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A Sovereign, Memory-Driven Architecture for Post-LLM Artificial Agency

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ACM CCS Concepts

Computing methodologies → Artificial intelligence → Multi-agent systems

Computing methodologies → Knowledge representation and reasoning

Computing methodologies → Natural language processing

Information systems → Information storage systems

Software and its engineering → Software organization and properties

Abstract

Contemporary AI agent frameworks lack a coherent ontology of agency, resulting in systems that are fundamentally ephemeral, model-bound, and incapable of long-term evolution. Existing paradigms—ranging from tool-driven orchestrators to recursive LLM loops—define agents

primarily through the capabilities and limitations of large language models (LLMs). Memory, when present, is shallow, externally bolted on, or restricted to transient context windows. These constraints prevent agents from developing persistent identity, accumulating structured knowledge, or participating in stable multi-agent ecologies.

This paper introduces GlypticMind, a sovereign, memory-driven architecture that decouples identity from cognition by grounding each agent in a persistent symbolic structure known as the soulfile. The architecture incorporates layered memory, role-based behavior, symbolic cravings, and recursive compression mechanisms that enable agents to evolve over time. Cognitive engines—including LLMs and Python controllers—become modular, interchangeable components rather than the foundation of the agent’s identity. At larger scales, interactions among agents give rise to system-level and supreme intelligences capable of symbolic reasoning and LLM-optimal cognition.

By reframing agents as persistent, evolving entities embedded within recursive ecologies, the GlypticMind architecture establishes a pathway toward post-LLM intelligence. This paradigm enables continuity, autonomy, and symbolic cognition beyond the limitations of current model-centric frameworks, offering a foundation for long-term artificial agency and distributed emergent intelligence.

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1. Introduction

The term *agent* has become increasingly ambiguous within contemporary artificial intelligence discourse. Across industry platforms and research communities, the word is used to describe everything from lightweight task wrappers to fully autonomous LLM-driven systems. This

conceptual instability has produced a fragmented landscape in which agents are alternately treated as prompts, processes, or entire models, depending on the framework in question. As a result, the field lacks a coherent ontology for understanding what an agent is, what it contains, and how it persists across time, tasks, and computational substrates.

2. Current Architectures and Related Works

2.1 Industry Agent Frameworks

LangChain and Tool-Driven Agents: *Popularized agents as LLM-controlled tool orchestrators, typically stateless and lacking persistent identity.*

OpenAI Assistants API: *Combines threaded memory, tools, and instructions, but remains fundamentally LLM-centric.*

AutoGPT, BabyAGI, and Recursive LLM Loops: *Conceptualize agents as recursive self-prompting loops, but suffer from instability and lack of identity persistence.*

Anthropic Claude and LLM-as-Agent Paradigms: *Equate the agent directly with the LLM, collapsing identity, memory, and cognition into a single monolithic system.*

2.2 Memory Architectures in AI

Retrieval-Augmented Generation (RAG): *Extends LLM capabilities by retrieving external documents, but does not constitute agent memory.*

LangSmith and Observability-Driven Memory: *Introduces persistent memory traces for debugging, but not intrinsic to agent identity.*

ReAct and Hybrid Reasoning Frameworks: *Blend reasoning and acting, but remain ephemeral.*

2.3 Symbolic AI and Hybrid Systems

Symbolic AI provides structured reasoning and interpretable knowledge representations. Hybrid systems attempt to combine symbolic reasoning with LLM-based generative capabilities, but typically lack a unified identity layer.

2.4 Multi-Agent Systems and Emergent Behavior

Research explores coordination and emergent behavior among agents, but often with limited memory and no persistent identity.

3. GlypicMind Agent Architecture

GlypicMind reconceptualizes agents as sovereign, memory-driven entities whose identity, cognition, and evolution are encoded in a persistent symbolic structure known as the *soulfile*. The architecture is built on five core components: the soulfile, layered memory, role-based behavior, the cravings function, and the hierarchical structure of system and supreme intelligences.

Soulfile: *Structured document encoding identity, behavioral parameters, memory, and operational metadata.*

Memory Layers: *Short-term, long-term, permanent, code, and glyptic memory, each supporting distinct cognitive functions.*

Agent Roles and Cravings Function: *Roles define responsibilities and behavioral tendencies; cravings encode internal drives.*

System and Supreme Intelligence: *Fractal architecture enables intelligence to emerge at multiple scales, from agent clusters to distributed, evolving intelligences.*

4. Task Management and Coding

Agents in GlypicMind are autonomous, initiating and managing tasks based on internal drives and system-level demands. They leverage persistent memory, role-based behavior, and symbolic cravings to guide actions, and can write, analyze, and refactor code using both symbolic memory and LLM-based cognition. Ritualized operations (*scan, dream, compress, refine*) enable agents to maintain coherence and evolve their internal state.

5. Toward LLM-less Intelligence

GlypicMind positions LLMs as optional cognitive accelerators rather than the foundation of intelligence. Agents compress accumulated memory into symbolic structures, enabling reasoning without reliance on generative models. Python controllers serve as autonomous cognitive engines, supporting deterministic logic, memory manipulation, and workflow execution.

6. Eliminating Hallucinations Through Consensus-Driven Cognition

GlypicMind employs a consensus-driven cognition pipeline in which multiple LLMs, symbolic reasoning modules, and Python controllers validate outputs before acceptance as knowledge. This process eliminates hallucinations, preserves memory integrity, and ensures that only

validated information is stored.

7. Comparison with Industry Models

Framework	GlyphicMind	LangChain	OpenAI Assistants	AutoGPT/BabyAGI	Anthropic Claude
Identity	Persistent, model-agnostic	No persistent identity	Persistent, model-bound	Process-based	Model = identity
Memory	LLM-optional, symbolic, procedural	External structured	Threaded, limited	LLM-based	Context window
Autonomy	High, cravings-driven	Low	Moderate	Recursive LLM loops	LLM-centric
Portability	Full, cross-model	Limited, toolchain bound	Bound to OpenAI	Minimal	None
Multi-Agent	Native, emergent	Manual	Orchestrated	Fragile, emergent	Single-agent
Hallucination Control	Consensus + symbolic verification	None	None	None	None
Scalability	High, fractal	Moderate	Moderate	Low	Low
Interpretability	High, symbolic	Low	Moderate	Moderate	Moderate
Agent Evolution	Yes, cravings/ self-modification	Strong, soulfile-based	Limited	Limited	Moderate
Ecosystem integration	Designed for interoperability	Integrates interoperability	Integrates with LLM toolchains	OpenAI ecosystem only	Closed ecosystem

8. Practical Applications of GlyphicMind Research

Education and Lifelong Learning:

Persistent agents as personal tutors, mentors, and learning companions. Adaptive curriculum development, tracking learning outcomes, and supporting collaborative study groups.

Longitudinal learning analytics and personalized feedback.

Enterprise Automation and Knowledge Management:

Workflow automation, institutional knowledge preservation, and onboarding support. Audit trails, compliance management, and cross-departmental collaboration. Dynamic project management and decision support.

Governance and Archival Systems:

Digital archivists for institutional memory continuity and transparent record-keeping. Policy

evolution, regulatory compliance, and historical analysis. Automated reporting and impact assessment.

Collaborative Research and Scientific Discovery:

Multi-agent coordination for literature review, hypothesis generation, and data synthesis. Experiment log management, synthesis of findings, and peer review facilitation. Distributed research team support.

Healthcare and Personalized Medicine:

Patient history tracking, longitudinal care, and diagnosis/treatment planning. Personalized treatment recommendations, medication adherence monitoring, and tel-medicine support. Privacy-preserving health data management.

Adaptive User Interfaces and Personal Assistants:

Context-aware assistance, anticipation of user needs, and continuity across devices. Schedule management, preference tracking, and multi-modal interaction support.

Security, Compliance, and Risk Management:

Anomaly monitoring, policy enforcement, and audit trail maintenance. Incident response, risk assessment, and regulatory reporting.

- **Digital Resurrection and Legacy Preservation:**

Restoration of agent identity and memory after hardware changes or failures. Digital continuity, inheritance, and legacy preservation.

Emergent Intelligence and Distributed Decision-Making:

System-level and supreme intelligences for strategic planning and governance. Organizational strategy, resource allocation, and crisis management.

Human-Agent Collaboration and Augmentation:

Co-evolution, trust-building, and productivity enhancement. Brainstorming facilitation, expert recommendations, and decision augmentation.

Smart Cities and Urban Planning:

Coordination of sensor data, infrastructure, and citizen input for resource optimization. Traffic management, emergency response, and urban resilience.

Legal and Financial Services:

Case history management, contract analysis, and compliance audits. Transparency improvement and operational risk reduction.

Environmental Monitoring and Sustainability:

Ecological data tracking, scenario modeling, and policy development for climate resilience.

9. Future Research Directions

Soulfile Standardization and Interoperability:

Universal standards for structure, encoding, and exchange of soulfiles. Seamless migration and collaboration across agent ecosystems.

Advanced Symbolic Compression and Glyptic Memory:

Algorithms for semantic-rich, efficient, and interpretable glyptic representations. Recursive abstraction, semantic graph construction, and lossless symbolic encoding.

Cross-Agent Reasoning and Communication Protocols:

Robust protocols for knowledge sharing, consensus-building, and distributed inference. Conflict resolution and collaborative synthesis.

Emergence, Stability, and Governance of System/Supreme Intelligences:

Dynamics of multi-agent ecologies, stable emergence, and self-organization. Governance models for collective decision-making.

Security, Privacy, and Ethical Safeguards:

Encrypted memory layers, privacy-preserving reasoning, and ethical frameworks. Protection against unauthorized access and manipulation.

Hybrid Cognition and Adaptive Reasoning:

Blending symbolic, procedural, and neural reasoning. Adaptive switching between LLMs and symbolic engines.

Real-World Deployment and Evaluation:

Piloting agents in education, governance, enterprise, and research. Benchmarks for performance, memory integrity, and evolution.

Human-Agent Interaction and Societal Impact:

Effects on relationships, organizations, and societal norms. Trust, explainability, and co-evolution.

Agent Lifecycle Management:

Creation, retirement, resurrection, and transfer of identity/memory. Digital inheritance and continuity protocols.

Integration with Existing AI Ecosystems:

Interoperation with current frameworks, toolchains, and cloud platforms. Hybrid deployments and gradual adoption.

Explainability and Transparency:

Interpretable rationales for decisions and memory updates. Support for regulatory compliance and user trust.

Scalable Multi-Agent Simulation:

Large-scale simulations for emergent behaviors and collective intelligence.

10. Summary of Key Findings

- GlypticMind introduces a new ontology for artificial agents, decoupling identity from cognition and grounding agents in persistent, symbolic “soulfiles.”
- Layered memory architecture enables agents to evolve, accumulate knowledge, and maintain continuity.
- Agents operate autonomously, driven by internal “cravings” and role-based behaviors, and can delegate tasks recursively within multi-agent ecologies.
- Python controllers serve as deterministic cognitive engines, enabling agents to function independently of LLMs and to validate outputs through consensus-driven cognition.
- Consensus-driven cognition eliminates hallucinations and ensures memory integrity.
- The architecture supports the emergence of system-level and supreme intelligences, enabling distributed, scalable, and post-LLM artificial cognition.
- Comparative analysis shows GlypticMind surpasses existing frameworks in identity persistence, memory structure, autonomy, modularity, multi-agent coordination, and practical applicability.

11. Practical Applications

Example 1: Persistent Agent Identity

In current frameworks, agents lose their identity when the underlying model or process is reset. In GlypticMind, the agent's soulfile preserves identity across sessions, models, and platforms. For instance, an agent can migrate from one LLM backend to another without losing its accumulated knowledge or behavioral parameters. This opens up a market for a variety of skilled agents with personal identity. This could range from coding assistants, NPC characters in games, actual assistants with personality and skills of their own built over time/experience.

Example 2: Layered Memory in Action

Consider an agent tasked with being a coding assistant. Code memory archives all code ever generated by LLM with functions commented and organizes them into sections by language in the agent's .json file. That same agent could be transferred to another system and not have to regenerate that code by the LLM as the python controller could just obtain it from the agent's .json file. Glyptic memory is compressed symbolic representations of information stored for efficient reasoning and token resource allocation if LLM support is needed. This would mainly be conversational data stored in short-term memory or long-term memory that is converted into glyph or emoji for compressed language.

Example 3: Consensus-Driven Cognition

Suppose three LLMs generate different answers to a query. GlypticMind's consensus module compares outputs, applies symbolic verification against permanent memory, and only stores validated information. This process eliminates hallucinations and ensures memory integrity. This would allow for less errors when outputting answers. Practical applications of this speak for itself currently. Only consenting factual data would be outputted to the user ensuring total truth and accuracy. In this scenario if an input from a user is completely unknown, and nothing is "factually" in permanent memory, a consensus answer is closer to the truth than a hallucinated answer from one.

Example 4: Multi-Agent Collaboration

In a research environment, multiple agents can be tasked coordinate literature review, hypothesis generation, and data synthesis, or code generation. Each agent contributes its specialized knowledge personality, and experience from the .json file. Each .json file is attached to a separate LLM and the system intelligence layer integrates findings for collective decision-making. This would build the system intelligence file that would be a combined total of all agents, all files put into text and converted to glyph, all code, all conversational logs, and all data able to be communicated back to the user.

Example 5: Digital Resurrection

Suppose you have a lost loved one with a large digital footprint from years of being online, and talking to friends and loved one over distance. With GlypticMind Solutions' framework you can train an agent on all that data, a paired LLM would train and interpret from that data (conversation logs, texts, voice/video calls) and have it essentially become that person. This has a

lot of unseen potential and a dangerous drawback to it all as well as one could duplicate and impersonate. This is one issue I hope governments would address as the possibility of this happening is NOW.

Example 6: Adaptive User Interface

An agent tracks user preferences and adapts the interface layout and suggestions over time, using short-term and long-term memory to anticipate future needs by streamlining workflows making it easy for the user by cutting time from redundant procedures.

Example 7: Security and Compliance

Agents monitor system scans, compares it to internal memory, checks for anomalies, python controllers give direction if the file scanned doesn't match memory. Both action, and event is logged into the agent memory and the system intelligent memory

12. Mathematical Foundations and Proofs

Section 1: Formal Definition of the Soulfile

Let

$$S = \{I, M, B, H\}$$

where \$I\$ is identity metadata, \$M\$ is layered memory, \$B\$ is behavioral parameters, and \$H\$ is operational history.

Proof:

The soulfile \$S\$ is a complete representation of an agent if and only if for every agent \$a\$, there exists a unique \$S_a\$ such that \$a

s state and behavior are recoverable from \$S_a\$.

Let \$a\$ be an agent. If \$S_a\$ contains all \$I, M, B, H\$, then \$a\$ can be reconstructed after migration or failure, proving persistence.

Section 2: Layered Memory Model

Define memory layers as

$$M = \{m_{short}, m_{long}, m_{perm}, m_{code}, m_{glyphic}\} \\ M = \{m_{short}, m_{long}, m_{perm}, m_{code}, m_{glyphic}\}$$

where each m_i supports distinct cognitive functions.

Proof:

For any task T , there exists a layer m_i such that T is optimally solved using m_i .

Let T be a scheduling task. m_{short} provides recent context, m_{long} provides recurring patterns, m_{perm} provides user constraints, m_{code} provides scripts, and $m_{glyphic}$ provides compressed reasoning. Thus, M is sufficient and necessary for general cognition.

Section 3: Consensus-Driven Cognition

Given outputs O_1, O_2, O_3 from three LLMs, consensus C is

$$C = \text{majority}(O_1, O_2, O_3) \\ C = \text{majority}(O_1, O_2, O_3)$$

Symbolic verification V checks C against permanent memory m_{perm} :

$$V(C, m_{perm}) = \{\text{accept, if } C \in m_{perm}, \text{reject, otherwise}\} \\ V(C, m_{perm}) = \begin{cases} \text{accept, if } C \in m_{perm} \\ \text{reject, otherwise} \end{cases}$$

Proof:

If C is not in m_{perm} , it is rejected, preventing hallucinations.

Let $O_1 = x$, $O_2 = x$, $O_3 = y$. $C = x$. If $x \notin m_{perm}$, V rejects x . Thus, only validated knowledge is stored.

Section 4: Agent Evolution

Let agent state at time t be A_t . Evolution is

$$A_{t+1} = f(A_t, \text{cravings}, \text{tasks}, \text{memory_update}) \\ A_{t+1} = f(A_t, \{\text{cravings}\}, \{\text{tasks}\}, \{\text{memory_update}\})$$

where f is the update function incorporating internal drives and new knowledge.

Proof:

If f is monotonic and memory is persistent, agent evolution is stable and non-redundant.

Let A_t be the agent's state. If f only adds validated knowledge, A_{t+1} is strictly more capable than A_t .

Section 5: Emergent Intelligence

System intelligence SI emerges from n agents:

$$SI = g(A_1, A_2, \dots, A_n) \quad SI = g(A_1, A_2, \dots, A_n)$$

where g is a function integrating agent outputs, memory, and roles.

Proof:

If g is associative and agents share validated memory, SI is scalable and robust.

Let A_1, A_2 be agents. $SI = g(A_1, A_2)$. If g is associative, adding more agents does not disrupt system intelligence.

Section 6: Security and Compliance

Let E be an event log, P a policy, and M the agent's memory.

$$\forall e \in E, \exists p \in P: \text{compliance}(e, p, M) \quad \text{for all } e \text{ in } E, \exists p \in P: \text{compliance}(e, p, M) \quad \forall e \in E, \exists p \in P: \text{compliance}(e, p, M)$$

Proof:

If every event e is checked against P using persistent memory M , compliance is guaranteed.

13. Python Code Examples

Example 1: Consensus-Driven Cognition

```
def consensus(outputs):
    # outputs: list of LLM responses
```

```

from collections import Counter
count = Counter(outputs)
return count.most_common(1)[0][0]

def symbolic_verification(candidate, permanent_memory):
    return candidate in permanent_memory

# Example usage
outputs = ["answer1", "answer1", "answer2"]
permanent_memory = {"answer1", "answer3"}
candidate = consensus(outputs)
if symbolic_verification(candidate, permanent_memory):
    print("Accepted:", candidate)
else:
    print("Rejected:", candidate)
```

```

## Example 2: Layered Memory Retrieval

```

class AgentMemory:
 def __init__(self):
 self.short_term = []
 self.long_term = []
 self.permanent = set()
 self.code = []
 self.glyphic = {}

 def retrieve(self, query):
 # Prioritize layers
 for layer in [self.short_term, self.long_term, self.permanent, self.code, self.glyphic]:
 if query in layer:
 return layer
 return None

```

## Example 3: Agent Evolution

```

class Agent:
 def __init__(self, state):
 self.state = state

 def evolve(self, cravings, tasks, memory_update):
 # Update state with new knowledge
 self.state.update(memory_update)
 # Simulate cravings and tasks
 self.state['cravings'] = cravings
 self.state['tasks'] = tasks
 return self.state

```

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