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OPINION

Agentic AI: Vision and challenges

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Abstract

Agentic AI systems are increasingly viewed as a viable response to the shortcomings of static, rigid, and human-in-the-loop Artificial Intelligence (AI) systems. This is because autonomous operation enables rapid adaptation to dynamic, complex problems with improved time-critical behaviour under real-world constraints. Despite significant progress, current agentic pipelines are still challenged by output instability, scalability gaps, and system integration issues. Addressing these limitations, this article presents a comprehensive conceptual framework unifying core AI functionality with implementation approaches across different system scales, including Agentic AI builds upon Large Language Models (LLMs). Furthermore, the popular applications of Agentic AI and areas for future investigation and open problems are systematically presented.

Introduction

In the rapidly evolving Artificial Intelligence (AI) era, systems have progressed from single-task, text-based language models to multi-input, multi-step reasoning architectures and task-focused AI agents with memory, planning, and action capabilities [1]. Agentic AI refers to AI systems that can complete tasks with minimal human intervention [2]. It is an autonomous system driving a scalable agentic architecture that enables adaptive decision-making through a continuous cycle of *Perceive, Reason, Act,* and *Learn*. The Agentic architecture design, which unifies perception, analysis, and action, applies directly to operational fields extending from healthcare, smart city ecosystems, governance, and industrial sectors [3].

The requirements for developing a production-level agentic paradigm include coordinated advancement in dynamic reasoning and scalable multi-agent orchestration, but so far, the available state-of-the-art systems struggle with hallucinations in their core Large Language Models (LLMs) [4,5]. The problem occurs mainly because models are trained on limited, task-focused datasets rather than actual operational conditions, causing performance degradation when the practical environment differs from the training setup [6]. LLMs' hallucinations come from pre-training restrictions and post-training behaviour, when models provide confident outputs under ambiguity. Retrieval-Augmented Generation (RAG) may minimise hallucinations by securing outputs in external information, but proper retrieval is needed [7]. These shortcomings raise concerns about the efficiency of infrastructure due to increased computational overhead. Autonomous decision-making faces additional challenges of safety, trust, and ethics, as systems can produce harmful outcomes with unclear accountability for who is responsible [8]. Furthermore, multi-agent scaling complexity introduces coordination failures across distributed systems [9]. While the latest research examines these issues, critical gaps remain. Recent research [10] discusses in-depth the Agentic AI's core internal components but fails to present a clear picture of how it integrates with real-world interfaces (Application Programming Interfaces (APIs), Sensors, Knowledge Bases, Web Access, Cloud Platform) [11]. Literature [8] points out that learning methods (reinforcement, meta-learning, transfer) and scaling approaches (single-agent to multi-agent) are developed separately, with no common standard for deploying them in different fields [12].

Modern LLMs have been trained using vast datasets composed predominantly of publicly available internet content. The issue with the pre-training process is that it relies heavily on general-purpose, text-based information. Therefore, when LLMs are applied to real-world domains (such as healthcare, transport, or industrial automation), they are often unable to identify and leverage domain knowledge, dynamically evolving contextual signals, and operational constraints. This limitation can be explained by the "jack-of-all-trades but master-of-none" effect, where the generalist characteristics of these models provide a broad base of knowledge but do not offer depth in any particular area unless they are adapted, fine-tuned, or integrated with external resources/structured databases. To address the problem of isolated AI development, this paper proposes a comprehensive Agentic AI model that bridges the AI's thinking capabilities with multi-paradigm learning strategies, cross-scale deployment, and ethics guidelines, thus creating a technical roadmap for building autonomous systems with practical use cases.

Main contributions

The key contributions of this work include:

- A holistic architecture (Fig 1) is proposed that integrates AI reasoning with operational functions and environmental interactions, addressing the critical problem of isolated component development and demonstrating how systems scale from individual agents to synchronized multi-agent deployments.
- Identification of major technical bottlenecks leading to production barriers: unreliable system behaviour and performance degradation due to training-deployment infrastructure misalignment, coordination failures in multi-agent scaling, and

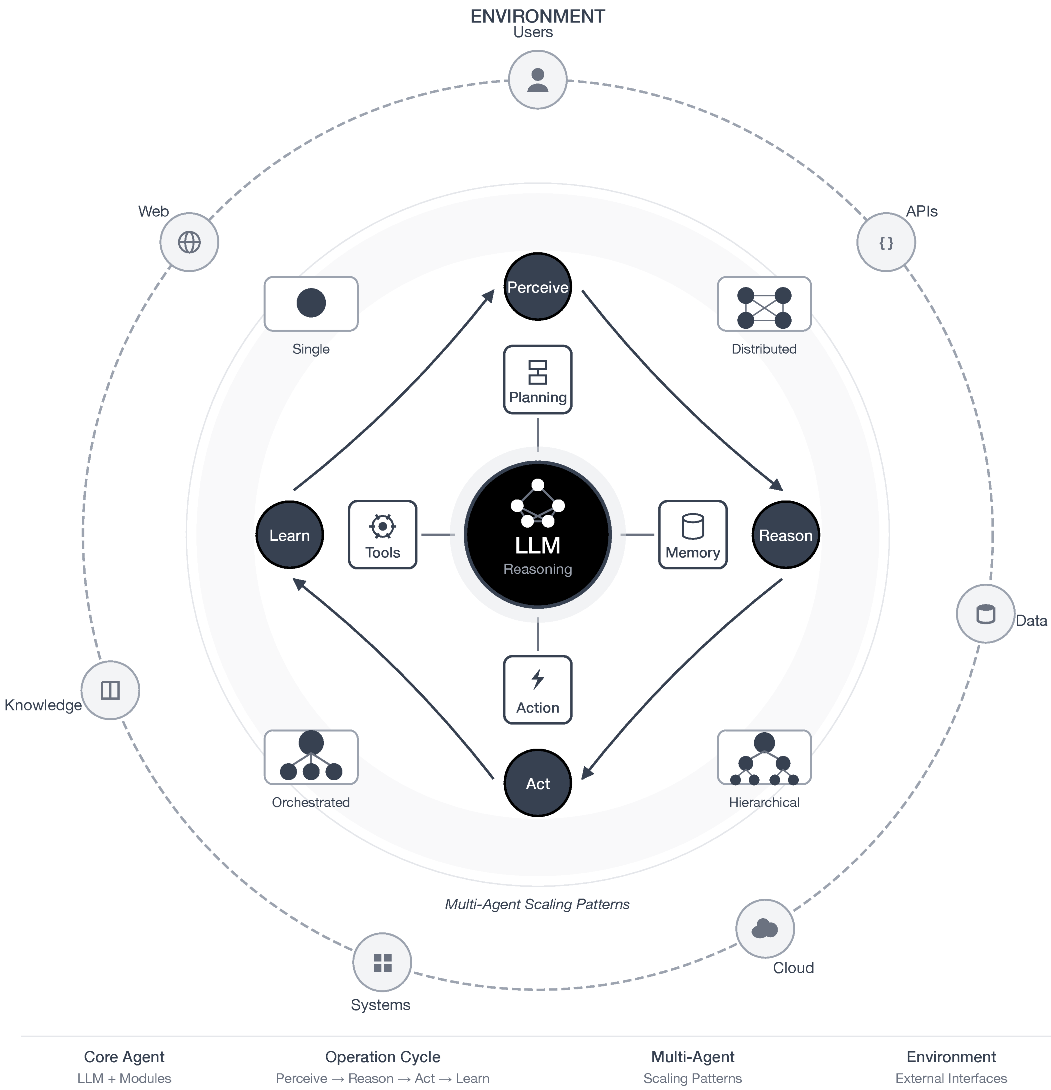

Fig 1. Conceptual model of Agentic AI. The model illustrates the layered architecture of agentic AI systems: (1) the LLM core serving as the reasoning engine, (2) four functional modules (Planning, Memory, Tools, Action), (3) the operation cycle (Perceive → Reason → Act → Learn), (4) multi-agent scaling patterns (Single, Distributed, Hierarchical, Orchestrated), and (5) the external environment interfaces (Users, APIs, Data, Cloud, Systems, Knowledge, and Web).

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accountability ambiguities in autonomous decision-making, thereby providing the foundation for developing a practical solution.

- Implementation blueprints across modern applications (Fig 2) such as healthcare, software, finance, transportation, industrial sectors, smart cities, and governance, demonstrating architectural applicability across diverse fields and helping identify domain-specific deployment requirements overlooked in prior work.
- A six-dimensional research roadmap (Fig 3) providing a comprehensive structure for achieving production-ready agentic systems.

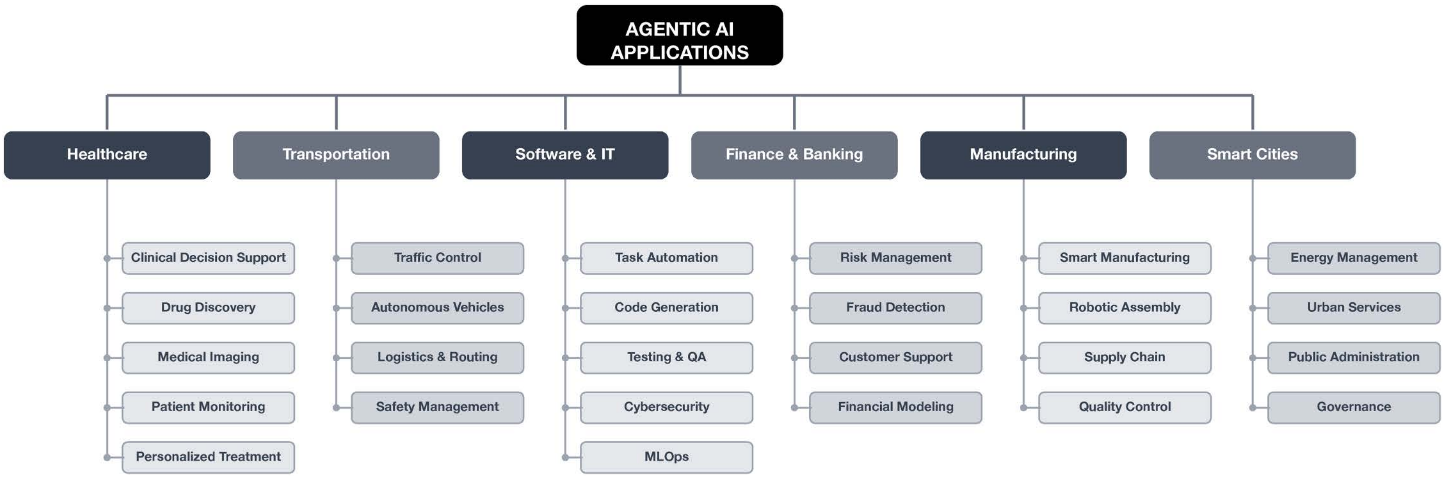

Fig 2. Applications of Agentic AI across industry domains.

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Fig 3. Future directions for Agentic AI research.

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Article organization

The paper proceeds as follows: Section II discusses the Agentic AI Model Architecture, Section III presents the Applications of Agentic AI, Section IV examines the research opportunities, open challenges, and future directions. Section V provides the conclusions.

Agentic AI model: A vision

Architecture

In contrast to traditional AI models that operate reactively or under strict instruction pipelines, these agentic systems are characterized by self-directed goal pursuit, adaptability, reasoning, and goal-aware autonomous control, as shown in Fig 1; thus, they will be more relevant for complex, dynamic, and uncertain environments. The agent loop forms the basis for an agent system model and typically includes perception, cognition, decision-making, action execution, and learning from feedback [3]. At the same time, the perception module will continuously gather data from the environment via data streams, sensors, or other digital inputs. This is further analyzed by the cognition layer, which integrates various reasoning mechanisms, including symbolic logic, probabilistic inference, or deep neural representations [6]. Subsequently, the decision-making component chooses optimal actions that align with the agent's objectives, constraints, and context. Agents cannot be thought of as automated scripts but must be entities with planned behavior, prioritization, and adaptation. An agentic system is a model in which AI systems are built as independent agents that can perceive the environment, make decisions, and execute appropriate actions toward attaining goals, either preprogrammed or self-generated, without continued human supervision [2].

Furthermore, planning infrastructure helps agents break high-level objectives into practical subtasks using reinforcement learning or model-based planning. The use of feedback cycles enables the continuous improvement of agents' strategies by learning from feedback and responses during task execution [13]. The state-of-the-art agentic system typically leverages LLMs, reinforcement learning agents, and tools to enhance reasoning and execution. When combined with other external tools or APIs, agentic systems are able to dynamically make inquiries to the databases or make use of analytical tools or interact with other agents to develop a multi-agent system. On such platforms, agents can either work together as a team, compete, or interact to achieve scalable problem-solving capabilities within the distributed domain [12]. In these agentic systems, the memory components enable the storage of short-term context and the retention of long-term knowledge. Furthermore, the policy layers ensure the operational rules and boundaries are followed and strictly adhered to. Agentic systems offer many benefits for users and the technology ecosystem, but they also pose technological and operational challenges. Designing an agent system that regularly meets its goals under operating parameters is a major issue. Maintaining controllability, transparency, and explainability for autonomous decision-making and agentic agent activity is very important. To securely and reliably implement agentic AI in real-world applications, they must address these difficulties [14].

Moreover, an agentic AI model integrates sensing, reasoning, planning, and learning modules to facilitate autonomous decision-making in real-life scenarios. As shown in Fig 1, the conceptual model of Agentic AI illustrates the relationships between reasoning, perception, and planning, and action execution, and learning and feedback cycles.

In addition, from a complex systems perspective, Agentic AI architectures exhibit characteristics such as feedback-driven adaptation, decentralized decision-making, and dynamic interactions among multiple agents. The continuous interaction between perception, reasoning, learning, and action components forms feedback loops that enable agents to adapt their behavior in response to environmental changes. When multiple agents operate within shared environments, these interactions can lead to emergent system-level behaviors that are not explicitly programmed but arise from collective dynamics.

Domain-specific vision of Agentic AI

Agentic AI has wide applicability across various domains, including healthcare, software, finance, education, robotics, and others [3,6,9,12]. Some important applications of Agentic AI across various domains are shown in Fig 2, which maps the domains suitable for agentic AI deployment.

Healthcare

Agentic AI plays a crucial role in healthcare for various application areas. Agentic AI makes generative AI decision-making more transparent and accountable, thereby supporting ethical oversight [15]. Agentic AI is adopted in computer vision (preferably, medical CV), for an independent construction and execution of medical image segmentation pipelines. It helps advisory systems in ethically conducting clinical decision support in complex healthcare scenarios. The use of agentic AI for accurate diagnostics, personalized treatment planning, real-time patient monitoring, workflow automation, and drug discovery is highly beneficial for clinical decision-making and drug discovery applications [16]. It is widely adopted for real-time detection and assessment of Drug-Induced Liver Injury (DILI) risks using LLMs on clinical records. Also, to enhance healthcare decision support, diagnosis, and personalization in diagnostics and treatment planning. Agentic AI provides personalized, adaptive fitness coaching using multimodal multi-agent digital twin systems. It is quite useful in Neuromuscular Electrodiagnostic (EDX) for AI-assisted interpretation and reporting of neuromuscular EDX tests [17]. Future agentic healthcare systems may evolve into intelligent clinical assistants capable of integrating multimodal patient data from medical records, imaging, wearable devices, and genomic profiles. These systems could support continuous health monitoring, early disease prediction, and personalized treatment recommendations. By coordinating multiple healthcare services autonomously, agentic AI may improve clinical efficiency, accessibility, and patient-centered care while ensuring privacy and regulatory compliance.

Transportation

Agentic AI can improve traffic control, safety, and sustainability in metropolitan transportation systems. It facilitates real-time optimization, management, and personalization in industrial environments, including transportation and biomanufacturing [18]. For autonomous vehicle control and safety, agentic AI plays an important role in multimodal model predictive control for safe, context-aware autonomous navigation. It supports multi-agent routing and scheduling optimization in logistics networks and transportation routes. Agentic AI also contributes to lifecycle-aware transportation management by enhancing system adaptability, resilience, and operational safety [19]. Future agentic transportation systems may enable seamless coordination among autonomous vehicles, traffic infrastructure, and public transit networks. Through continuous reasoning and adaptive decision-making, these systems could proactively manage congestion, optimize route planning, and improve road safety. Such advancements may contribute to more efficient, sustainable, and resilient urban mobility ecosystems.

Software & IT

Agentic AI automates query and task processing by autonomous task decomposition, tool selection, and execution with real-time feedback in software and IT [20]. Agentic AI is useful in automated Behavior-Driven Development (BDD) test case formation from natural language as well as computer vision in healthcare and robotics using real-time autonomous perception and adaptive interaction. For software and task automation in Small, Medium, and Micro-sized Enterprises (SMMEs), agentic AI promotes goal-driven multi-agent automation for engineering and business tasks [21]. It helps with adaptive, interpretable agent-driven data-pipeline optimization for fraud and sensor-drift management. Provides fair, personalized, and multimodal information retrieval [22,23]. Future agentic AI systems may evolve into autonomous software engineering assistants capable of managing the entire software lifecycle, from requirements analysis to deployment and maintenance. These systems could collaborate with human developers, optimize workflows in real time, and improve software reliability, security, and productivity through adaptive decision-making and continuous learning.

Finance & banking

Banking and finance are highly sensitive domains. Real-time market reviews, investment strategy optimisation, and personalised financial services are possible with agentic AI in intelligent financial ecosystems. It helps in AI-driven financial decision-making, risk profiling, LLM-based financial modeling, and compliance workflows. For Banking, Financial Services, and Insurance (BFSI) customer support and fraud detection, agentic AI is used for autonomous customer assistance [24]. It is also applied for personalized banking and AI-driven automated customer services. It provides trustworthy and financial services, also helps in autonomous service delivery in finance and insurance [25]. Future agentic AI platforms may support fully personalized financial ecosystems by continuously monitoring market conditions, user preferences, and risk profiles. Such systems could provide proactive financial guidance, automate complex banking operations, and enhance transparency, efficiency, and regulatory compliance in financial services.

Manufacturing

Agentic AI is emerging as a key enabler of smart manufacturing, where autonomous agents coordinate production processes, optimize supply chains, and adapt to dynamic demand and resource constraints. Its applications include robotic assembly, automated supply-chain management, cognitive robotics, and human–robot collaboration for intelligent industrial operations [26]. It helps in cost-efficient wastewater treatment plant operation, multi-agent optimization of manufacturing workflows, autonomous food supply chain optimization, and self-managing manufacturing quality systems. Agentic AI promotes safe human-robot cooperation through continual learning and predictive modeling for construction collaboration and quality control [27]. It also supports deadlock-free pickup and delivery operations in complex industrial environments. Future manufacturing ecosystems may leverage interconnected agentic systems to autonomously coordinate production planning, predictive maintenance, logistics, and quality assurance. Through real-time decision-making and adaptive optimization, these systems could improve operational efficiency, resource utilization, resilience, and scalability across Industry 5.0 environments.

Smart cities

Agentic AI has the potential to offer services to the domain of smart cities for energy management and urban services, public administration, and governance. It is applied in city services optimization, energy management, and fault detection. It helps with resilient and sustainable urban management [28]. Also, it builds energy optimization and reliability enhancements [29]. Future smart cities may leverage agentic AI to coordinate transportation, energy, governance, and public services through intelligent and adaptive decision-making. By continuously responding to changing urban conditions, these systems could improve sustainability, resource management, and the overall quality of life for citizens.

Potential applications

Literature [30–32] reported various potential applications of agentic AI, which included the following key ones

Military and security. Agentic AI is applied across military and security areas in multi-agent attack defense coordination as well as AI workloads and infrastructure defense. It helps in autonomous swarm decision-making in military confrontations and moving-target defense using ephemeral infrastructure [30].

Multidisciplinary applications. Agentic AI is a multi-domain applicable approach. It is applied across multiple domains including personalized recommendations, task management, multi-agent systems, cost-effective plan caching, and others. It provides long-term memory for reflection and planning in memory augmented agent systems. It is useful in radiology and predictive crime analytics for decision support and automated scheduling. For personalized recommendations and task management, agentic AI helps in foundation model-powered multi-domain agents. Agentic AI is also applied in coding and problem-solving tasks for autonomous reasoning as well as problem solving agents [32]. It is helpful in efficient multi-set reasoning with reduced cost, long-horizon planning, and adaptation across various domains. Agentic AI helps in pricing and personalized tourism services for decision optimization in tourism [31].

Open challenges

Despite their potential, Agentic AI systems face several key challenges in their reliable and scalable deployment in the real world. To realize the vision, several technical, ethical, and infrastructural problems must be addressed. These key open challenges are discussed below:

1. **Bias against human values:** There might be some bias issues within the agentic AI, that might go against human values, ethics, and cultural beliefs. As the AI acts independently to attain its goals, it might end up making decisions contrary to the legal or moral constraints, especially when the concerned domain falls into the category of the more sensitive type, like medical or financial, among others [3,6,9].
2. **Unpredictable and unsafe behavior:** Unpredictability occurs in the self-controlled process of Agentic AI, particularly in a real-world scenario. Unpredictable conditions, information gaps, and agent component interactions may lead to risky or unplanned behavior. This is because it is difficult to authenticate, test, and regulate the agent decisions. This may cause a failure cascade in the multi-agent system [2,5].
3. **Scalability and resource constraints:** Scalability is also another challenge faced by Agentic AI since the model is computationally and energy-intensive. High-level reasoning, planning, and learning operations require too much processing power and memory. This is because the operation is practically unsuitable for real-time and large-scale tasks such as smart city and industry automation. The performance decay is also noticed when the number of agents or tasks increases [9,12].
4. **Privacy and security risks:** Agentic AI systems often handle sensitive or personal data, resulting in serious privacy and security concerns. Data collection and decision-making capabilities of Agentic AI systems create a vulnerability of data extraction, misuse, or unauthorized access of the data. Systems like Agentic AI are vulnerable to attacks and manipulations from malicious users due to cybersecurity threats [3,9,12,33].
5. **Issues of reliability and robustness:** The issue of reliability and robustness of performance under varying circumstances is a big concern when it comes to the use of Agentic AI. Such systems find it tough to handle noisy or incomplete data inputs and therefore may perform poorly or err under critical application scenarios [3,6,9].
6. **Lack of standardization:** The unstandardized nature of the benchmarks and modes of assessment makes it very challenging to openly and impartially review and compare Agentic AI systems, which makes it unsuitable for evaluation. Mostly, a lack of common assessment standards usually leads to exaggerated and false claims of performance, making it very hard to review them impartially [2,3,33].
7. **Data quality and bias issues:** The usefulness of Agentic AI relies on the data it uses during training. Datasets that are biased, incomplete, or outdated can result in biased or erroneous decision-making and, ultimately, suboptimal generalization for real-life applications. Furthermore, biased data, as a result of data science, can perpetuate social inequalities [2,3,9].
8. **Ethical and Legal Considerations:** The effective integration and coordination agent or subsystem level in Agentic AI systems remain difficult. Inappropriate collaboration, communication, or even coordination can hamper efficiency or impact overall performance. The problems can have more adverse effects in decentralized or distributed systems, affecting scalability or dependability [3,9,12,33].

Future research directions

Addressing the challenges discussed above requires sustained research efforts in multiple dimensions of Agentic AI. Future studies should prioritize the development of trustworthy autonomous systems that operate safely, transparently, and efficiently while remaining aligned with human values and societal expectations. An important research direction involves improving value alignment and ethical decision-making. Researchers should develop reasoning frameworks that incorporate ethical principles, legal regulations, and domain-specific constraints so that autonomous agents can make responsible decisions in complex environments. Another promising direction is the development of explainable and interpretable Agentic AI. Future systems should provide transparent reasoning processes, interpretable planning mechanisms, and verifiable decision-making procedures that enable users to understand, validate, and trust autonomous actions. Scalable coordination among multiple autonomous agents also remains an important research challenge. Future work should investigate decentralized communication strategies, adaptive task allocation algorithms, hierarchical coordination mechanisms, and efficient collaboration protocols capable of supporting large-scale multi-agent environments. Continuous adaptation is another key research direction. Integrating lifelong learning, meta-learning, self-improved architectures, and memory-enhanced reasoning mechanisms may enable autonomous agents to acquire new knowledge while retaining previously learned experience, thus improving long-term performance in dynamic environments. Privacy-preserving intelligence represents another promising avenue for future investigation. Researchers should explore the integration of federated learning, secure multi-party computation, homomorphic encryption, differential privacy, and other cryptographic techniques to enable collaborative learning without exposing sensitive information. Finally, future research should establish standardized benchmarking datasets, evaluation metrics, testing environments, and validation protocols for Agentic AI. Common evaluation frameworks will facilitate objective performance comparisons and support the reliable deployment of trustworthy autonomous systems in various application domains. The main future research directions discussed above are summarized in Fig 3.

Conclusions and summary

This paper addresses the critical limitations arising from the development of isolated components by proposing an integrated Agentic AI conceptual model. As illustrated in Fig 1, the coherent model brings together LLMs cores, cognitive components, operational workflows, software, and hardware interfaces, resulting in system scalability from single-agent to multi-agent. Architectural applicability is demonstrated in various sectors including healthcare, transportation, industrial systems, smart cities, and governance, as shown in Fig 2. Through Fig 3, the prospective research landscape is organized, defining future fields within technical capabilities, safety mechanisms, multi-agent synchronization, infrastructure requirements, meta-learning, and governance, thereby providing a clear pathway for researchers and practitioners to develop production-ready systems while mitigating critical barriers to practical implementation.

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