Editorial | Uncover This Tech Term

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Uncover This Tech Term: Agentic Artificial Intelligence in Radiology

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AI Agent and Foundational Models

Recent advances in artificial intelligence (AI) have been driven by the development of foundational models (FMs) [1]. Large language models (LLMs) are FMs pretrained on a large corpus of text data followed by fine-tuning specifically for instruct-tuned models, with remarkable capabilities to 'understand' and generate natural language conversations [2]. Extending beyond text alone, large vision-language models (LVLMs) integrate visual understanding with linguistic skills, enabling the simultaneous processing of both textual and imaging data [3]. Further leveraging the advanced reasoning capabilities of recent-generation LLMs, newly developed technologies have led to the emergence of agentic AI systems, which differ from their predecessors by possessing 'agency': the ability to 'observe' their environment, 'plan,' and 'act' autonomously [4]. Relevant terms are summarized in Table 1.

AI agents leverage FMs as their cognitive core—or "brain"—to communicate, reason, and make decisions. A crucial distinguishing feature of agentic AI is its capability to engage in a plan-action-observation cycle. In this iterative cycle, the AI internally 'reasons' (plan), executes tasks using available tools (action), and evaluates outcomes (observation), continuously refining its decisions based on environmental feedback to reach a certain predefined goal. This iterative cycle empowers agentic AI to autonomously handle complex multistep tasks, including diverse radiology workflows.

AI agents differ from stand-alone FMs in three primary components: agent-specific task system prompts, tool utilization, and iterative interactions.

AI agents can be primed with specific prompts that substantially and consistently modify the behavior of the underlying FM, making them versatile and adaptable to specialized tasks [5]. A significant strength of AI agents lies in their ability to employ various tools, including a code interpreter (to execute internally generated or external code snippets), databases, and application programming interfaces (APIs) [6]. This capability enables them to perform tasks autonomously, without continuous human intervention. By leveraging these tools, agentic AI can dynamically interact with its environment (which may consist of more agents, human users, or APIs) and undertake tasks that exceed the capabilities of standalone FMs. Furthermore, AI agents can observe the results of their actions and improve their next set of actions. While a simple LLM cannot retrieve the clinical data necessary to interpret imaging findings accurately, an AI agent can first identify the clinical information required for a diagnosis (plan), directly access this information through APIs or a retrieval pipeline (tools), gather the relevant clinical details (action), and finally assess whether the collected data are sufficient (observation) for a confident diagnosis. This iterative cycle may be repeated multiple times until all pertinent clinical information is acquired, substantially enhancing the LLM's capabilities and closely mirroring a

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Table 1. Glossary of key terms related to agentic AI systems in radiology

Term	Definition
FMs	Large-scale AI models pre-trained on vast datasets using self-supervised learning methods. These models serve as a flexible and powerful backbone for various downstream AI applications, including LLMs and LVLMs
LLM	A type of FM trained on extensive text corpora. LLMs can understand and generate natural language but operate passively and require user prompts to function
LVLM	An extension of LLMs that integrates visual and textual modalities, enabling the model to simultaneously interpret and analyze both images and language
LMM	A type of FM trained on multiple data modalities, such as text, images, audio, and video. LMMs extend beyond vision-language capabilities to enable joint understanding and generation across diverse input types
Reasoning LLM	An LLM with enhanced capacity for multi-step logical reasoning beyond surface-level pattern recognition—capable of decomposing complex tasks, generating intermediate steps, and following structured chains of thought—making it suitable for agentic AI applications
AI agent	A system that embeds an FM as its cognitive core and can autonomously perform tasks through an iterative plan-action-observation loop. These agents are capable of dynamic decision-making and tool usage
Tools	Functional components—such as code execution engines, external APIs, databases, or retrieval pipelines—that AI agents can utilize to extend their abilities beyond language generation
Action	The step in which an AI agent performs a task based on its internal reasoning. This may include interacting with a system, querying a database, or initiating another agent's function
Environment	The ecosystem in which the AI agent operates and interacts. This may include clinical databases, web services, APIs, human users, imaging platforms, or other agents
Prompt	A user-provided instruction or input that guides the response of an LLM or LVLM. Prompts can significantly shape how the model behaves
System prompt	A predefined instruction embedded in the context window that consistently guides the model's behavior and responses
Agent-specific task system prompt	A structured instruction within the context window that defines the AI agent's role, goals, and constraints, enabling consistent and repeatable execution of specialized tasks
APIs	A set of defined rules and protocols that allow software components to communicate. In the context of AI agents, APIs provide access to external systems (e.g., clinical databases, imaging viewers, or computation services), enabling automation and real-time data integration
Retrieval-augmented generation	An advanced AI method that enhances response accuracy by retrieving relevant external information (e.g., from knowledge bases or document stores) and integrating it into the generation process. This allows agents to generate more contextually accurate and up-to-date content beyond their training data
Database	Structured collection of data that can be queried for relevant information. In clinical settings, this may include patient records, imaging metadata, radiology reports, and lab results—serving as a crucial source of truth for agentic decision-making

AI = artificial intelligence, FM = foundational model, LLM = large language model, LVLM = large vision-language model, LMM = large multimodal model, API = application programming interface

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real-world radiology workflow.

Applications in Radiology

Agentic AI extends beyond individual tasks, enabling complex, interconnected workflows through multi-agent systems. In these systems, specialized AI agents collaborate under the guidance of a central orchestrator. This multi-agent architecture facilitates distinct roles for each agent while maintaining centralized oversight [7]. One notable application of multi-agent systems is clinical decision-making. Researchers have proposed "virtual hospital" and "virtual tumor board," where distinct AI agents analyze MRI scans, pathology slides, and genomic data, collectively reaching a diagnostic and management consensus [8,9]. Beyond clinical applications, these systems have also shown promise in research settings, enabling virtual teams of AI-driven scientists to collaborate on scientific discovery [10]. They can also automate the development of AI algorithms for medical imaging by taking free-text descriptions of the task and dataset at hand [11]. Additionally, Agentic AI can assist in managing longitudinal patient data, leveraging clinical and imaging trajectories to navigate personalized medicine [12].

The potential combinations of various tools and prompts within a multi-agent system are limitless, enabling customized designs tailored to specific radiology tasks. For example, consider a trauma patient presenting with a suspected cervical spine injury. An agentic AI system can autonomously select an appropriate imaging protocol based on the patient's history and clinical records (Agent-1), triage the imaging request based on urgency (Agent-2), enhance image quality through denoising techniques (Agent-3), detect critical findings, such as a cervical spine fracture involving the C1 lateral mass (Agent-4), and subsequently trigger a CT angiogram in response to the potential for vertebral artery dissection (Agent-5). The report generation tool could be leveraged to draft an initial diagnostic report (Agent-6), notify the radiologist to accept or reject the critical findings (Agent-7), and, if required, communicate preliminary findings to the primary team (Agent-8), all under the coordination of an orchestrator agent (Agent-9) (Fig. 1).

Future Trends and Considerations

As FMs continue to evolve with expanded context windows, we can expect exponential improvements in the

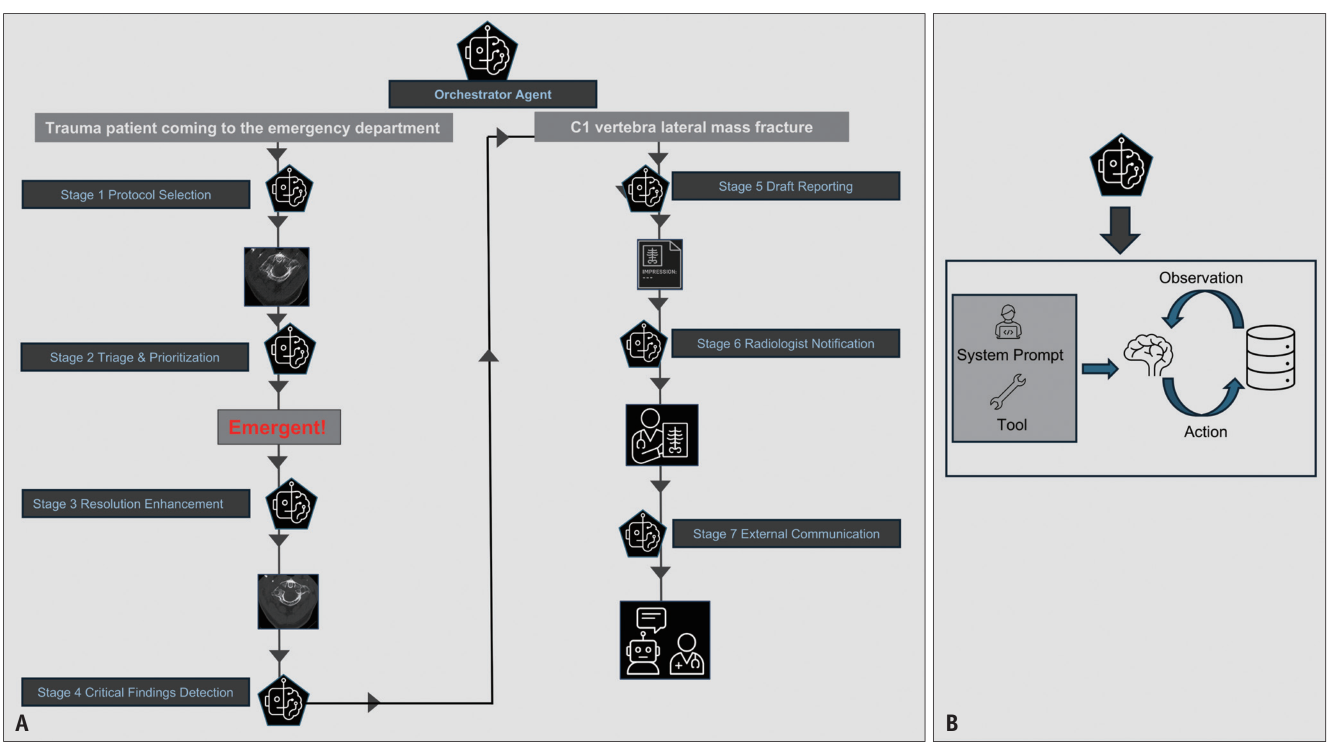

Fig. 1. Examples of agentic AI in radiology workflow. **A:** Schematic representation of a basic multi-agent AI system within a radiology workflow. **B:** Illustration of a single AI agent. AI = artificial intelligence

performance of agentic AI systems in radiology. Additionally, it is predicted that the collaborative work of multiple specialized AI agents, particularly multiple agents with the same expertise, will significantly boost overall performance through the cumulative effects achieved over iterative feedback rounds, mirroring historical human advancements through communication [13]. Future AI agents in radiology are expected to demonstrate self-evolving intelligence, autonomously optimizing themselves, as early evidence of these capabilities is emerging [14-16]. For example, AI might automatically find its own workflow bottlenecks, enhance its instructions, test them, and eventually deploy them with minimal human intervention.

However, such increasing autonomy introduces critical ethical and regulatory challenges, necessitating new frameworks for continuous validation, robust oversight mechanisms, regular audits, fail-safe modes, and human-in-the-loop checkpoints to maintain patient safety and clinical reliability [17,18]. Crucially, these systems require guardrails with uncertainty-aware agents to build safe and trustworthy systems [19]. Additionally, sustainability and environmental concerns related to the computational costs and pollution associated with training and large-scale deployment of FMs must be thoughtfully considered [20].

CONCLUSIONS

Agentic AI represents a paradigm shift in the application of AI in radiology by integrating FMs to create autonomous systems capable of observation, planning, and action in clinical environments. These intelligent agents may potentially automate radiology workflows, reduce physician burnout and help maintain diagnostic accuracy. Rather than replacing radiologists, agentic AI fosters a complementary relationship, allowing clinicians to transition toward supervisory roles that involve overseeing AI output, interpreting complex cases, and enhancing patient interaction. By handling routine and mundane tasks, agentic AI could enable radiologists to focus on nuanced clinical decisions, driving radiology toward a more efficient, accurate, and patient-centered practice. However, successful implementation requires addressing critical challenges such as ethical considerations, regulatory oversight, and environmental sustainability to fully realize the transformative potential of this technology.

Conflicts of Interest

Bradley J. Erickson: Chair, Society of Imaging Informatics in Medicine (SIIM) Research Committee. Board Member: Enquanta Inc, FlowSIGMA Inc. Advisor or Consultant: Yunu Inc, HOPPR Inc, FindMedTech Inc.
Mana Moassefi: Vice Chair, Society of Imaging Informatics in Medicine (SIIM) Member In Training Committee.
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