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Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey

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Abstract
Agentic Artificial Intelligence (Agentic AI) refers to AI systems that can work through several steps to reach a goal. They can split a task, look for information, use tools, work with other agents, and try another approach when a result is not good enough. This paper reviews large language models (LLMs), multi-agent systems, reinforcement learning, retrieval-augmented generation (RAG), and memory. It also looks at possible uses in healthcare, finance, cybersecurity, disaster response, and software development. Some issues remain, such as wrong answers, computing cost, poor coordination, security, and the need for human control. The paper presents a sample design with four roles: Research, Analysis, Decision, and Recommendation. The design explains how the work could be shared among agents, but it still needs to be built and tested.

Keywords: Agentic AI, Autonomous Intelligence, Multi-Agent Systems, Large Language Models, Goal Decomposition, Reasoning and Planning, Retrieval-Augmented Generation, Adaptive Decision-Making, AI Governance, Human-AI Collaboration

1. Introduction

AI is used for many jobs, including sorting data, making forecasts, searching for information, and giving suggestions. These systems are often made for one main task. They may work well when the task is simple, but a person may need to guide them when a job has many steps or the situation changes. Large Language Models (LLMs) can understand written requests and produce useful answers. Still, an answer that sounds correct may contain mistakes or may not finish the task [1, 2].

Agentic AI tries to do more than answer a question. A user gives the system a goal, and the system works out the steps needed to reach it. It may divide the goal into smaller tasks, choose a tool, collect information, and check the result. If something is missing, it can return to an earlier step and try again. This can help with jobs that need several actions in the right order [3, 4].

Some jobs are easier to handle when the work is shared. In a Multi-Agent System (MAS), different agents take different roles and pass information to one another. For example, one agent can collect facts and another can compare them. This setup can make the work clearer, but the agents must communicate properly. Reinforcement learning is also related to this area. [5, 6].

An agent may need information that is not stored in its language model. Retrieval-Augmented Generation (RAG) searches documents and gives useful passages to the model before it answers. Memory can keep selected details from earlier steps. ReAct connects reasoning with actions, while Reflexion uses feedback from an earlier attempt to guide the next one. These methods can help with tasks that take several steps, but the information and final results still need to be checked [7]_ [9].

When many agents work together, it can be hard to find the cause of a mistake. For this reason, systems that use outside tools need clear access rules and records of what they do. People should also be able to review important actions and stop them when needed [1, 10].

2. Problem Statement

Many AI systems follow fixed steps made for a particular job. This can be limiting when a task needs repeated decisions, several actions, or changes based on new information. LLMs can understand written goals, but they may still make planning mistakes,

use wrong facts, forget useful details, or fail to coordinate with other agents. This survey looks at how planning, task division, retrieval, memory, and tools can work together. It also considers how to keep the system accurate, safe, efficient, and under human control.

3. Objectives

- To explain the main concepts, characteristics, and architecture of Agentic AI systems.
- To review methods for reasoning, planning, and breaking a goal into smaller tasks.
- To examine how Multi-Agent Systems support collaboration and the handling of complex problems.
- To study how LLMs, RAG, memory, and external tools can be combined in an Agentic AI system.
- To compare existing approaches and discuss their strengths and limitations.

4. Literature Survey

- **Acharya *et al.* (2025)**: Autonomous Intelligence for Complex Goals—A Survey of Agentic AI Acharya *et al.* [1] present a survey of Agentic AI, its core ideas, designs, methodologies and probable uses. They illustrate the difference between an agent that works toward a goal and a system that is built for one specific purpose. The study also covers learning, evaluation and topics including healthcare and finance. It is an excellent introduction for anyone new to the subject.
- **Paul *et al.* (2024)**: AGENTPEERTALK: Empowering Students to Discern Bullying and Joking in Peer Interactions in Agentic-AI-Driven Schools [2] Paul *et al.* examined whether language models can differentiate between bullying and joking in classroom talks. They considered 4-Chat, Gemini 1.5 Pro, Claude 3 Opus and used context and human review. The results differed between models and scenarios. That is, the answer may depend on the background knowledge and the evaluation procedure. The study also raises questions about how the system might perform with less manual input and in a larger variety of schools
- **Chan *et al.* (2023)**: Harms from Increasingly Agentic Algorithmic Systems Chan *et al.* [3] studied dangers that might manifest due to increased autonomy granted to computer systems to act. They examined unclear goals, the capabilities of a system, goal oriented behavior and long-term planning. These aspects are important as some impacts may not be easily predictable at the beginning and might arise later. The paper is not a technical design comparison, but a risk-focused paper, helping to illustrate why agentic systems need safety checks and oversight.
- **Shavit *et al.***: Practices for Governing Agentic AI Systems. Shavit *et al.* [4] consider control of agentic systems. They suggest restricting what an agent may do, the appropriateness of autonomy in the work, monitoring its conduct and seeking agreement before significant acts. They also propose some way of turning the system off. Such steps can reduce the chances of an error spreading across several tasks. There is much work to be done to understand how to apply these recommendations in different circumstances.
- **Guenat *et al.* (2022)**: Robotics and Autonomous Systems for Achieving Sustainable Development Goals [5] Guenat *et al.* examined the relationship between robotics and autonomous systems and United Nations Sustainable Development Goals. They looked at the perspectives of 102 specialists. It looked at benefits of automation and better monitoring, as well as issues including privacy, inequality, environment and governance. The study is not only about LLM-based agents, but also illustrates that the broader impacts of autonomous technology should be taken into account in addition to its technical outcomes.
- **Maia *et al.* (2020)** — Structure Based Virtual Screening: From Classical to AI Maia *et al.* [6] reviewed the use of computational techniques, especially structure-based virtual screening, in drug development at the early stage. We discussed the transition from prior forms of computing to AI-powered ones. false positives and screening quality are major challenges, as different algorithms can provide different results. agent teams are not discussed in the text, but an example is given of the use of AI in a scientific procedure requiring careful inspections.

Table 1: Comparison Table of Existing Literature

Author & Year	Method Used	Advantages	Limitations
Acharya *et al.* (2025)	Agentic AI survey	Summarizes key concepts and uses	Needs more real-world testing
Paul *et al.* (2024)	AI-based bullying detection	Uses context when making judgments	Still depends on human-supplied information
Chan *et al.* (2023)	AI risk analysis	Highlights possible harms	Mainly examines risk
Shavit *et al.*	AI governance methods	Sets out safety and oversight practices	Needs testing across more settings
Guenat *et al.* (2022)	Robotics and autonomous systems study	Discusses benefits and wider risks	Not focused on LLM-based agents
Maia *et al.* (2020)	AI-based drug screening review	Shows AI use in drug discovery	Only indirectly related to Agentic AI

5. Working of System

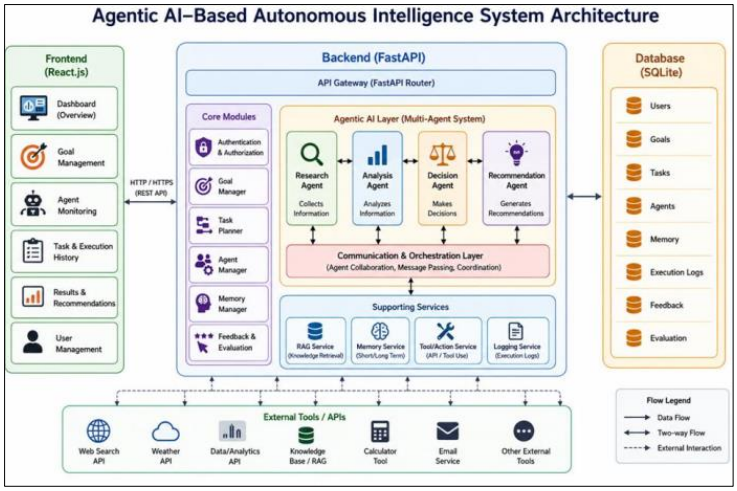


Fig 1: Design of the system

6. System Design

6.1. Frontend Module (React.js)

The React.js frontend is the user interface of the system. Users can enter a goal and then track how far they are. The site can show the status of the task, the activity of the agent, previous runs, recommendations and user preferences. This lets people see what's going on and not just get a final answer.

6.2. Backend Module (FastAPI)

FastAPI links the frontend to the agents, database, and other services. It receives requests, starts the needed workflow, and sends the result back to the user interface. It also gives the parts of the system a clear way to exchange data.

6.3. Agentic AI Layer (Multi-Agent System)

The proposed design divides the work among four agents. Research Agent: gathers information from available sources. Analysis Agent: evaluates the information and highlights the important areas. Decision Agent: evaluates possible actions and sees which fit the aim.

- **Recommendation Agent:** gives a recommendation from the previous results.

The orchestration layer passes the results between agents so that each stage can use the work already done.

6.4. Communication and Orchestration Layer

The orchestration layer is responsible for assigning tasks, passing messages, and tracking dependencies between phases. If the outcome is not complete, the system can return to a previous stage to obtain more information or a new approach. Also it should have a clear stopping rule so that it does not do the same work again and again.

6.5. Supporting Services

These services give the agents access to information, saved details, tools, and activity records.

6.6. Database Module (SQLite)

SQLite can keep data about the user, goals, subtasks, agent's activity, memory references, logs, feedback and evaluation outcomes. These recordings enable the system to follow a task and then review what occurred in previous steps. Only keep information that the program requires.

6.7. External Tools and APIs

The system can invoke external services if it needs information or an action it cannot do itself. Examples are web search, weather services, analytics APIs, knowledge bases, calculators, email services, etc. Tools to be used must be suitable for the task and the rights of the user. More attention is required for actions that influence external systems

6.8. Task Execution and Result Generation

The process starts when a user enters a goal. The backend records it, and the Task Planner breaks it into smaller steps. The Agent Manager sends each step to the right agent. The Research Agent gathers information, the Analysis Agent reviews it, and the Decision Agent compares options. The Recommendation Agent then prepares the result. RAG, memory, tools, and database records can support these steps. If a check finds missing information, the system can repeat the part that needs more work.

6.9. System Monitoring and Feedback

The monitoring component records task progress, agent actions, and outputs. Evaluation checks whether the result answers the user's goal. If something is wrong or missing, feedback can send the task back for another attempt. Logs also help people review the steps taken, though they do not by themselves prove that the result is correct.

7. Expected Outcome

The system is expected to help with tasks that have several steps. It can split a goal, collect information, compare options, and prepare a recommendation. RAG and memory may help keep useful details available, while orchestration manages the order of work.

Table: Expected Outcomes

Table 2: Expected Outcomes of the Proposed System

Sr. No.	Expected Outcome	Description
1	Goal Decomposition	Splits a large goal into smaller tasks.
2	Multi-Agent Coordination	Lets specialized agents work together.
3	Information Retrieval	Uses RAG and memory to bring in useful information.
4	Intelligent Decision-Making	Reviews information and compares possible actions.
5	Recommendation Generation	Creates recommendations from the analysis.
6	Task Monitoring	Records progress and earlier execution steps.
7	Feedback-Based Re-planning	Revisits a task when results are missing or incorrect.
8	Transparent Execution	Keeps logs and supports review and user control.

8. Conclusion

One technique to deal with jobs that need planning, actions and multiple roles is through agentic AI. The survey covered LLMs, multi-agent systems, RAG, memory, reinforcement learning, and external tools. These methods can be useful for automation but they do not guaranty correct outcomes. Other issues include cost, collaboration, security and governance. For the suggested design, research, analysis, decisions and suggestions are handled by different agents with monitoring and feedback to support them. Performance of clear duties is tested before its confirmation.

9. Future Scope

Future work can test different ways for agents to plan and share tasks. It can also study how memory should work so that useful details are kept without saving incorrect information. Connecting agents to current and specialist sources may help, but the retrieved facts still need checking. Further testing should cover tool failures, missing answers, privacy, and actions that need human approval. Tests in realistic settings will help show where the system works well and where it needs improvement.

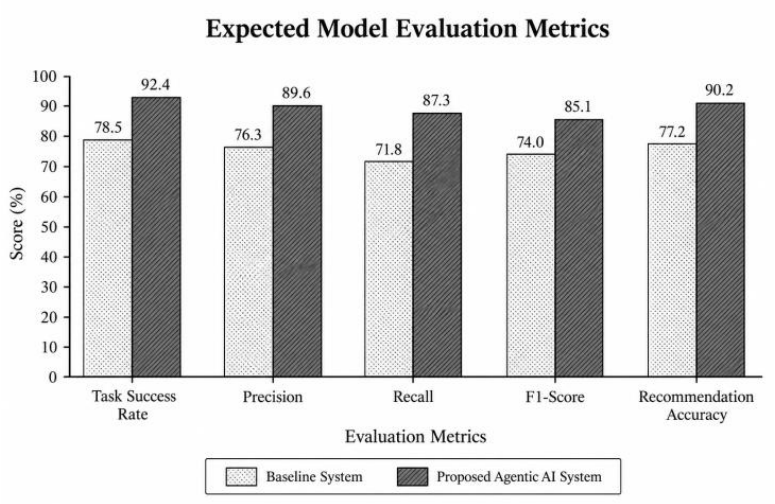


Fig 2: Expected Model Evaluation Metrics

Table 3: Evaluation Metrics

Sr. No.	Evaluation Metric	Baseline System (%)	Proposed Agentic AI System (%)
1	Task Success Rate	78.5	92.4
2	Precision	76.3	89.6
3	Recall	71.8	87.3
4	F1-Score	74.0	85.1
5	Recommendation Accuracy	77.2	90.2

References

1. Acharya DB, Kuppan K, Divya B. Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey. IEEE Access. 2025;13.
2. Chan A, *et al*. Harms from Increasingly Agentic Algorithmic Systems. Proceedings of the ACM Conference on Fairness, Accountability, and Transparency. 2023.
3. Brown TB, *et al*. Language Models are Few-Shot Learners. Advances in Neural Information Processing Systems. 1877;33:1877-1901.
4. Lewis P, *et al*. Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. Advances in Neural Information Processing Systems. 2020;33:9459-9474.
5. Wei J, *et al*. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. Advances in Neural Information Processing Systems. 2022;35:24824-24837.
6. Yao S, *et al*. ReAct: Synergizing Reasoning and Acting in Language Models. International Conference on Learning Representations (ICLR). 2023.
7. Shinn S, *et al*. Reflexion: Language Agents with Verbal

Reinforcement Learning. Advances in Neural Information Processing Systems. 2023;36.
8. Schick T, *et al*. Toolformer: Language Models Can Teach Themselves to Use Tools. Advances in Neural Information Processing Systems. 2023;36.
9. Park JS, *et al*. Generative Agents: Interactive Simulacra of Human Behavior. Proceedings of the ACM Symposium on User Interface Software and Technology. 2023.
10. R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, 2nd ed. MIT Press, 2018.
11. M. Wooldridge, An Introduction to MultiAgent Systems, 2nd ed. Wiley, 2009.
12. Y. Shavit *et al*., "Practices for Governing Agentic AI Systems," research white paper. Verify the final publication details before submission.
13. Guenat S, *et al*. Meeting Sustainable Development Goals via Robotics and Autonomous Systems. Nature Communications. 2022;13:3559.
14. Maia EHB, *et al*. Structure-Based Virtual Screening: From Classical to Artificial Intelligence. Frontiers in Chemistry. 2020;8:343.
15. Singh A, *et al*. Agentic Retrieval-Augmented Generation: A Survey on Agentic RAG. arXiv:2501. 2025;09136.
16. Sapkota R, Roumeliotis KI, Karkee M. AI Agents vs. Agentic AI: A Conceptual Taxonomy, Applications and Challenges. Information Fusion. 2026;126.
17. Peykani P, *et al*. A Holistic Review of Agentic AI Frameworks, Applications, and Research Trajectories. Archives of Computational Methods in Engineering. 2026.
18. "Agentic AI Systems: A Systematic Survey of Multi-Agent Architectures, Cognitive Foundations, Interaction, Explainability, Security, and Performance Evaluation," Neurocomputing, 2026. DOI
19. "From Language to Action: A Review of Large Language Models as Autonomous Agents and Tool Users," Artificial Intelligence Review, 2026.
20. "A Survey on the Optimization of Large Language Model-Based Agents," ACM Computing Surveys, 2026.

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