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A Survey of Agentic AI: Architectures, Reasoning, Planning, Memory, Collaboration, and Real-World Applications

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Abstract: *Agentic Artificial Intelligence (AI) is a new paradigm that allows intelligent systems to behave independently, pursue specific objectives, and adapt to changing circumstances. Agentic AI combines reasoning, planning, memory, learning, and tool utilization to do complicated tasks with minimal human involvement, in contrast to traditional AI systems that mainly react to user inputs. In this article, takes a look at Agentic AI from every angle: its theoretical underpinnings, technological supports, architectural blueprints, and real-world uses. Many models and frameworks are covered, including cognitive and modular designs, systems based on reinforcement learning, hybrid models, and multi-agent systems. Symbolic, probabilistic, and self-reflective reasoning are some of the reasoning methodologies covered. Classical, hierarchical, and adaptive planning strategies are also covered. Agents' ability to reliably and efficiently execute tasks is investigated by looking at memory management, communication protocols, coordination mechanisms, and collaborative decision-making. A wide range of business, medical, financial, academic, and personal aid apps are evaluated in the poll. Privacy, security, computational costs, scalability, and unexpected behavior are the main issues that are highlighted in the end. The study emphasizes the need for more investigation into how to create Agentic AI systems that are reliable, flexible, and effective.*

Keywords: Agentic AI, Autonomous Agents, Enterprise, Multi-Agent Systems, Memory Management, Reinforcement Learning, AI Applications

I. INTRODUCTION

The design, deployment, and conceptualisation of intelligent systems have been transformed by the fast development of Artificial Intelligence (AI) in the last several decades [1]. The field of artificial intelligence has recently progressed toward systems that exhibit greater degrees of autonomy, flexibility, and goal-directedness, in contrast to the early views of AI as a tool for automating certain jobs under heavy human supervision [2]. Along these lines, the concept of agentic AI has been gaining traction: these are systems that do more than just respond to inputs; they actively seek goals, adjust methods, and start activities in dynamic contexts [3]. The advancement of AI technology is paving the way for a revolutionary shift in the financial industry, thanks to Agentic AI. Agentic AI can observe, reason, take direct action, and even learn on its own without constant human intervention, in contrast to traditional generative AI that always relies on human inputs to produce results [4]. A watershed moment in AI history has arrived with the rise of agentic AI systems; these new creatures are able to actively seek complicated goals in chaotic settings, marking a departure from task-specific, reactive models [5]. The rise of agentic AI, defined by its ability to behave autonomously, is directly attributable to developments in reinforcement learning and large language models (LLMs) [6].

Traditional LLMs are still mostly reactive, even with these improvements. They can respond to user input by producing outputs, but they often can't remember much, plan on their own, or carry out complicated operations without human

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intervention. This shortcoming has led to the development of Agentic AI, a paradigm in which AI systems function as independent actors with the ability to perceive goals, plan multi-step actions, use external tools, interact with dynamic environments, and adjust their strategies according to feedback. Agentic AI builds on generative AI by creating fully autonomous systems that can reason, plan, maintain their memory, invoke tools, and reflect on their own actions. The agent can do more than just generate text; it may break down a high-level aim into smaller tasks, gather information from external knowledge sources, call upon APIs or software tools, assess intermediate outputs, and improve its actions until it achieves the intended target. Agentic AI is well-suited to tackle complicated real-world issues that include adaptive reasoning, collaboration amongst several specialized agents, and sequential decision-making because of these features [7].

The structure of this article is as follows: The fundamentals of Agentic AI, including its fundamental functions, enabling technologies, architectures, and difficulties, are covered in Section II. Section III delves into the following topics: reasoning, planning, memory management, multi-agent collaboration, and application scenarios. The literature on Agentic AI is reviewed in Section IV, with an emphasis on previous work, important results, caveats, and potential future paths. Section V wraps up the work and provides a roadmap for further research.

II. FOUNDATIONS OF AGENTIC ARTIfiCIAL INTELLIGENCE

Agentic AI refers to agents that may make decisions on their own, as opposed to the usual AI approach of reactively responding to user commands. Agentic AI decides on actions, orchestrates multi-step workflows, and makes real-time modifications; traditional AI obtains or creates replies. A combination of LLMs, RL, RAG, and multi-agent systems allows these systems to delegate large-scale, high-level talks with minimal human supervision [8]. These businesses are using Agentic AI to do more than just automate rules-based operations; it's also helping humans make better financial decisions.

A. The Core Triad of Agentic Artificial Intelligence Capabilities

Autonomy, flexibility, and goal-oriented planning are the hallmarks of agentic AI systems. In order to accomplish predetermined goals, these agents use perception, reasoning, action, and cooperation [9]. Their ability to think for themselves, adapt to new situations, and get things done quickly and effectively is seen in Fig. 1 below. There are four main types of agentic AI systems, each with its own unique operational approach: reactive, goal-based, utility-driven, and self-improving agents.

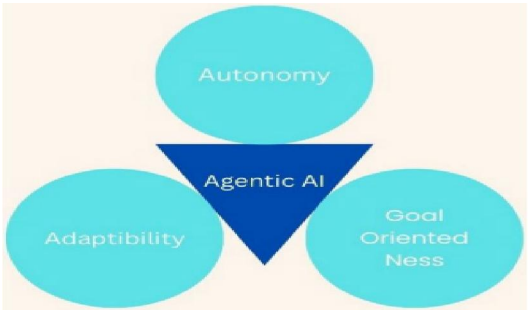


Fig. 1.Features of Agentic AI

Autonomy:

This accomplishes its goals autonomously, without the intervention of a person. The term "autonomy" is used to describe a self-driving car's capacity to sense its surroundings using sensors like lidar and cameras, analyses data about pedestrians and traffic signals in real-time, and make decisions about how to proceed around obstacles like intersections and highway lanes without any human input.

Adaptability:

This goes a step farther by allowing for incremental enhancements based on past performance. Not only does a self-

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driving car document the near-collision-causing slippery road conditions, it also actively adjusts its driving models to compensate for the lower traction.

Goal Orientation:

Organizes and carries out activities to accomplish the goals. The system does more than simply get to the specified location. It incorporates real-time traffic updates with map data. When faced with roadblocks, the automobile navigates via other routes while staying true to its initial goal.

B. Core Technologies Enabling Agentic Artificial Intelligence

Autonomous computers that can make proactive decisions and interact with complicated surroundings are the goal of agentic AI, a cutting-edge AI method [10]. Its core technologies span several areas of artificial intelligence, each of which may boast its own set of advantages:

Reinforcement Learning (RL):

Agents interact with their environment to maximize cumulative rewards, using methods like Q-learning, deep Q-networks (DQN), and policy gradients [11]. Agentic AI relies heavily on RL as it allows systems to learn how to interact with their environment in the most efficient way possible to maximize cumulative rewards.

Multi-Agent Systems (MAS):

A number of AI agents work together to accomplish goals, either individually or collectively, via interaction, communication, and coordination [12]. Emergent behaviors, cooperation, competitiveness, and negotiation are all made easier in complicated situations by MAS frameworks. When tackling problems in a distributed or cooperative setting, these agents are crucial.

Symbolic Reasoning & Automated Planning:

Agents are able to think strategically and manipulate symbols because they employ logic-based approaches and organized representations to plan action sequences [13]. Tasks requiring explicit reasoning, such knowledge representation and deductive logic, rely on symbolic reasoning, which entails rule-based systems that enable logical conclusions.

Cognitive Architectures:

AI agents that reason and adapt more naturally are created using models like SOAR, ACT-R, and LIDA, which mimic human cognition, memory, perception, attention, and learning [14]. For jobs that call for reasoning and decision-making at a high level, similar to human thinking, these designs mimic human-like cognitive processes by integrating mechanisms like learning and memory.

Natural Language Processing (NLP):

NLP facilitates integration into human-centric processes by allowing agents to interpret human language, comprehend instructions, and engage in conversational interactions [15]. Natural Language Processing (NLP) enables Agentic AI systems to understand and interpret human language, which improves their ability to communicate.

C. Architectures of Agentic Artificial Intelligence Systems

The term "artificial intelligence agent" refers to a type of computer system that can learn and adapt to its surroundings, remember and use information, reason about its goals, and act on those goals, frequently with the help of other tools, in order to achieve user intents [16][17].

Cognitive and Modular Architectures:

Processing in agentic AI is structured using autonomous logic units, which are based on cognitive and modular architectures [18]. In order to make them more scalable and adaptable, these designs segregate critical cognitive functions like planning, learning, and decision-making into autonomous modules [19].

Multi-Agent and Distributed Architectures:

The broad usage of agentic AI systems is made possible by distributed and multi-agent systems, wherein networks of cooperating agents work together to achieve common objectives. To help manage complex decisions in a collaborative

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setting, these designs employ negotiation methods, coordination algorithms, and communication syntaxes [20]. With distributed models, separate agents can work together to get a common result.

Reinforcement Learning-Based Architectures:

The body of RL-based systems is another fundamental pillar of agentic AI, since the architectures may be taught to identify optimum action structures in dynamic contexts through trial-and-error. The foundation of these systems is the use of feedback signals based on rewards to improve the system's decision-making capabilities, leading to improved performance and adaptability.

Hybrid and Hierarchical Models:

Knowledge-driven and data-driven models are combined in hybrid models, which allow the systems to manage both the flexibility of context and organized, well-reasoned judgements. A hierarchical architecture's organized decision-making procedures employ several levels, from basic perception to advanced planning, to maximize the efficiency of tasks being executed in real mode.

D. Challenges in Agentic AI

Agentic AI improves autonomy and decision-making, but it also raises a number of outstanding issues [21]. The ability of agentic AI systems to operate autonomously in an unpredictable environment gives rise to these issues. Agentic AI still has a long way to go before it satisfies human expectations for control, predictability, and value alignment.

Bias against Human Values

The agentic AI may have biases that are incompatible with human morals, ethics, and cultural norms. If the AI is left to its own devices to achieve its objectives, it might make choices that go against moral or legal principles, which is particularly problematic in highly sensitive domains like healthcare or finance.

Unpredictable and Unsafe Behavior

The autonomous operation of agentic AI introduces uncertainty, especially in practical environments. Dangerous or unforeseen activities may result from a lack of information, unpredictable circumstances, or interactions between the agent's components. The reason for this is the difficulty of verifying, testing, and controlling the agent's actions.

Scalability and Resource Constraints

Agentic AI also has problems with scalability due to the model's high computational and energy requirements. There is a severe shortage of computing power and memory for tasks involving higher-level thinking, planning, and learning.

Privacy and Security Risks

There are significant privacy and security issues with agentic AI systems since they handle personal or sensitive data. A data extraction, abuse, or unauthorized access risk exists in Agentic AI systems due to their data collecting and decision-making capabilities.

E. Main Components of Artificial Intelligence Agentic Workflows

Several interdependent components make up the agentic work processes of AI agents, as seen in Fig. 2. that enable such agents to interact with other agents, learn, make decisions, perform actions, and perceive the surrounding world. Task execution, issue resolution, and effort coordination are all made easier by these components.

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Fig. 2. Key Components of AI Agentic Workflows

- **Perception:** Artificial intelligence agents learn about their surroundings by collecting data from sensors and cameras [22]. The AI system is able to comprehend its surroundings and recognise activities at this level.
- **Decision-Making:** The AI agent processes environmental input and decides through real-time computations and learned policies. The procedure takes input from the user and uses reinforcement learning algorithms to determine the best course of action.
- **Action:** Once a choice has been made, the agent can carry out the action by breaking down the task into smaller components. Actions include changing settings, moving things, and offering replies.
- **Feedback and Learning:** AI agents gain knowledge from their actions by continuously receiving feedback on how well their decisions have worked in the past. The agents use supervised or reinforcement learning approaches to improve their strategies through feedback loops.
- **Collaboration:** Problems in AI processes are resolved by many agents working together. Operations in the factory, the supply chain, and the game are all coordinated by agents. They enhance group performance by communicating and exchanging information.

III. REASONING, PLANNING, MEMORY, COLLABORATION, AND REAL-WORLD APPLICATIONS IN AGENTIC ARTIfiCIAL INTELLIGENCE

Agentic system reasoning differs from conventional inference procedures in that it is context-driven, repetitive, and often merges with planning and action execution [23]. The frontiers of autonomous intelligence have been expanded by new paradigms of reasoning that combine symbolic logic, probabilistic inference, and techniques based on language models.

- **Logical and Symbolic Reasoning:** The foundation of both symbolic and rational logics is the use of logical operators, predicates, and rules to formalize information representations in order to draw conclusions about known facts [24]. In areas where it is necessary to portray the reasoning behind a decision, such approaches are applicable since they are standard and extensively comprehensible.
- **Chain-of-Thought and Tree-of-Thought Reasoning:** Language models follow the concept of chain-of-thought (CoT) reasoning in agentic systems such that they may reason step-by-step utilizing intermediate textual forms [25]. In order to make multi-step issues more accurate and easier to understand, CoT breaks them down into a series of reasoning steps.
- **Probabilistic and Causal Reasoning:** Probabilistic reasoning helps agentic systems cope with uncertainty by providing a model of the probability of various outcomes based on perceived information. This comes in handy, especially in unsteady settings where inaccurate or misleading feedback is prevalent.

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- **Self-Reflection and Meta-Reasoning:** Agentic systems may evaluate their reasoning process and look for ways to improve it through processes like self-reflection and meta-reasoning. These procedures provide an extra level of intelligence as the system keeps an eye on the intermediate results, finds any discrepancies, and modifies the selections.
- **Comparative Perspective on Reasoning Paradigms:** There must be trade-offs between interpretability, scalability, and flexibility due to the variety of reasoning processes. There is a lack of adaptability in unpredictable situations when using symbolic thinking, which has clarity and logical consistency. Contrarily, language model-based reasoning has greater generalizability and flexibility, but it is inconsistent and does not provide any guarantees.

A. Planning Strategies in Agentic Systems

An agent's planning includes the intermediary tasks, tactics to adopt, and implementation adjustments as time goes on. Planning is the relationship between cognition and action [26].

- **Classical Planning:** A highly organized and time-tested approach to autonomous decision-making, in which an agent calculates a sequence of actions to go from an initial state to a desired objective state [27].
- **LLM-Based Planning:** In recent years, LLM-based planning has emerged as the go-to agentic AI strategy, especially for jobs with clear, natural-language specifications that call for semantic interpretation [28].
- **Hierarchical Task Planning:** The decision-making process may be broken down into several objectives, subgoals, and actions that can be carried out by a specific agent by dividing task planning into hierarchical levels of abstraction.
- **Dynamic and Adaptive Planning:** The creation of these strategies involves allowing a goal and/or constraint (or context) to alter while execution is taking place, and agents are tasked with constantly revising their plans in response to feedback, unforeseen occurrences, or failures.

B. Collaborative Decision-Making in Agentic Systems

Advanced agentic AI systems are characterized by collaborative decision-making, in which several agents cooperate to achieve shared objectives in complex and ever-changing environments [29].

- **Multi-Agent Coordination Mechanisms:** The process entails coordinating the actions of several independent individuals to accomplish common objectives [30]. The three main types of coordinating systems are centralized, decentralized, and hybrid.
- **Communication Protocols in Agentic Systems:** Since the agents must share knowledge, intents, and intermediate results in order to coordinate actions through predetermined protocols, effective communication is crucial to collaborative decision-making in agentic systems.
- **Consensus and Negotiation Models:** Agents are able to settle disagreements and reach shared conclusions through negotiation and consensus mechanisms even when individuals involved may have conflicting goals. Consensus models aim for actors to reach an agreement by exchanging knowledge and transforming it into a consensus.
- **Distributed Decision-Making Frameworks:** Distributed decision-making models provide agents more autonomy by allowing them to work independently of a central authority while yet contributing locally to a solution on a global scale.

C. Challenges of Memory in AI Agents and Agentic Systems

The following are only a few of the numerous difficulties associated with memory in AI agents and Agentic Systems:

Scalability and Capacity Limitations

Scalability is a major obstacle when it comes to managing AI memory [31]. As agentic systems interact for longer periods of time and gain more experiences, the amount of data that has to be stored and managed increases at an

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exponential rate.

Information Quality and Relevance

The value of information might fluctuate over time, making the relevance judgement more intense in dynamic situations. Data that doesn't appear significant when stored first might end up being very vital in the future, while data that was important before could become unimportant. Further difficulties arise when dealing with data that is either missing or distorted, as well as material that is conflicting or otherwise difficult to manage.

Context Coherence and Consistency

The difficulty increases when there are several turns in a conversation or when the interaction is ongoing and the agent is required to uphold consistency with prior remarks, judgements, and promises. Consistency isn't only an issue in one-on-one communications; it also involves being consistent across encounters, situations, and even time.

Privacy and Security Considerations

Determining what data to store, for how long, and by whom is one of the biggest obstacles to privacy. Data integrity, protection from malicious modification of memory systems, and unauthorized access to stored information are all aspects of security.

D. Real-World Applications of AI Agents

AI agents are transforming industries with practical applications.

- **Enterprise Applications:** Automated business processes, decision-making, supply chain optimization, HRM, finance, and IT operations are all being propelled by AI agents. Intelligent automation is also being made possible by these agents, and customer service is being improved through personalized replies [32][33].
- **Personal Assistance:** LLMs help 51% of users learn and 24% of users work through task management, information retrieval, and personalized support, increasing productivity (54%), learning (50%), and creativity (42%).
- **Healthcare:** AI agents help with healthcare tasks such as diagnosis, medication development, and clinical decision-making; yet, there are concerns about privacy and compliance.
- **Financial Services:** Despite ongoing challenges with scalability and regulations, AI agents improve risk management by boosting trading, aiding in fraud detection, and providing customer service.
- **Education:** Promote content production and individualized coaching while addressing ethical problems related to privacy, integrity, and partiality.

IV. LITERATURE REVIEW

This section provides an overview of relevant research on Agentic AI, with a focus on agent designs, reasoning and planning processes, memory systems, multi-agent cooperation, reinforcement learning, and practical uses to enhance intelligent problem-solving, flexibility, and autonomous decision-making in a variety of creative environments.

Y. Jin et.al. (2026) give a unified synopsis of the data-centric AI groundwork. to begin, describe the steps involved in extracting, building, and fusing data in order to create organized and interpretable knowledge that can be used to make better decisions and use reasoning. Afterward, we will delve into the four ways these data-centric approaches are put into practice. The first is memory systems, which keep experience and continuity intact. The second is multiagent coordination, which allows for collaborative intelligence. The third is self-evolving agents, which improve their own knowledge and behavior. Lastly, there are safety mechanisms that guarantee privacy, trustworthiness, and reliability [34].

L. R. Alva and H. S. R. Resu (2026) Introducing Agentic Multimodal Pattern Recognition (AMPR), a system for formal reasoning and planning that integrates hierarchical decomposition, probabilistic self-checking, and dynamic cost-conscious inference based on a shared optimization issue. Unlike previous models, AMPR incorporates episodic and semantic memory to facilitate reasoning rather than relying on a single step. It is a transparent graphical reasoning system that uses latency, cost, and accuracy as constraints in an optimization issue. Using visual question responding,

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detection, classification, and segmentation as benchmarks, provide both theoretical justification and empirical results [35].

T. Ali Syed et.al. (2025) present a price-aware agentic AI system that integrates nutrition optimization with personal financial management. The algorithm takes into account household income and fixed expenditures, health and wellness status, real-time food pricing, and other factors to provide reasonably priced meal plans that are both nutritionally adequate and responsive to market fluctuations. In a modular multi-agent architecture, the framework is put into action with the help of dedicated agents that handle budgeting, nutrition, price monitoring, and health personalization, among other things. The agents pool their expertise and employ the substitution graph to keep nutritional quality high while keeping costs low [36].

M. K. K et.al. (2024) examine the theoretical underpinnings and real-world uses of Agentic AI, emphasizing how it has the potential to revolutionize a number of industries, including robotics, autonomous vehicles, finance, and healthcare. They show how cognitive architectures like ACT-R and Soar, integrated with advanced RL techniques like Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), help build AI agents that can reason and make decisions like humans by reviewing current research in detail [37].

A. M. Abdulghani et.al. (2023) investigate a conflict scenario as part of the StarCraft II Multi-Agent Challenges (SMAC) setting in order to set up a multi-agent system. A popular MARL technique, Multi-Agent Proximal Policy Optimization (MAPPO), was utilized for the training process. Collaborative goal attainment is the focus of this algorithm's navigational efforts. Then, to measure how well the MAPPO algorithm worked in the SMAC environment, two metrics were proposed: the mean of battles won and the mean of dead allies [38].

A. Fuchs, A. Passarella, and M. Conti (2022) explore the application of behavior models that are influenced by cognition to forecast the actions of agents with artificial intelligence and those without. A third party uses the expected actions and related results in relation to a predetermined objective to transfer authority between humans and AI agents. This permits us to circumvent the limitations that agents or people may have while working toward a common objective [39].

A comparison of recent research on agentic AI is presented in Table I. Agent architectures, reasoning and planning, memory systems, multi-agent cooperation, reinforcement learning, and real-world applications of autonomous intelligent agents are discussed in detail, along with the research's emphasis, techniques, important discoveries, limits, and future prospects

TABLE 1: COMPARATIVE ANALYSIS OF RELATED STUDIES ON AGENTIC AI

Reference	Study Focus	Approach / Methodology	Key Findings	Challenges / Limitations	Future Directions
Y. Jin et al. (2026)	Data-centric agentic AI	Data extraction, construction, fusion, memory, and multi-agent coordination	Supports knowledge-driven reasoning, collaboration, and reliable decision-making	Data quality, privacy, and reliability	Improve data integration, agent evolution, and safety
L. R. Alva and H. S. R. Resu (2026)	Multimodal pattern recognition	Hierarchical reasoning, probabilistic self-checking, and episodic and semantic memory	Improves accuracy-efficiency trade-offs and reasoning consistency	Balancing accuracy, latency, and computational cost	Enhances scalability and resource-efficient reasoning
T. Ali Syed et al. (2025)	Personal finance and diet optimization	Modular multi-agent system for budgeting, nutrition, price monitoring, and	Generates affordable meal plans while maintaining	Dependence on real-time prices and reliable personal data	Improve adaptability and personalized optimization

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		personalization	nutritional quality		
M. K. K et al. (2024)	Foundations and applications of agentic AI	Cognitive architectures, reinforcement learning, DQN, and PPO	Highlights agentic AI potential in robotics, finance, healthcare, and autonomous systems	Complex reasoning and practical implementation	Develop more capable and adaptable autonomous agents
A. M. Abdulghani et al. (2023)	Cooperative multi-agent decision-making	MAPPO evaluated in the StarCraft II Multi-Agent Challenge environment	Evaluates cooperation using battle-win and allied-death metrics	Coordination complexity and environment-specific performance	Improve cooperative learning and generalization
A. Fuchs, A. Passarella, and M. Conti (2022)	Human–AI collaboration	Cognitive behavior modeling and dynamic control delegation	Supports task delegation by leveraging human and AI capabilities	Accurate behavior prediction and delegation decisions	Improves adaptive collaboration and task allocation

V. CONCLUSION AND FUTURE WORK

Agentic AI is a significant step forward in the field of artificial intelligence as it allows for cooperative problem-solving, goal-oriented planning, adaptive reasoning, and autonomous decision-making. This overview looked at the building blocks of agentic systems, including ideas, architecture, reasoning, planning, memory management, and collaboration amongst several agents. Data from the research we looked at show that these technologies might revolutionise workplace operations, healthcare, finance, education, and personal support by automating tasks, improving coordination, and making better decisions. Concerns about privacy and security, processing demands, memory constraints, unexpected behaviour, and problems with sustaining dependable coordination among agents make their practical deployment problematic. Ensuring safe and successful functioning in dynamic contexts requires addressing these problems. Intelligent systems that can autonomously handle complicated processes while adjusting to new needs are within reach, thanks to the potential presented by agentic AI. The advancement of real-world adoption will depend on ongoing research into trustworthy cooperation, efficient memory methods, transparent reasoning, and resilient structures.

The development of energy-efficient, scalable agent architectures that can reliably reason, adapt, and remember should be the emphasis of future research. Collaboration between several agents can be enhanced with better protocols for coordination. Verified implementation of Agentic AI in complicated real-world applications requires more research into privacy protection, security, explainability, and human supervision.

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