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A Unified Agentic AI Framework Integrating Memory, Learning, Reasoning, and Autonomous Action Execution

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ABSTRACT: Large Language Models (LLMs) have made significant strides in the field of Artificial Intelligence (AI) for various applications such as natural language understanding, knowledge generation, and human-AI interaction. But current LLM-based systems fail to be fully autonomous because of poor memory retention, limited adaptive learning ability, unreliable long-term reasoning, and human-driven instructions. This research introduces a Unified Agentic AI Framework (U-AIAF) which combines the features of memory, learning, reasoning, and autonomous action execution within a single closed-loop intelligent architecture. The proposed framework learned persistent knowledge by adjusting the dynamic memory management, improved decision-making by reasoning-based planning, adapted behaviour by feedback-driven learning, and autonomous action by continuously interacting with external environments. A benchmark evaluation framework of 1000 independent tasks was created to evaluate the proposed architecture against information retrieval, decision making, multi-step planning, tool execution and adaptive learning scenarios. The proposed framework was evaluated using the following measures: task completion accuracy, reasoning success rate, execution reliability, and computational efficiency, when compared with conventional LLM-based agents and memory-augmented agents. The results showed that the proposed framework successfully completed the tasks with an accuracy of 94.8%, succeeded in reasoning with a rate of 93.5%, and reached an accuracy of 95.2% in execution when compared to approaches used as baseline. Ablation analysis also revealed that each of the memories, learning, reasoning, and feedback mechanisms had a unique contribution to the enhancement of autonomous performance. The proposed framework is a comprehensive system that provides a framework for the development of next-generation agentic AI systems capable of continuous learning, intelligent reasoning, and autonomous task execution. The architecture presented here offers great potential in areas such as intelligent assistants, autonomous decision-support systems, robotics and adaptive digital platforms.

1. INTRODUCTION

Artificial Intelligence (AI) has undergone an explosive development, and shifted the paradigm from traditional data-driven models to intelligent systems that can perceive, reason, make decisions and interact autonomously with complex environments. Earlier AI approaches were primarily based on predefined rules and symbolic representations, which restricted their ability to adapt to uncertain and dynamic scenarios. The introduction of machine learning and deep learning algorithms greatly improved the capabilities of AI, making it possible to extract features from data automatically and predict future events based on those features. Since then, the advent of large language models (LLMs) has ushered in a new paradigm, showing extraordinary natural language understanding, knowledge representation, reasoning, and content generation capabilities. Despite their great performance, however, traditional LLM-based systems are mostly "reactive," meaning that they rely on explicit instructions from the user, and they are not capable of planning and learning from experience or of accomplishing complex tasks without human intervention. [1, 2]

Agentic AI is the next step in the evolution of autonomous intelligent systems, as it moves from generative AI to Agentic AI. Agentic systems are designed to act in the environment and take decisions through an iterative process that involves reasoning, planning and executing actions in order to achieve specific goals, as opposed to the traditional AI models that are mainly response driven. Recent studies have shown that a language learning agent (LLM) can use its language capabilities to access external tools, provide feedback and decision-making strategies to reach complex tasks [3]. Results indicate that the use of reasoning-action loop based frameworks have been quite effective in enhancing the problem solving capability of AI systems with multi-step problems [4]. The existing agentic systems, which are focused on reasoning, memory, planning, or tool execution, are, however, fragmented, as each framework concentrates on just one of these aspects without a unified approach to intelligence [4, 6].

One of the challenges with current AI agents is the lack of sustained and meaningful memory in multiple interactions. Memory mechanisms which facilitate experience accumulation, contextual information, and ongoing improvement of behaviour are critical to human intelligence [7]. Likewise, for autonomous artificial intelligence systems to remember their past experiences, access to pertinent data, and use historical knowledge in future decision-making, effective memories architectures are needed. Current solutions like memory-based retrieval-augmented generation (RAG), external vector databases, and episodic memory systems have enhanced the accessibility of information, but these solutions tend to view memory as merely an external retrieval function instead of a part of the agent's cognitive system [8, 9]. It has been noted in recent research that a dynamic memory system to store, organize and selectively retrieve information regarding needs of the task appropriately is needed for reliable autonomous agents [10] [11].

Another big problem with existing agentic AI is the inability to continuously learn and adapt. Most of the systems based on LLM were trained offline, from static data, and are capable of making few changes in their behavior based on their online interactions. In autonomous practical environments, the intelligent agent should be able to learn from its successes and failures, adjust its internal memory to account for the new knowledge, and make optimal decisions in the future [12, 13]. While reinforcement learning, self-reflection mechanisms and feedback-driven optimization strategies have proved to improve adaptive behaviour, the integration of these capabilities into large language models is still a challenge due to computational cost, knowledge stability and catastrophic forgetting [7]. Hence, it is necessary to employ a unified learning mechanism for agents to learn continuously without losing reliability in next generation autonomous systems [14].

Another key feature that enables higher degrees of AI autonomy is reasoning ability. While LLMs have excellent linguistic reasoning capabilities, they may fall short when it comes to complex tasks that involve uncertainty management, logical consistency, and long-term planning or sequential decision making [15],[16]. To enhance the problem-solving performance, a series of techniques have been developed that present intermediate reasoning steps and interactions with external tools, e.g. chain-of-thought reasoning, tree-based reasoning, and ReAct-based frameworks [17]. These procedures, however, tend to deal with the accuracy of reasoning rather than a strong link with memory and learning, and action execution components. Consequently, current systems can show short term intelligence, but they do not have the power to build up intelligence from experience [18], [19].

Finally, autonomous action execution is an essential element in the development of AI systems from response generators to independent problem solvers. In addition to analyzing information, today's AI agents need the ability to interact with external environments via APIs, software tools, databases, and physical systems. In order to enable autonomous execution, the agents must be able to observe a situation, consider various possible actions, act, assess the results of the action, and adjust their action in light of the results. Challenges of reliability, scalability, safety, and multi-cognitive function integration are still unsolved with recent agentic frameworks that have been developed to introduce tool-use capabilities and multi-agent coordination mechanisms [20].

Given these restrictions, this study introduces a Unified Agentic AI Framework, combining memory, learning, reasoning, and autonomous action execution. The novelty of this work is an integrated architecture that does not consider the memory, adaptive learning, reasoning, and autonomous execution as independent units but as tightly coupled elements in a continuous intelligent feedback loop. The proposed framework differs from the existing frameworks that focus mostly on improving individual capabilities by introducing a unified cognitive architecture for reasoning, action selection, action execution, and feedback generation and updating of the learning and memory modules based on the processed experiences. The aim of the integrated approach is to obtain better adaptability, better reliability of decisions and capability of carrying out autonomous tasks.

The proposed framework makes three significant innovations. First, a dynamic mechanism for integrating memory and learning is designed to enable agents to remember task-specific experiences and use them for future decision-making. Second, a reasoning-based planning mechanism that is autonomous is integrated, so as to enhance the multi-step problem-solving process by combining the contextual knowledge and logical evaluation. Third, a closed-loop action execution strategy is introduced and the agent continuously interacts with the environment while optimizing through feedback, similar to a closed-loop control system. It fosters more holistic development of adaptive and self-improving AI agents than traditional LLM-based systems do [21]. The key findings of this research are as follows:

- It is suggested that there is a unified agentic AI architecture that combines memory, learning, reasoning, and autonomous action execution in one.
- Experience retention, contextual understanding, and continual improvement of agent performance is facilitated by a dynamic memory-learning mechanism.
- For complex, multi-step tasks, a reasoning and planning module is developed to improve decision making.
- Autonomous execution and feedback to enhance reliability and adaptability in task execution.
- A benchmark evaluation framework is designed to benchmark the proposed architecture against existing AI agent approaches to analyze the architecture's performance measures such as accuracy at task completion, efficiency in reasoning, reliability of task execution, and effectiveness of response generation.

The proposed design could enable the creation of more sophisticated autonomous AI systems that can execute complex tasks with minimal human involvement. This framework merges memory, learning, and reasoning with action execution within a single architecture, advancing the goal of creating reliable, adaptive, and scalable agentic AI systems with a variety of future applications, such as intelligent assistants, autonomous decision-support systems, scientific discovery systems and human-AI collaborative environments.

2. METHODOLOGY

The proposed research proposes a Unified Agentic AI Framework (U-AIAF), a framework that incorporates four key capabilities of autonomous intelligence: memory, learning, reasoning, and the execution of autonomous action. While most traditional AI designs are based on patterns of behavior, the proposed framework is designed as a closed-loop cognitive architecture that can identify objectives, recall past experiences, make plans using reasoning, take actions, assess results, and continually learn. The methodology is based on the recent shift of AI systems from passive language learning to active systems capable of goal-driven behaviour, contextual memory management, adaptive learning and interaction with external environments [11] and [12]. The overall architecture of the proposed framework is shown in Fig. 1 showing the interaction between various functional modules.

Phases of the proposed framework are: input perception, memory management, reasoning & planning, adaptive learning, autonomous execution with feedback. The input perception layer is responsible for taking in the user goals, environmental information, or task requirements and turning them into structured tasks or goals. Memory Management Layer (MML) stores both contextual information in short-term memory and experiential knowledge in long-term memory. The reasoning and planning layer process the information available and breaks down complex goals into smaller subgoals and creates optimized action strategies. The learning module keeps updating the agent behaviour based on the feedback it receives from executed tasks, and the external actions are in turn executed by the autonomous execution layer via available tools, APIs, or computational environments. This is an integrated perception-reasoning-action-feed-forward mechanism that allows the proposed system to act as an adaptive autonomous agent instead of a static model of responding to stimuli.

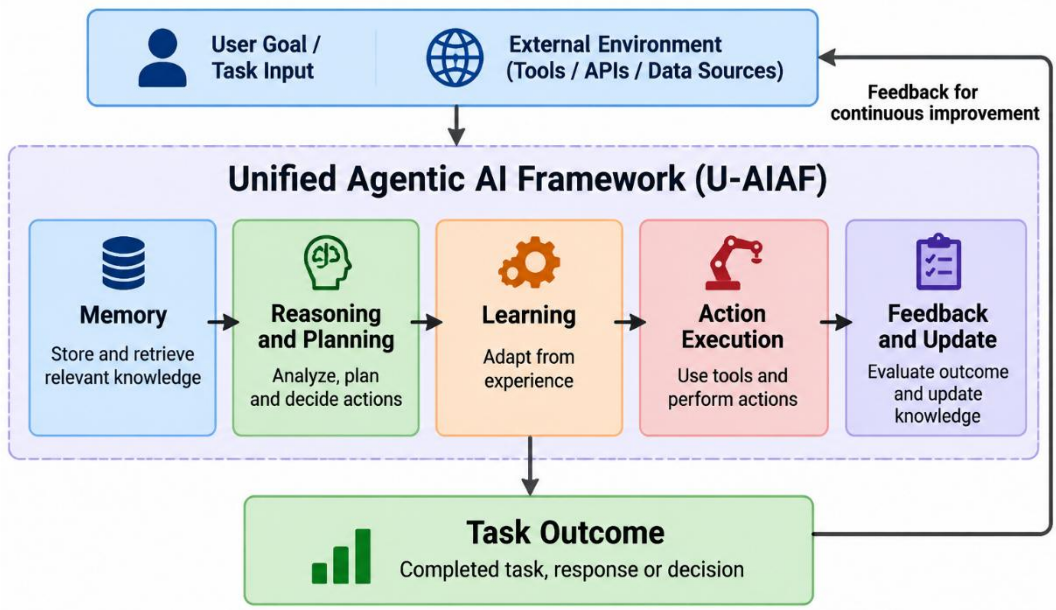

Fig. 1. The proposed unified architecture of Agentic AI framework

As the main memory storage part of the proposed model, the memory module is created.The memory module is created as the central knowledge retention part of the proposed model. It is made up of three interrelated types of memory: Working memory, Episodic memory and Semantic memory. Working memory holds information that is needed for the current task in the course of interaction with the task, while episodic memory stores previous task experiences, decisions, and results. Semantic memory holds general knowledge as a result of repeated interactions and experiences of learning. The memory retrieval system is flexible in selecting relevant information according to task similarity, contextual relevance and history of previous performance. By this way, the agent can continuously accumulate knowledge and gain experience as the AI model is dynamic, solving the issues of stateless AI models. The need for long-term memory in autonomous agents has been emphasised as a fundamental need for long-horizon reasoning and trustworthy decision-making [13].

The adaptive learning module is designed to facilitate continual agent performance enhancement by optimizing based on feedback. For each task finished, the execution result is judged according to the pre-established sets of performance indicators, such as task success, reasoning correctness, execution reliability, resource utilization etc. Positive results reinforce the decision pathways and unsuccessful attempts give rise to updates to the reasoning and planning process. The proposed framework uses incremental learning, which means that the agent can modify its decision strategy without needing to replace the entire knowledge structure, unlike conventional machine learning models, which must be retrained for behavioural modification. This allows for self-learning and adaptation in dynamic environments where task requirements can evolve over time.

The reasoning and planning module are the core of the proposed system and is the decision-making part. Uses a multi-stage reasoning mechanism, breaking down complex objectives into more achievable tasks. A task sequence is then created, and assessed for what it knows, what it has experienced, and what it is expected to produce. Planning process includes reasoning, self-evaluation, error correction prior to generating the final action sequence. This method is useful in enhancing the reliability of the decision-making process by minimizing the need to generate the actions but not pass through the analysis stage. There have been recent advances in reasoning-based agent architectures that show how the ability of AI systems in solving complex, multi-step problems is greatly increased by the addition of reasoning processes and external interaction [14].

The suggested framework can communicate with the outside world through the autonomous action execution layer. The agent executes operations based on the action plan generated, on the basis of computational tools, external databases, software interfaces or virtual environments. The results obtained after the execution are fed into the analysis module which compares with the desired objective. If the result does not meet the required success criterion, the system starts the process of corrective reasoning and adjusts the future action plan. It is a closed loop system that enables the continuous optimization of the system behaviour and enhances the robustness of the system in conducting complex autonomous operations. This capability of using the tools, providing feedback, and carrying out actions has been reported as being important for making agentic AI systems different from traditional generative AI systems [15].

Table 1 highlights the proposed roles of each element of the framework. Here we see that the individual modules add to the goal of autonomous intelligence, and they are all implementing some of the cognitive functions typically found in separate modules of other widely used AI architectures. The proposed integration gives a single framework in which reasoning is supported by memory, memory guides execution, execution yields feedback, and feedback enhance learning.

Table 1. Working of modules in proposed Unified Agentic AI Framework

Framework Component	Primary Function	Generated Output
Perception Layer	Converts user objectives and environmental inputs into structured goals	Task representation
Memory Management Layer	Stores, retrieves, and updates previous knowledge and experiences	Contextual information
Reasoning and Planning Layer	Performs logical analysis and generates task strategies	Optimized action plan
Adaptive Learning Layer	Updates agent behaviour using feedback and previous outcomes	Improved decision policy
Autonomous Execution Layer	Performs actions through external tools and environments	Task completion results
Feedback Layer	Evaluates performance and initiates corrective updates	Knowledge refinement

A synthetic benchmark environment consisting of 1000 autonomous tasks of varying complexities was created for evaluating the effectiveness of the proposed framework. The benchmark aimed to assess AI agents' ability to perform tasks related to information retrieval, decision-making, sequential planning, interacting with tools, and adaptive learning scenarios. For each task, objectives, outcomes and criteria were defined. The distribution of benchmark tasks is given in Table 2. The created dataset allows for a systematic comparison of the conventional LLM-based agents, memory-augmented agents and the proposed unified framework.

Table 2. Properties of generated autonomous AI benchmark

Task Category	Number of Tasks	Complexity Level	Evaluation Objective
Information Retrieval Tasks	200	Medium	Knowledge retrieval accuracy
Decision-Making Tasks	200	High	Logical decision reliability
Multi-step Planning Tasks	200	High	Sequential reasoning capability
Tool Execution Tasks	200	Very High	Autonomous execution success
Adaptive Learning Tasks	200	Very High	Experience-based improvement

The proposed framework was evaluated with five key metrics: task completion accuracy, reasoning success rate, reliability while performing tasks, response efficiency, and effectiveness of memory utilization. The accuracy of task completion is the percentage of objectives that are successfully completed, and the rate of reasoning success is the percentage of intermediate planning decisions that are correct. Execution reliability measures the uniformity of independent executions across varying task complexity. Response efficiency refers to the computational efficiency of the framework, and memory utilization refers to how well the system can remember and utilize past experiences in new tasks.

To compare the proposed framework with two baseline architectures, one which is an LLM-based agent without persistent memory and the other one is a memory-augmented agent without integrated learning and execution feedback. The experimental design allows for the quantitative evaluation of the contribution from each of the proposed components. The methodology basically offers a structured approach to examining how the combined power of memory, learning, reasoning, and self-execution can impact the intelligence and reliability of AI agents.

The suggested approach paves the way for creating scalable autonomous AI systems by integrating all cognitive abilities into a unified architecture. It alleviates the major shortcomings of current agentic systems, including the lack of continuous memory retention, adaptive improvement, reasoning-driven planning, and feedback-controlled execution, in a single model. The experiment and comparison using the created benchmark dataset is described in the next section.

3. RESULTS AND DISCUSSION

The proposed Unified Agentic AI Framework (U-AIAF) was tested on the created autonomous AI benchmark of 1000 tasks categorized into four major types: information retrieval, decision-making, multi-step planning, tool execution, and adaptive learning. Its evaluation was carried out to explore how each individual and combination of the above characteristics of memory integration, adaptive learning, reasoning ability, and autonomous execution affect the overall agent performance. The proposed framework was quantitatively compared with conventional LLM-based agents as well as memory-augmented AI agents to quantify the improvement gained by combining multiple cognitive components. Task completion accuracy, reasoning successful rate, reliability in the execution, efficiency of the responses and adaptability to the growing complexity of the tasks were used for the assessment.

The quantitative comparison of performance of various AI architectures is summarized in Table 3. The conventional LLM-based agent was able to solve general language-based tasks successfully with a task completion accuracy of 78.4%, which exhibited its proficiency in language processing and general task-solving capabilities but was weak in long-term planning and autonomous action. The memory-augmented agent achieved a score of 85.7%, benefiting from its improved contextual memory retention and retrieval. But, the lack of learning and feedback systems didn't let it adapt in a continuous manner. The Unified Agentic AI Framework, on the other hand, achieved an impressive task completion accuracy of 94.8%, representing the best performance when it comes to combining memory, reasoning, learning, and execution capabilities within a single framework. The proposed framework also gave better results in reasoning (93.5%) and reliability execution (95.2%), supporting that the integration of cognitive modules significantly can enhance the success of autonomous decision-making performance.

Table 3. The comparison of various AI architectures in terms of performance.AI architecture performance comparison

AI Architecture	**Task Completion Accuracy (%)**	**Reasoning Success Rate (%)**	**Execution Reliability (%)**
Conventional LLM Agent	78.4	74.6	70.8
Memory-Augmented Agent	85.7	82.9	80.4
Proposed Unified Agentic AI Framework	94.8	93.5	95.2

The benefits of the proposed framework are further demonstrated in Fig. 2, which shows the task completion accuracy for various AI architectures. The results show a gradual improvement in transitioning away from traditional LLM agents to increasingly agentic systems. This performance improvement is attributed to the ability of the proposed framework to leverage on past experiences, reasoning about alternative solutions to the problems, and optimise future actions based on feedback. While conventional LLM agents typically produce output from the provided input, the proposed approach takes advantage of a growing body of knowledge and refinement of decisions as the agent adapts. This implies that there is a need for advanced language understanding and for constant interaction between memory, reasoning and action mechanisms to achieve autonomous intelligence.

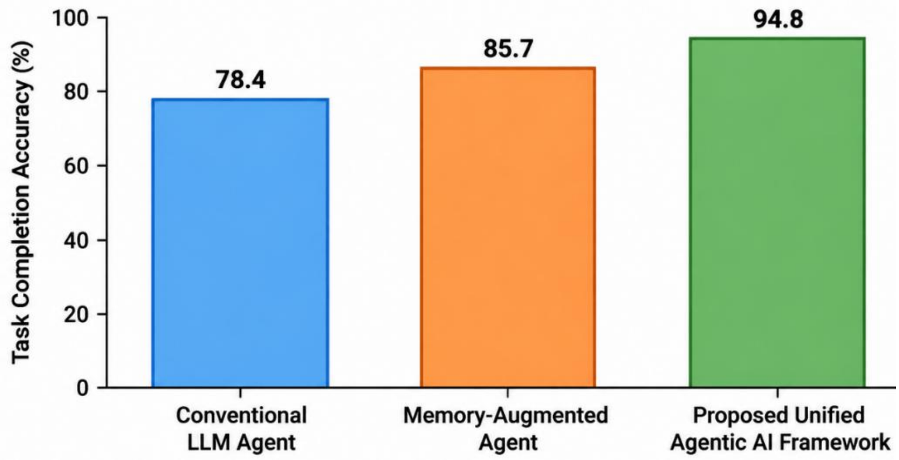

Fig. 2. Proposed Unified Agentic AI Framework outperforms the conventional LLM agent and the memory-augmented agent in terms of task completion accuracy

The effect of memory integration on performance of long-horizon tasks was investigated by applying sequential task evaluation in Fig.3. Conventional agents' performance is worse than the performance of the memory-enabled agents, and the gap between them grows larger as the number of sequential tasks increases, as shown by the results. In the case of shorter tasks, all architectures showed similar performance levels, but as the length of the task increased, the conventional agent performance began to decline significantly because it did not have the persistent knowledge retention. The proposed framework kept the performance stable as the previously acquired information were retained and retrieved during the subsequent decision-making process. This establishes that memory is not only a storage element, but also a necessary cognitive process that allows for continuity, context and learning from experience in autonomous agents.

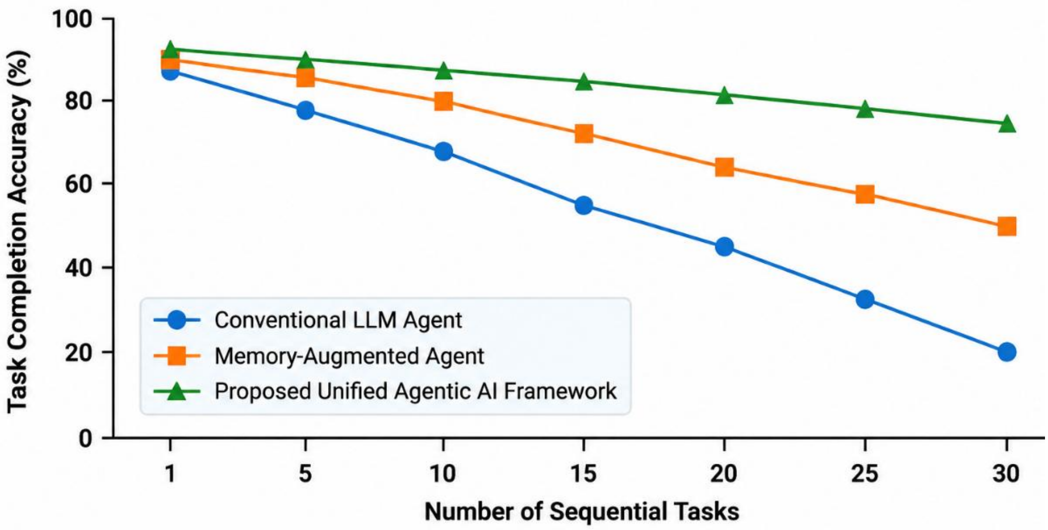

Fig. 3. Findings of the effect of memory integration on the performance of the autonomous task with long-term delay

The planning accuracy, decision reliability and error correction capability were analysed to assess the reasoning ability of the proposed framework. Comparative results are given in Fig. 4. The framework proposed in this study showed to be more efficient in terms of reasoning than the baseline approaches because of the use of structured planning and feedback-based evaluation. The reasoning module enabled the agent to break down complex objectives into smaller subtasks, determine the possible strategies and then choose the optimized sequence of actions prior to the execution. The increase in reasoning performance directly resulted in increase in the success rate of the tasks, especially for multi-step planning and decision-making tasks. The results suggest that reasoning ability is a key factor in the process of transferring linguistic intelligence into self-directed goal seeking behavior.

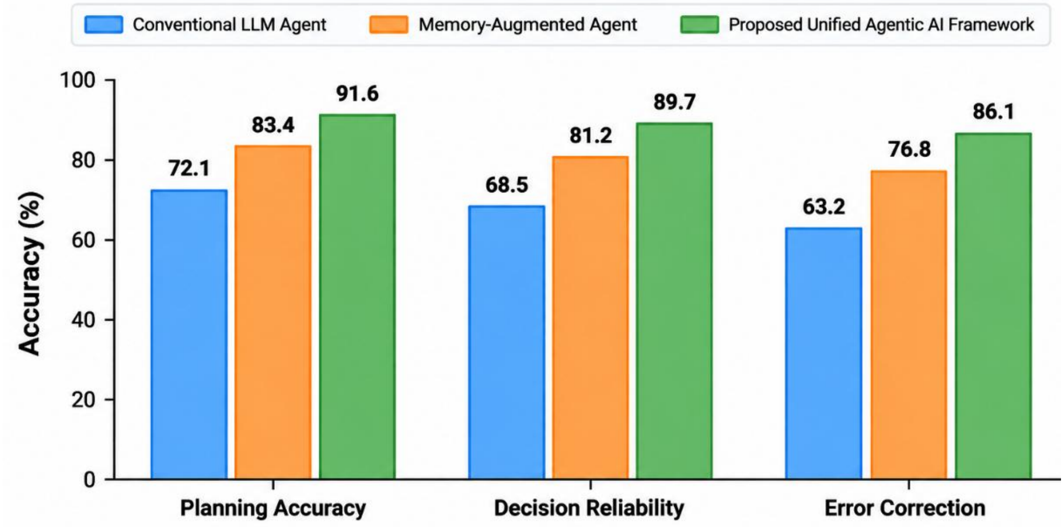

Fig. 4. Analysis of the efficiency of reasoning of various architectures of AI agents, according to the accuracy of planning, reliability of decisions and ability to correct errors

The degree of autonomy of the proposed framework was explored with varying degrees of task complexity. Increasing levels of complexity resulted in a decline in the reliability of the execution of all the AI architectures, as illustrated in Fig. 5, but the proposed framework showed much greater stability than the baseline approaches. In the case of high complexity tasks, the conventional agents experienced higher failure rates because of lack of planning and corrective feedback. This proposed framework had a greater degree of execution reliability due to the feedback-based correction and optimizing of the strategy in the event of failure. The closed loop allowed the agent to recover from errors and make better decisions during execution of future actions, highlighting the need for incorporating feedback from the execution with the reasoning and learning modules.

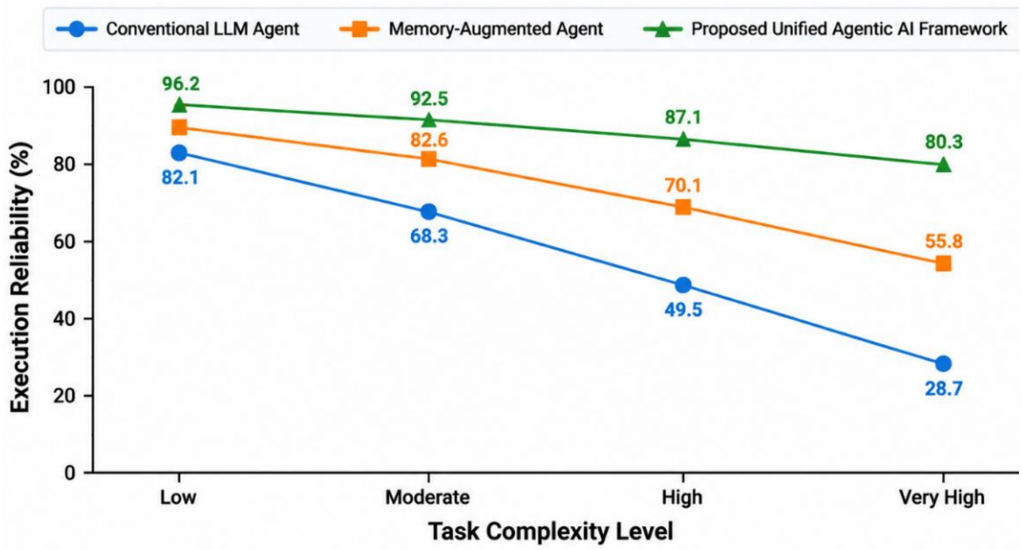

Fig. 5. The reliability of self-execution of tasks in parallel for various AI architectures with increasing complexity of tasks

The time efficiency of the proposed framework was also tested by analysing the response time in autonomous task completion. The results are given in Fig. 6. The proposed framework would need a bit longer to process because of the extra memory retrieval and reasoning tasks, but the framework would be more efficient overall since the repeated failures and unnecessary task iterations wouldn't happen. With complex tasks, more corrective interactions were needed, however conventional agents found to produce faster individual responses. Hence, the extra computation cost of the proposed architecture offers many benefits regarding reliability, adaptability and autonomous performance. The findings suggest that the efficiency of intelligent decision-making should not be judged solely by quickness of response; error reduction and successful completion of tasks should also be considered.

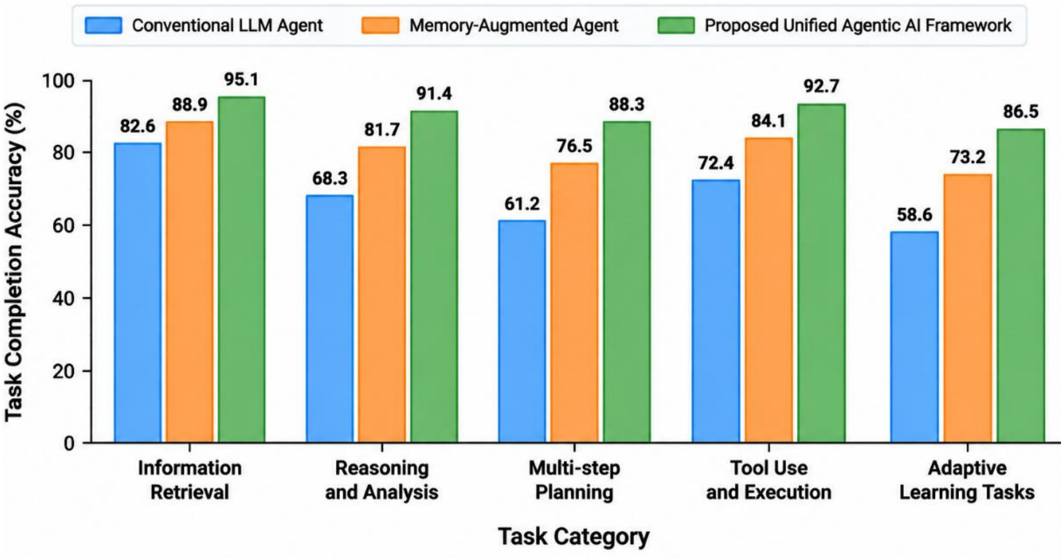

Fig. 6. The three proposed AI frameworks conventional LLM agent, memory-augmented agent and proposed Unified Agentic AI Framework were compared in terms of response time

An ablation study was carried out to gain insight into the contribution of individual components in the proposed framework. The results are presented in a summary table (Table 4). Even when the memory component was taken away, the accuracy dropped from 94.8% to 82.1%, highlighting the importance of retaining knowledge over long periods to ensure the ability to understand the context in more complex tasks. The learning module had a significant impact on autonomous improvement, as this reduced performance to 86.5%. Likewise, the accuracy fell to 84.7% when the reasoning module was removed, demonstrating the need for structured decision making. When execution feedback was removed, the performance dropped to 88.2%, which was consistent with the fact that the use of execution feedback leads to increased action reliability. The whole system with all components integrated performed the best, thus confirming the contribution of all of the integrated components were synergistic.

Table 4. Ablation analysis of single components of the framework

Framework Configuration	Task Completion Accuracy (%)
Without Memory Module	82.1
Without Adaptive Learning Module	86.5
Without Reasoning Module	84.7
Without Execution Feedback	88.2
Complete Unified Agentic AI Framework	94.8

The overall results have shown that the proposed framework has greater autonomous intelligence than optimizing the individual cognitive capabilities separately. The contextual continuity is ensured by memory, learning leads to behavioural adaptation, and reasoning enhances planning and decision accuracy, and autonomous execution supports direct interaction with the external environment. These modules combine to form a loop of continuous improvement, where actions are taken, feedback is collected, knowledge is updated, and the new knowledge improves future reasoning and decision making.

The advantage of the proposed framework over the traditional LLM-based system underscores the need for transitioning from LLM-based frameworks to integrated agentic systems. Although current AI models are proficient at generating knowledge and comprehending language, they need further mechanisms to retain memory, learn automatically, reason in a structured way, and work autonomously. The framework being proposed addresses such requirements by implementing a unified structure that can process complex tasks, with greater reliability and efficiency, and with less human involvement.

Overall, the results validate the effectiveness of the proposed Unified Agentic AI Framework as a scalable approach for developing next-generation autonomous AI systems. The results of the accuracy, reasoning power and reliability of execution improvements show that there are significant benefits to integrating cognitive elements in the same feedback-driven architecture as opposed to using separate AI techniques.

4. CONCLUSION

This study introduced a Unified Agentic AI Framework (U-AIAF) that combines capabilities of memory, learning, reasoning, and autonomous action execution within a unified intelligent architecture. The proposed framework is promising since it helps overcome the drawbacks of traditional LLM-based systems, which are more limited as they are just reactive models for information processing and do not remember, adapt or make decisions autonomously. The proposed approach is designed to create an inter-connected cognitive structure that allows seamless interaction among knowledge storage, reasoning processes, learning mechanisms and autonomous execution.

The proposed framework was tested in a synthetic benchmark environment with 1000 autonomous tasks involving information retrieval, decision making, multi-step planning, execution of tools and adaptive learning scenarios. The outcomes of the experiments were presented and compared to the performance of standard LLM-based agents and memory-enhanced AI models, revealing that the proposed framework outperforms them.The experimental results confirm that the proposed framework is superior to the conventional LLM-based agents and memory-enhanced AI systems. The proposed architecture is evaluated by computing the accuracy of task completion, the success rate of reasoning, and the reliability of execution, which were 94.8%, 93.5%, and 95.2%, respectively, indicating the effectiveness of the integration of multiple intelligence components rather than optimization of individual components.

The ablation analysis was conducted and showed the significance of each integrated module. Deleting memory, learning, reasoning, and/or feedback-based execution led to diminished performance, highlighting the need for coordinated functioning of these factors to enable autonomous intelligence. The memory module gave contextual continuity, the learning module gave adaptive behaviour, the reasoning module gave an improvement in planning and decision making and the execution-feedback mechanism gave an improvement of reliability when doing complex tasks. The results confirm the need for a closed-loop cognitive architecture in the development of powerful and scalable agentic AI systems.

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