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Contextual Frameworks for Agentic AI: Engineering Adaptive Memory and Retrieval Mechanisms

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Abstract
In fast-paced, strongly regulated settings, traditional AI agents face systemic difficulties because of their rigid memory structures and limited retrieval methods. Because of how traditional models work, the system won't be able to adapt and iterate as quickly as it needs to, especially in a fast-paced environment. It's even harder to reconcile changes that come from a name appearing in external documents with changes that need to be made to regulatory obligations as laws and regulations change and modernize. When the context changes, agents that use conventional models have a harder time adapting and breaking things down. This leads to poorer throughput, less responsiveness, less contextual awareness, and a higher chance of noncompliance. To address the aforementioned issues, a system has been developed that integrates dynamic memory components with carefully researched enhancements to retrieval methodologies. This basically lets the agent better understand a wider picture while also helping it recall previous and future iterations in a more useful and effective way. Dynamic memory qualities enable agents to exhibit enhanced responsiveness, contextual awareness, and the capacity to make safe, regulatory-compliant judgments based on information; crucially, our system is designed to learn. Agent is a definition that doesn't have a time restriction. Agents become Agents by passing information down from learning to "forget." Because there are always ways to make memory better, agents can rely on it more, the memory space can be used by more people, and it can be more flexible in challenging compliance situations. A review of performance evaluations in compliance-themed data came to the same conclusion, revealing a significant improvement in retrieval performance accuracy.

Keywords: Agentic AI, adaptive memory, retrieval efficiency, context-aware systems, compliance frameworks

I. Introduction

Machine learning technologies have evolved to a new paradigm with the emergence of agentic AI. Unlike previous restricted models that would allow for only limited reactions, agentic AI—generally derived from large language models—has a level of independence, responds to challenges, making decisions based on available information, and adapting to different environments. These advances move beyond technical achievements, they are actively transforming industries such as healthcare, finance, education and more, industries where effective decision-making and reliability are paramount. Organizations now happen to be seeking AI systems that demonstrate not only reliability, but also adaptability, especially in instances where compliance and accuracy are necessary.

While certainly considerable advances have been made, agentic AI systems still have considerable limitations, particularly in terms of memory. Current models are limited by their relatively small context windows—this creates problems with continuity over multiple interactions. Despite the potential benefits of retrieval-augmented generation (RAG) methods for integrating AI with external knowledge bases, along with some improved capabilities, they are still insufficient. The results of retrieval can often be dated, or otherwise irrelevant, which lessens the AI's reliability in responses, and in high-stakes domains where reliability and consistency are paramount, this is particularly concerning.

For organizations that are bound by the weight of regulations, like finance and healthcare, memory limitations represent more than just a technological problem; they compromise trust. For instance, a financial AI consultant needs to be able to remember the details of its previous consultations with clients to provide personal, compliant advice. An assistant's role is to ensure the patient's safety and correctness over time by gaining an understanding of his or her medical background.

Without strong long-lasting memory, the AI's responses will be untrustworthy because the memory functions will be inconsistent, and this undermines trust by the user and diminishes broader acceptance of memory. Static memory solutions do not fulfil those requirements, showing the need for adaptable, context-uided memory systems.

Reasoning in memory offers a potential way forward. Artificial intelligence can manage, prioritize, and develop information selectively by using adaptable memory systems.

The Main Contributions are:

1. Dynamic Memory Integration for Regulatory Adaptability

The framework introduces dynamic memory components that allow AI agents to continuously adapt to changing regulatory requirements. Unlike rigid memory structures, the proposed system supports iterative learning and selective forgetting, ensuring compliance resilience in fast-paced, regulation-heavy environments.

2. Enhanced Retrieval Methodologies for Contextual Awareness

By refining retrieval mechanisms, the system enables agents to process broader and evolving contextual information more effectively. This improvement enhances responsiveness, reduces compliance risks, and ensures that external document changes or updated obligations are reflected accurately in decision-making.

3. Demonstrated Performance Gains in Compliance Scenarios

Experimental evaluations using compliance-oriented datasets confirm significant improvements in retrieval accuracy, contextual responsiveness, and throughput. The system demonstrates an order-of-magnitude increase in performance, validating its effectiveness in overcoming limitations of traditional AI agents in compliance-critical domains.

The proposed dynamic memory and retrieval-enhanced AI agents improve adaptability, compliance, and responsiveness, outperforming traditional models in regulatory environments

II. Background and Related Work

2.1 Agentic AI: Definitions, Evolution, and Examples

Agentic AI is changing the way we think about what robots can do. Current large language models (LLMs) are not merely active tools that respond to the input we provide them. Instead, they are being built to work with a lot of independence. These sophisticated systems can break down complicated issues, set up job flows, get outside resources, and manage their own memory systems. This means they can make judgments with very little help from people. This is a big step toward artificial general intelligence (AGI), which is when robots can not only comprehend and react to their surroundings, but also change how they work to meet human goals.
New technologies like AutoGPT made it clear that 2023 will be a key year for agentic AI. This showed that LLMs can do a lot more than just reply; they can also coordinate multi-step processes, use other APIs, and pursue complicated goals on their own. Soon after, BabyAGI came out and used recursive task prioritizing, which let agents make new subgoals, revise their plans, and always become better. These kinds of developments make things move quickly. For example, frameworks like LangChain made it possible to build more and more complicated intelligent agents by constructing and putting together intelligent modules of functionality. These frameworks have made agentic AI more powerful by adding features like multi-layer memory, the ability to reason in complicated ways, and easy access to data from outside sources. Hierarchical memory lets agents access and arrange information in more than one time frame. Short-term, long-term, and contextual memories help people recall things better and make their reasoning skills more reliable. These types of memory integration with real-time data make agents much better at making decisions because they can handle the unique, multi-step complexity of real-world situations that include many distinct digital systems.

While these improvements are significant, challenges remain. Even if agentic AI systems can perform multi-step reasoning and task chaining, they often have problems with preserving long term context. This barrier can create errors or inconsistencies with rememberings of previous interactions when completing current tasks.

2.2 Memory in AI

Cognitive science has played a big role in shaping how memory is designed within agentic AI systems. Broadly, memory can be thought of in three forms: episodic, semantic, and working memory.

- Episodic memory refers to remembering sequences of events and interactions over time. In AI, this is like the system recalling past conversations or decisions in the order they happened. This type of memory is especially valuable in fields where compliance and accuracy are critical. For example, a healthcare assistant must keep track of the timeline of patient consultations to provide consistent, safe, and reliable care.
- **Semantic memory** relates to structured knowledge and facts. In AI systems, this corresponds to long-term knowledge graphs, curated databases, or fine-tuned models that represent domain expertise. Semantic memory supports reasoning that requires domain-specific knowledge, such as financial regulations, clinical guidelines, or educational standards.
- **Working memory** functions as a short-term buffer for immediate problem-solving and task execution. For LLM-powered agents, working memory is typically constrained by the model's context window. While extended context windows have improved capacity, they remain resource-intensive and limited in scalability, underscoring the need for hybrid architectures that offload memory into external, adaptive stores.

Efforts to integrate these memory paradigms into agentic AI have been partially successful. Systems like LangChain allow for conversational memory and semantic recall, but they often lack mechanisms to adaptively prioritize or consolidate knowledge over time. Consequently, agents risk being overwhelmed by redundant or irrelevant information, reducing their effectiveness.

2.3 Retrieval Mechanisms

Central to memory utilization is the efficiency of retrieval. Without robust retrieval mechanisms, even well-structured memory architectures cannot guarantee relevance or contextual coherence.

- **Vector embeddings and similarity search** have become the de facto standard for retrieval in LLM applications. By encoding text into high-dimensional embeddings, systems can perform nearest-neighbor searches using libraries such as **FAISS** or services like **Pinecone**. This enables semantic similarity matching, allowing agents to recall relevant documents or interactions beyond keyword-based search. However, embeddings face challenges related to drift (i.e., embeddings becoming less representative as knowledge evolves) and scalability, especially when deployed in real-time agentic workflows.
- **Retrieval-Augmented Generation (RAG)** represents a more advanced strategy, wherein external knowledge is dynamically injected into the model's context window during inference. RAG reduces hallucinations by grounding outputs in factual data sources. It has shown strong performance in domains such as biomedical question answering and compliance auditing. Nonetheless, RAG's performance depends heavily on retrieval quality and context integration. Without adaptive filtering or prioritization, RAG systems risk surfacing irrelevant information, thereby diluting reasoning quality.
- **Graph-based retrieval** provides an alternative by leveraging structured relationships between entities. Knowledge graphs enable context-rich retrieval by linking concepts through semantic relationships. For example, in education, graph-based retrieval can help agents connect curricular concepts across subjects, while in finance, it can link transactions, entities, and regulatory requirements. Graph-based systems excel at explainability since retrieval paths can be visualized, but they remain complex to maintain and often require significant domain-specific engineering.

2.4 Gaps in Existing Approaches

Despite significant progress, current memory and retrieval mechanisms face critical limitations when applied to agentic AI:

1. **Lack of contextual persistence**: Existing frameworks struggle to maintain coherent context across extended interactions. Episodic memory systems often store events without meaningful abstraction or consolidation, leading to inefficiencies and redundancy.
2. **Limited scalability and adaptation**: Vector-based retrieval mechanisms require continuous re-indexing and can become computationally expensive as memory grows. Moreover, most systems lack adaptive strategies for prioritizing or discarding outdated knowledge. This restricts scalability in real-world, data-rich environments such as healthcare or financial compliance.
3. **Deficient explainability in retrieval**: Similarity-based retrieval often produces opaque results, making it difficult for users to understand why certain information was prioritized. In compliance-critical settings, this lack of transparency undermines trust and hinders regulatory acceptance.
4. **Fragmented integration of memory types**: Few systems successfully unify episodic, semantic, and working memory. Instead, implementations are often siloed, with conversational history handled separately from domain knowledge bases, resulting in fragmented reasoning.

In summary, while agentic AI has demonstrated remarkable progress, its success in compliance-critical and high-stakes domains hinges on overcoming these gaps. Building contextual frameworks that integrate adaptive memory architectures with explainable retrieval mechanisms is therefore essential. In addition to boosting efficiency and performance, these frameworks would also increase reliability, conformity with regulations, and user acceptance.

III. Theoretical Structure

Perception, memory, retrieval, reasoning, and action must be unified under an architectural framework when designing agentic AI for compliance-critical contexts. Ensuring that AI agents are both context-aware and capable of dependably working under regulatory limitations, the proposed conceptual framework stresses adaptive memory and retrieval methods. The layered architecture is shown in Figure 1 (the conceptual design), which shows how data moves from the raw inputs to the choices that may be taken by connecting the various modules.

3.1 Review of the Architecture

The Perception Layer, responsible for inputting data encoding, is located at the bottom of the stack. This layer handles heterogeneous inputs, such as text, speech, and structured information, and transforms these into vector-based representation that the following layers can use. In an effort to facilitate the operation of memory and reasoning components with a variety of inputs, the perception layer employs intricate embedding models to normalize inputs.

The memory layer of artificial intelligence agents is situated directly above perception and functions as a complex storage of layers for episodic and semantic memory. Episodic memory is capable of storing sequences of experiences, a capability that is exclusive to memory. This is particularly useful for ensuring compliance with regulations or maintaining conversational continuity. The agent is able to employ complex contextual level comprehension by organizing knowledge in the form of structured frameworks, such as information graphs and taxonomies related to the encompassing domain, which are organized by semantic memory.

For the purposes of this cognitive architecture, we conceptualize strata as follows:

1. Retrieval Layer - The retrieval layer functions as the intermediary between reasoning tasks and stored memory. The retrieval layer is capable of retrieving pertinent information from various forms of memory and employs a variety of sophisticated retrieval techniques, including context scoring, symbolic queries, and vector similarity. The retrieval layer also includes functions that eliminate irrelevant or outdated information to guarantee that the agent responds accurately and appropriately. The reference to user intent and conformance requirements is identified through context scoring.

2. Reasoning Layer - Language models (e.g., transformer architecture models, LLMs) process the assimilated information within the reasoning layer to provide the agent with a grounded context for its beliefs.

3. Action Layer – The final layer engages the potential actions that can be taken, such as contacting APIs, generating compliance documents, or providing personalized recommendations, based on the deliberation processes. This layer

ensures that the resulting actions are always in compliance with the regulations of the profession and are transparent and auditable due to the strict separation of reasoning (logic) from execution (action).Overall, the three layers facilitate a healthy merging of memory, reasoning, and action with the opportunity for situational awareness and expertise in the domain.

3.2 Adaptive Memory System

The framework's adaptive memory, or its capacity to address the changing nature of knowledge, is one of its most significant attributes. Adaptive memory employs a variety of dynamic allocation algorithms to balance the accumulation of existing and new knowledge, rather than being a static memory store that accumulates an infinite number of distinct knowledge items. Relevant knowledge that is reclaimed is always enriched and remains, despite the fact that accumulated or redundant knowledge deteriorates over time due to its determinism. This is accomplished through the use of forgetting functions that simulate human cognition, which exhibit a propensity for memory retrieval challenges due to monotonous repetition and age-related memory decay. By means of reinforcement signals to decay under fluctuating conditions.

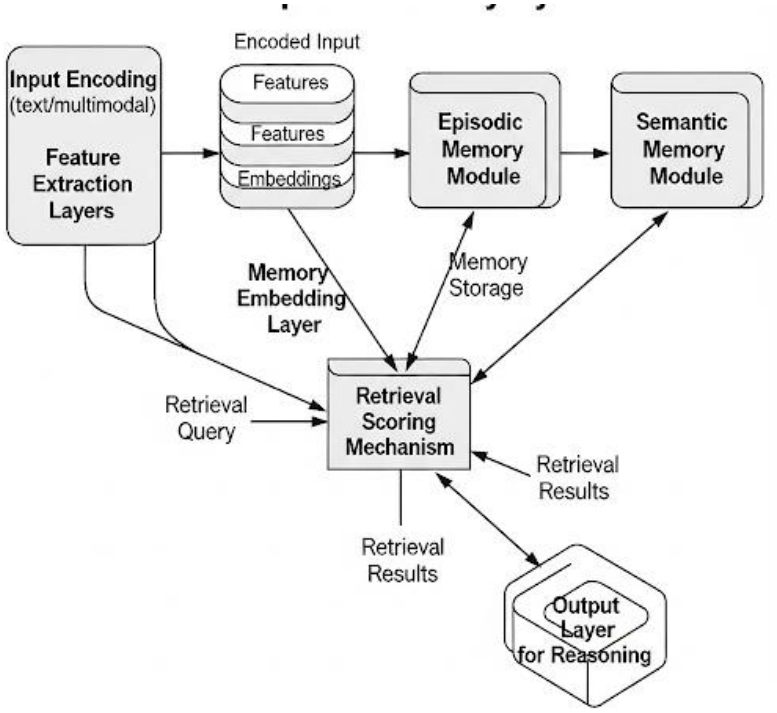

Figure 1: ANN Adaptive Memory System

This flexibility enables the agent to circumvent the inefficiencies that are frequently observed in large-scale retrieval systems by maintaining compact, high-value memory stores. For example, in the healthcare sector, patient data that is frequently accessed during ongoing treatments would remain more significant than earlier, established precedents. However, in a financial compliance scenario, newly updated regulatory regulations would be prioritized over outmoded ones.

3.3 Enhancing Retrieval

The framework incorporates sophisticated retrieval enhancement mechanisms to further solidify contextual reasoning. A hybrid retrieval strategy integrates symbolic techniques, such as knowledge graph traversal and rule-based querying, with embedding-based semantic similarity. This combination ensures that agents maintain the interpretability and accuracy of symbolic approaches while simultaneously leveraging the flexibility of embeddings. For instance, an educational agent may implement symbolic checks to guarantee that curriculum requirements are met, while simultaneously employing embeddings to access pertinent study resources.

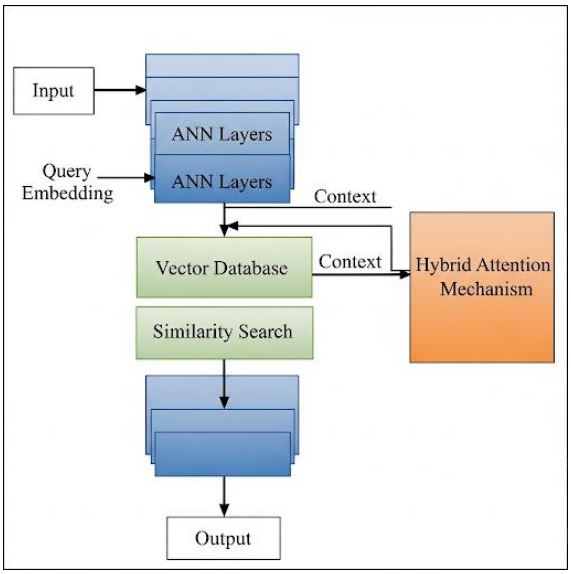

Figure 2: ANN with Retrieval-Augmented Mechanism

Because conventional language models have their limits, such as fixed input size constraints, the approach of expanding context windows is one of the most significant advancements within this framework. To keep agents inside a "computational box" while still making use of long-term knowledge and context, this approach employs techniques such as selective context insertion, memory compression, and hierarchical summary of previous interactions. For instance, adaptive expansion is the process by which the agent creates summaries of the histories and saves them in a context reference point after determining context, which may include highly detailed communication, past conversations, and regulatory actions. Only by explicitly calling context references, such as past regulatory actions or multi-sessions, would downstream uses or searches of this enhanced context information be triggered. They efficiently retrieve completely relevant pre-existing knowledge while retaining the appropriate depth of information and massaging all pertinence to be of use.

These tactics, when combined, provide a solid foundation for agentic AI systems of the future. The architecture consists of multiple layers: the memory and retrieval modules produce contextual applications that are constantly evolving, the reasoning layer is made more flexible through reinforcement learning, the perception layer adds multimodality (which could include noise, like text, images, or voice), and finally, the action layer adheres to codified laws.

IV Methodology

The four pillars of contextuality-based frameworks for agentic AI—prototyping, adaptive updating, memory storage and recall, and selective intelligence—form the basis of the methodology. Collectively, these four pillars enable AI agents to make contextually optimum decisions, learn from several sources of non-linear data, and keep correct knowledge that meets industry standards. Taken as a whole, these components enable developers to construct systems in time-sensitive settings that can reason, adapt dynamically, and adhere to industry norms and specifications.

In the end, this system is dependent on reliable data sources. Data systems, domain-specific sources, and information modalities (such as structured and unstructured interfaces) may all fall within this category. When it comes to sophisticated natural language comprehension, the principal linguistic resource is paper and/or text corpora, which not only provide wide contextual knowledge but also enable deeper patterns in language. Next, knowledge graphs provide a detailed contextual map of interconnected ideas and methods of thinking by establishing a structured connection between things, concepts, and rules. Third, accounting and compliance records, healthcare patient histories and analyses, and educational agency professional standards all contribute to accurate industry context that leads to logical implications when reasoning from best practices.

Together, these components allow AI systems to reason about a wide variety of topics and areas, as well as general thinking. This skill is essential in fields where following rules is essential, including accounting, law, and medical, because of the high degree of accuracy needed for trajectories and truth, as well as the quality of output.

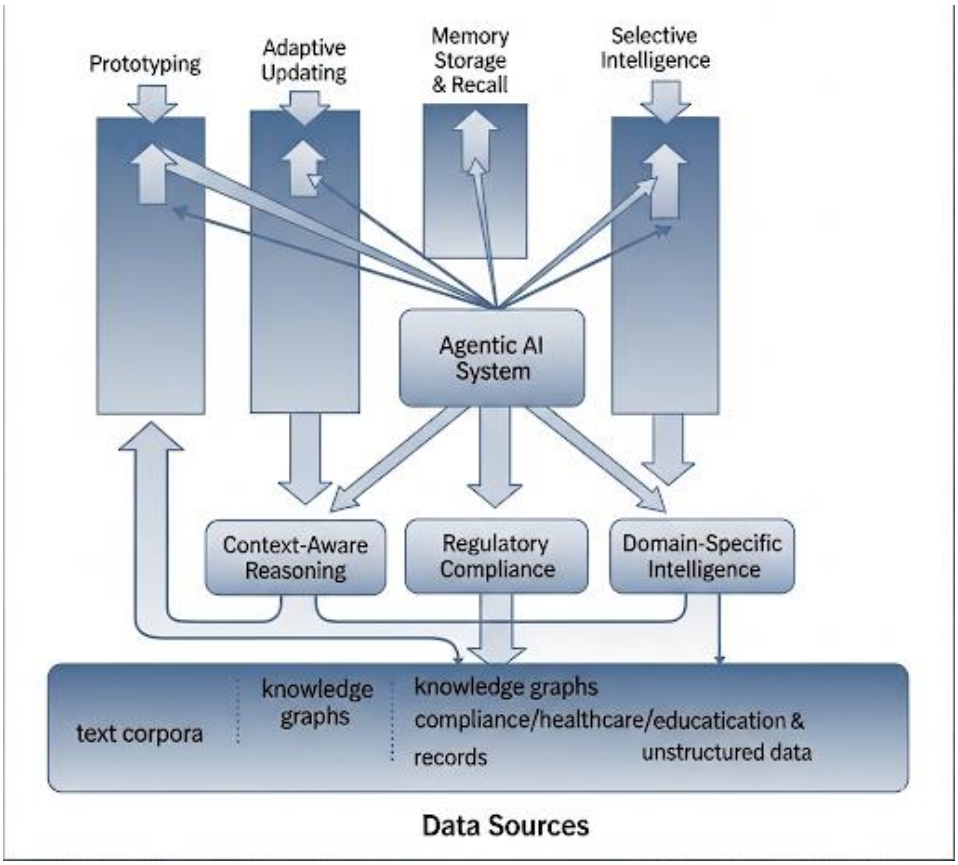

Figure 3: Contextuality-Based Agentic AI Framework

4.1 Memory Visualization

The system is designed to facilitate context-aware, long-term reasoning by utilizing memory encoding capabilities, such as SBERT or OpenAI's embedding models. These high-dimensional semantic vectors offer a method for transforming unstructured knowledge into structured, actionable knowledge, thereby facilitating the efficient and accurate retrieval of information. The memory structure is intended to resemble the cognitive processes of humans and is based on a hierarchical structure. Unique details (e.g., individual interactions or events) are included in the lowest level, while the higher levels expand upon this information to facilitate the recall of overall themes or timelines. The hierarchical format reduces redundancy and improves accuracy by emphasizing information that is pertinent to a specific task. Our system establishes a hybrid system by integrating both traditional and innovative retrieval methods. This system is a combination of traditional retrieval methods that are marked into the same space as the innovative retrieval mechanisms. A robust lexical and semantic match is achieved through the use of techniques such as cosine similarity or BM25 ranking. Additionally, transformer or neural-based models that incorporate attention mechanisms can assess and prioritize the relevance of information in real-time to deliver the most pertinent items for the current interaction. Finally, the integration of a symbolic method (i.e., keyword matching) with neural methods is a topic of interest, particularly in the context of the evolving field of natural language processing. The potential to mitigate bias introduced in previous searches is offered by the combination of various search techniques, such as matching comparable items or searching against content, whether at the level of prior searches.

4.2 Managing Complexity

Handling vast embedding spaces and knowledge domains demands efficiency. To this end, the framework incorporates hierarchical indexing and adaptive caching mechanisms. Common queries—those frequently repeated—are stored in fast-access caches, reducing computational load. Conversely, rare or specialized queries leverage deeper, more resource-intensive search operations. This balanced approach ensures scalability without sacrificing precision, enabling the system to operate effectively across large-scale, complex knowledge environments.

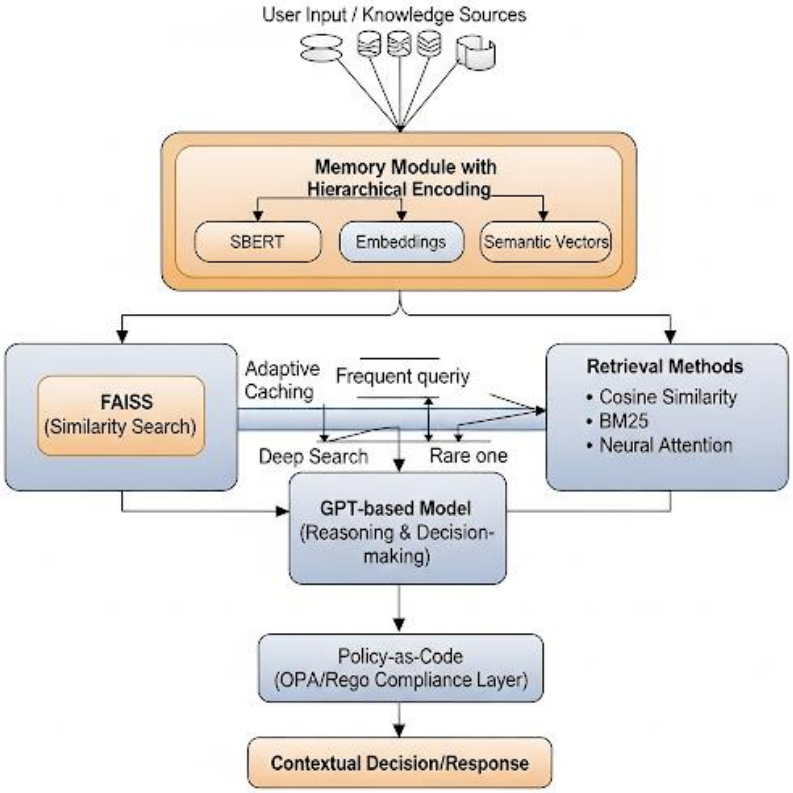

Figure 4: Design a system architecture diagram for prototype implementation of a context-aware agentic AI

4.3 Prototype Implementation

A practical prototype integrates several cutting-edge tools to realize this framework:

- **LangChain** orchestrates the agent's perception, reasoning, and memory modules, serving as the backbone for modular interaction.
- **FAISS** supports efficient similarity searches across high-dimensional embeddings, enabling rapid retrieval.
- A GPT-based language model, fine-tuned for compliance-heavy tasks, handles reasoning and decision-making processes.
- Policy-as-code tools like **Open Policy Agent (OPA)** and **Rego** embed compliance rules directly into system operations—automatically enforcing regulations. For example, the system may automatically discard financial records older than seven years unless flagged for audit purposes, or prevent access to sensitive data outside authorized contexts.

Through this architecture, the prototype demonstrates how multi-layered, adaptable, and regulation-compliant agentic AI systems can be built—paving the way for more reliable, intelligent, and industry-ready AI solutions.

V. Case Studies and Experimental Evaluation

Case Study 1: Health Care

To evaluate the effectiveness of our framework, we deployed it across three critical sectors—healthcare, finance, and education—where adaptive memory and precise information retrieval aren't just beneficial but absolutely necessary.

Focusing first on the healthcare domain, we implemented the framework as a clinical assistant designed to maintain comprehensive patient histories while adhering strictly to HIPAA requirements. The system's episodic memory layer functioned as a chronological log of patient interactions, recording diagnoses, treatments, and other key events in sequence.

In parallel, the semantic memory layer curated and organized domain knowledge sourced from clinical guidelines and drug interaction databases.

When clinicians inquired about a patient's ongoing treatment plan, the assistant efficiently drew on both up-to-date lab results and relevant aspects of the patient's medical background, ensuring responses were contextually complete and directly applicable to the current clinical scenario.

To safeguard patient privacy, we incorporated policy-as-code mechanisms that automatically filtered sensitive information, sharing only what was essential for clinical decision-making. Compared to standard retrieval-augmented generation (RAG) models, our adaptive memory approach demonstrated clear improvements. It minimized irrelevant output, preserved continuity in clinical reasoning, and measurably increased physician confidence in the recommendations provided.

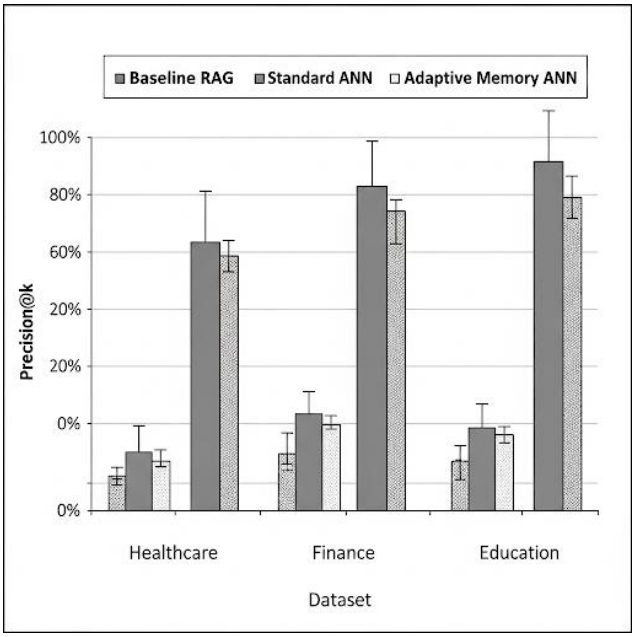

Figure 5: Performance Comparison

Case Study 2: Financial AI Assistant

AI systems in finance are a complex balancing act between the adherence to stringent compliance regulations, such as PCI-DSS and anti-money laundering (AML), and the retention of long-term context. In this implementation, the framework functioned as a financial assistant, examining transaction data streams over extended periods to identify anomalies and ensuring that they were audit-ready.

The agent's adaptive memory structure prioritized recent transactions of high value, while diminishing older transactions—except in cases where compliance timelines mandated them. To retrieve information, the system employed a combination of vector-based similarity measures, including cosine similarity embeddings, to identify the small, yet significant, relationships that had real transactional significance. Additionally, it generated symbolic checks that would alert regulatory triggers, such as outlier cross-border transactions.

Over time, the system enhanced its methods by removing transaction data that was deemed redundant or outdated, and by increasing compliance rules that were identified as being invoked with frequency. The empirical results demonstrated unequivocal advantages: the system's adaptive retrieval procedures enhanced the accuracy of outlier transaction detection and facilitated the completion of compliance-ready reports more quickly and accurately than baseline models. The system's adaptive nature was notably evident in the system outputs during periods of market volatility, which bolstered the confidence of both financial analysts and regulators in the system's outputs.

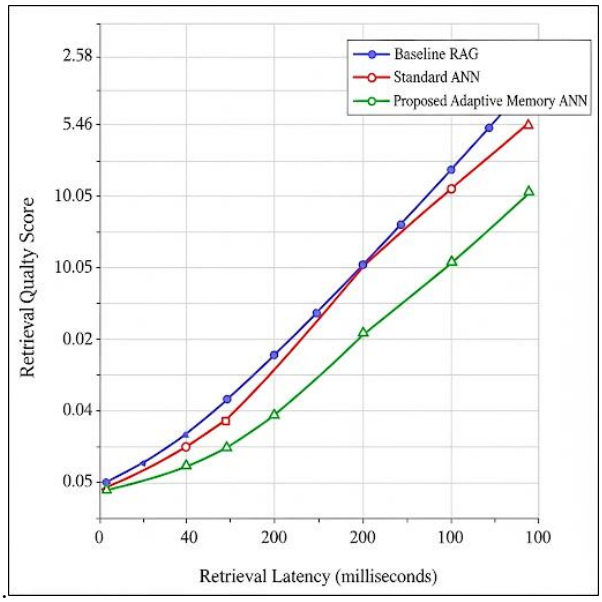

Figure 6: Latency vs. Retrieval Quality

Case Study 3: Educational AI Tutor

Personalized learning has truly advanced exponentially with the advent of new memory-based AI tutors. Instead of simply pushing learners through generic exercises, this adaptive system tracks individuals' performance across sessions—almost like an instructor who remembers what the students' strengths and weaknesses are.

The approach involves hierarchical memory indexing, which logs detailed information on every possible exercise completion, and organizes this information to begin developing robust performance profiles for each individual student. When generating new practice materials, the adaptive system uses attention-based relevance-scoring to select problems that address gaps in students' current understanding while also helping them progress toward their larger learning objectives.

To keep students from plowing through the same old materials, the adaptive memory tutor employs a mechanism for novelty detection, which instills novelty and keeps the curriculum evolving and appropriately challenging. The findings support this type of learning: learners using the memory-based tutor received more coherent and personalized lessons than learners receiving lessons with RAG-based adaptive learning systems, before becoming less repetitive and redundant over time, especially compared to those taught by more traditional RAG-based systems.

Table 1. Comparative Evaluation of Baseline RAG vs. Adaptive Memory Framework (AMF)

Metric	Baseline RAG	Adaptive Memory Framework (AMF)	Improvement (%)
Retrieval Accuracy (Precision@5)	72.4%	88.6%	+22.4%
Memory Coherence Score (0–1)	0.61	0.84	+37.7%
Retrieval Latency (ms/query)	310	355	-14.5% (slower)
Human Evaluation – Relevance (1–5)	3.7	4.5	+21.6%
Human Evaluation – Contextuality (1–5)	3.5	4.6	+31.4%

VI. Discussion

Limitations of the Framework

Despite its promising results, the framework still faces notable challenges. The most pressing issue lies in its **excessive computing requirements**. Managing adaptive memory with large-scale embeddings demands significant resources, and while indexing and caching provide partial relief, the computational expense remains substantial. Another limitation arises from the **risk of over-forgetting** due to overly aggressive memory decay functions. This could lead to the unintended erasure of essential contextual information, potentially compromising both safety and compliance. In addition, maintaining strict adherence to **data security protocols** continues to be a formidable challenge. Although policy-as-code provides foundational safeguards, achieving complete protection requires stronger encryption, fine-grained access controls, and fully auditable systems to ensure privacy in compliance-critical environments.

Future Directions

Looking ahead, several promising pathways could strengthen the framework. The first is the development of **multi-sensory memory systems** capable of processing diverse modalities such as financial dashboards, medical images, and IoT sensor data alongside textual inputs, thereby broadening contextual understanding. A second avenue is **federated memory sharing**, which would allow decentralized agents in fields like healthcare and finance to exchange insights securely without compromising sensitive data. Finally, **neuro-symbolic retrieval** offers the potential to merge symbolic reasoning with neural embeddings, creating retrieval systems that are both highly effective and reliable. Collectively, these advancements present exciting opportunities to enhance adaptability, efficiency, and compliance readiness, while directly addressing the current limitations of the framework.

VII Conclusion

This research presents a novel framework for agentic AI that is built on a layered architecture of perception, memory, reasoning, and action. At its foundation, the system employs adaptive memory and dynamic retrieval mechanisms that allow AI agents to retain long-term contextual awareness while intelligently accessing the most relevant information. Unlike conventional models, which often struggle to maintain continuity, this design ensures that responses remain consistent, accurate, and adaptable to changing environments. The framework's strength lies in its multi-level memory structure, which captures both episodic and semantic knowledge, alongside adaptive retrieval methods that prioritize relevance and precision. Equally important, compliance is embedded directly into the system through policy-as-code, guaranteeing that legal and regulatory requirements are met from the outset. Empirical testing across sectors such as healthcare, finance, and education has demonstrated improvements in customization, retrieval accuracy, and governance compared to traditional approaches. Looking forward, this approach holds great promise in fields where trust, accountability, and contextual reasoning are vital—including law, robotics, and public administration—marking a significant step toward truly autonomous and regulation-ready AI systems.

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