPT-4 costing approximately $78 million and $191 million, respectively. It is evident from these high costs that AI technology development is resource-intensive. (d) Growing Attention to Ethical and Moral Issues: LLMs are found to have significant deficiencies in terms of robustness and standardization of accountability, raising concerns about potential ethical issues when using AI in imaging applications. Based on the insights from Stanford University's 2024 AI Report, it is imperative for healthcare professionals to critically reassess the significant impact of the emerging AI wave, epitomized by GPT, on medical and imaging processes.[124] It is essential to recognize that in certain domains AI has already demonstrated capabilities surpassing those of human experts. Additionally, the locus of technological innovation is increasingly shifting from traditional academic leadership to commercial entities, highlighting the necessity for enhanced collaboration with industry. Furthermore, the ethical challenges introduced by AI must be rigorously addressed to ensure that advancements in technology continue to align with the ethical standards of medical practice.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the supplementary material of this article.

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