iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.82713

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

Autonomous Task-Planning Using Agentic AI: A Comparative Experimental Study

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Abstract: ***Recent advancements in Artificial Intelligence have enabled the development of intelligent systems capable of performing tasks autonomously. Agentic AI represents a modern approach in which systems act as independent agents that can analyze problems, plan actions, and execute tasks without continuous human intervention. This research focuses on evaluating and comparing different Agentic AI frameworks used for autonomous task planning. The study considers frameworks such as AutoGPT, ReAct agents, and LangChain agents. These frameworks are analyzed based on their ability to perform task decomposition, reasoning, execution, and interaction with external tools. An experimental methodology is used where predefined tasks are assigned to each framework, and their performance is measured using metrics such as accuracy, execution time, and resource utilization. The findings indicate that Agentic AI significantly improves automation and decision-making capabilities. Each framework demonstrates unique strengths, with ReAct excelling in reasoning, LangChain in tool integration, and AutoGPT in autonomous execution. This research provides valuable insights into the effectiveness of agent-based AI systems and their future potential in real-world applications.***

Keywords: Agentic AI, Autonomous Systems, Task Planning, Artificial Intelligence, LangChain, ReAct, AutoGPT.

I. INTRODUCTION

Artificial Intelligence has witnessed rapid growth over the past decade, driven by advancements in machine learning, deep learning, and large language models. Traditional AI systems are typically designed to follow predefined rules and workflows, making them less flexible in dynamic environments. As modern applications become more complex, there is a growing need for systems that can operate independently and adapt to changing conditions.

Agentic AI is an emerging concept that addresses this need by enabling intelligent systems to act as autonomous agents. These agents are capable of understanding tasks, planning actions, and executing them without constant human supervision. Unlike traditional systems, Agentic AI focuses on decision-making and reasoning, allowing machines to solve complex multi-step problems.

The integration of large language models, planning algorithms, and memory modules has significantly enhanced the capabilities of agent-based systems. These systems can interact with external tools, retrieve relevant information, and continuously refine their actions based on feedback.

Applications of Agentic AI are rapidly expanding across various domains, including robotics, healthcare, finance, and intelligent assistants. For example, autonomous agents can manage workflows, assist in decision-making, and automate repetitive tasks in organizations.

Despite these advancements, there is limited research comparing different Agentic AI frameworks. Most studies focus on individual systems rather than evaluating their performance collectively. This research aims to fill this gap by conducting a comparative experimental study of popular Agentic AI frameworks.

Agentic AI is increasingly being applied in real-world systems such as intelligent assistants, autonomous robotics, and workflow automation. These systems reduce human effort and improve efficiency by handling complex tasks independently. The growing demand for automation highlights the importance of developing and evaluating agent-based AI systems.

II. LITERATURE REVIEW

A. ReAct Framework

The ReAct (Reasoning and Acting) framework combines reasoning and action within language models. It allows agents to generate reasoning steps while simultaneously performing actions. This approach improves decision-making and enables agents to handle complex tasks effectively.

B. AutoGPT

AutoGPT is an experimental framework that enables fully autonomous task execution using large language models. It can generate goals, plan tasks, and execute actions iteratively. However, it often requires high computational resources.

C. LangChain Agents

LangChain provides a flexible framework for building AI agents capable of interacting with external tools such as APIs and databases. It supports memory and context handling, making it suitable for multi-step reasoning tasks.

D. Multi-Agent Systems

Multi-agent systems involve multiple agents working collaboratively to solve problems. These systems enhance efficiency and scalability but introduce challenges related to coordination and communication.

E. Research Gap

Although significant progress has been made in Agentic AI, there is a lack of standardized evaluation methods. Most existing studies focus on individual frameworks, making it difficult to compare their performance objectively.

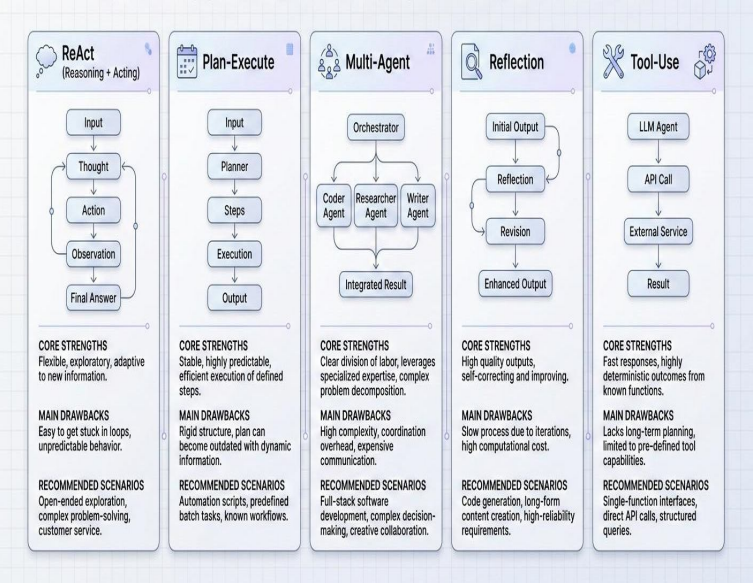

Fig. 1 Architecture of Autonomous Task-Planning System

III. PROBLEM STATEMENT

Traditional AI systems lack the ability to autonomously plan and execute complex tasks. These systems rely on predefined workflows and struggle with multi-step reasoning. Additionally, there is limited research comparing different Agentic AI frameworks. This research aims to address these limitations by evaluating and comparing multiple frameworks to determine their effectiveness in autonomous task planning.

IV. METHODOLOGY

A. Research Design

This study follows an experimental research design in which different Agentic AI frameworks are tested under controlled conditions. The frameworks selected for evaluation include AutoGPT, ReAct agents, and LangChain agents.

B. Tools and Technologies

The implementation of this research involves the use of Python programming language along with various AI tools and libraries. Technologies such as OpenAI APIs, LangChain framework, and Jupyter Notebook are used for experimentation and analysis.

C. Data Collection

The experiments involve predefined tasks such as data retrieval, code generation, and multi-step reasoning problems. These tasks simulate real-world scenarios where autonomous task planning is required.

D. Evaluation Metrics

The performance of each framework is evaluated using the following metrics:

1) Task completion accuracy
2) Execution time
3) Resource utilization
4) Reasoning efficiency

E. Experimental Setup

The experimental setup was designed to ensure a fair comparison between different Agentic AI frameworks. Each framework was tested under identical conditions using predefined tasks. The tasks included data retrieval, multi-step reasoning, and code generation.

The experiments were conducted using Python-based implementations and supported by tools such as Jupyter Notebook and AI APIs. Each task was executed multiple times to minimize variability and ensure consistency in results.

The collected data was analyzed using statistical methods, and performance metrics were calculated to evaluate each framework. This approach ensures reliability and accuracy in the comparative analysis.

V. PROPOSED SYSTEM

The proposed system is designed to evaluate the performance of Agentic AI frameworks in autonomous task planning. The process begins with a user-defined task input. The system analyzes the task and decomposes it into smaller subtasks.

Each framework processes the task using its reasoning and execution capabilities. The system records performance metrics and compares the results.

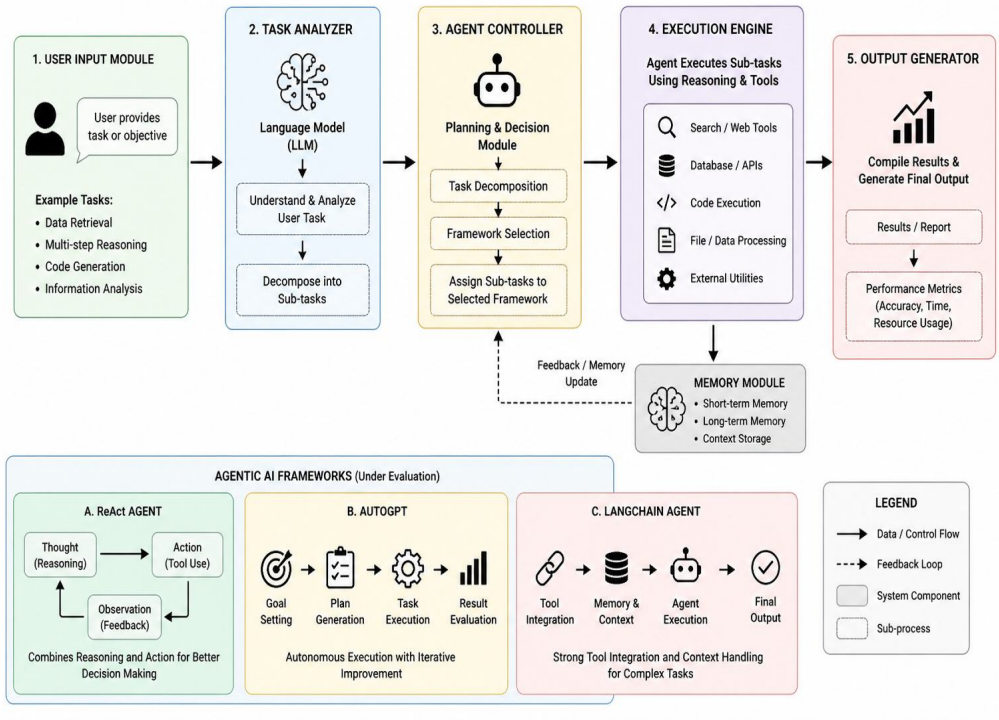

Fig. 2 Flowchart of Task Planning Process

VI. ALGORITHM

1) Step 1: Define the task or objective
2) Step 2: Select Agentic AI framework
3) Step 3: Decompose task into subtasks
4) Step 4: Execute tasks using reasoning
5) Step 5: Collect performance data
6) Step 6: Compare results

VII. RESULTS AND DISCUSSION

A. *Experimental Results*

The experiments were conducted using predefined tasks such as data retrieval, code generation, and multi-step reasoning. The performance of each framework was evaluated based on execution time and task completion accuracy.
The results obtained from the experiments are summarized in Table 1.
A detailed analysis of the results is discussed in Section 7.3.

B. *Performance Comparison*

Table 1 Performance Comparison of Agentic AI Frameworks

Framework	Execution Time (sec)	Accuracy (%)	Key Strength
ReAct	4.2	92	Strong reasoning
AutoGPT	5.1	90	Autonomous execution
LangChain	4.8	94	Tool integration

C. *Analysis*

The experimental results reveal significant differences in the performance of the evaluated frameworks. ReAct agents demonstrated strong reasoning capabilities, particularly in tasks requiring logical decision-making. The ability to generate intermediate reasoning steps allowed ReAct to perform effectively in complex scenarios. LangChain agents showed superior performance in structured tasks due to their ability to integrate external tools. This made them highly efficient in tasks involving data retrieval and API interactions. Additionally, LangChain maintained high accuracy while keeping execution time moderate. AutoGPT exhibited strong autonomy by executing tasks independently without human intervention. However, this came at the cost of increased computational resource usage and longer execution time. Despite this limitation, AutoGPT proved to be effective in scenarios requiring minimal supervision. The comparative analysis indicates that no single framework is universally optimal. Instead, the effectiveness of each framework depends on the type of task being performed. This highlights the importance of selecting the appropriate framework based on specific requirements.

D. *Graph Analysis*

A graphical representation of the results was used to compare execution time and accuracy across different frameworks. The graph shows that LangChain achieves the highest accuracy, while ReAct maintains consistent performance across tasks. AutoGPT, although slightly slower, demonstrates strong autonomous capabilities.
The analysis confirms that Agentic AI frameworks outperform traditional AI systems in handling complex multi-step tasks.

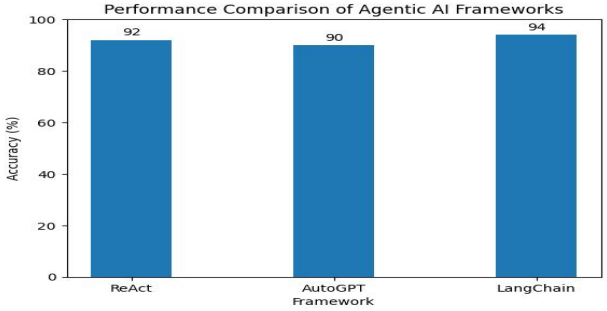

Fig. 3 Performance Comparison of Agentic AI Frameworks

VIII. CONCLUSION AND FUTURE SCOPE

This research highlights the growing importance of Agentic AI in modern intelligent systems. The comparative study demonstrates that autonomous agents significantly improve task planning and execution efficiency.

Each framework offers unique strengths, and their performance varies depending on the nature of the task. ReAct is suitable for reasoning tasks, LangChain excels in structured environments, and AutoGPT is ideal for autonomous execution.

Future research can focus on developing hybrid systems that combine the strengths of multiple frameworks. Improvements in memory management, reasoning capabilities, and resource optimization can further enhance the performance of Agentic AI systems.

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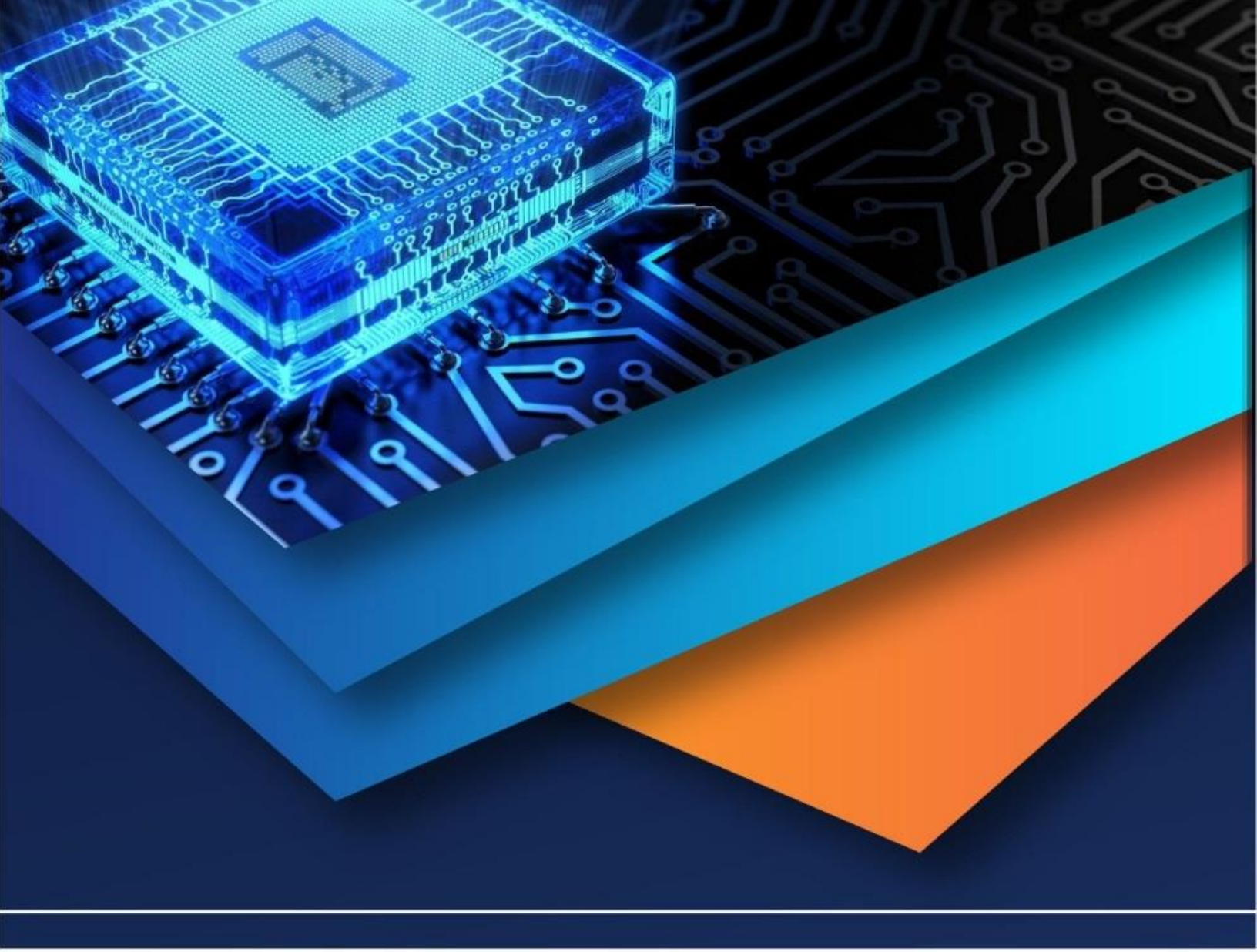

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