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Towards a Unified Model of Narrative Memory in Conscious Agents: From Human Cognition to Artificial Consciousness

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Abstract

This study seeks to bridge the gap between narrative memory in human cognition and artificial agents by proposing a unified model. Narrative memory, fundamental to human consciousness, organizes experiences into coherent stories, influencing memory structuring, retention, and retrieval. By integrating insights from human cognitive frameworks and artificial memory architectures, this work aims to emulate these narrative processes in artificial systems. The proposed model adopts a multi-layered approach, combining elements of episodic and semantic memory with narrative structuring techniques. It explores how artificial agents can construct and recall narratives to enhance their understanding, decision-making, and adaptive capabilities. By simulating narrative-based memory processing, we assess the model's effectiveness in replicating human-like retention and retrieval patterns. Applications include improved human-AI interaction, where agents understand context and nuance, and advancements in machine learning, where narrative memory enhances data interpretation and predictive analytics. By unifying the cognitive and computational perspectives, this study offers a step toward more sophisticated, human-like artificial systems, paving the way for deeper explorations into the intersection of memory, narrative, and consciousness.

Keywords: Narrative Memory, Consciousness, Cognition, Artificial Intelligence, Memory Retrieval

INTRODUCTION

The concept of narrative memory is deeply embedded in human cognition, forming the basis for an individual's ability to construct meaning from experiences, retain detailed memories over time, and establish a coherent sense of identity. Unlike simple factual or semantic memory, narrative memory is organized in a story-like sequence, connecting disparate events within a meaningful temporal and contextual framework. This structuring enables humans not only to remember events but also to place them within a subjective understanding of the past, present, and future, providing a basis for self-reflection, planning, and decision-making (Azam et al., 2024; Azam et al., 2024). In cognitive neuroscience and psychology, narrative memory is closely linked with episodic memory, where specific life events are remembered with context, time, and location. Such memories are not merely stored but are actively reconstructed, adapting to changes in context or perspective. This flexibility and structured organization are significant in defining human consciousness and subjective experience. For humans, narrative memory aids in organizing past experiences, anticipating future scenarios, and forming judgments about new situations based on past narrative patterns(Azam et al., 2024; Azam et al., 2024; León, 2016). In artificial intelligence (AI), mimicking human memory has predominantly focused on data storage, retrieval, and processing capabilities without a structured narrative or the nuanced layering seen in human cognition. Current AI memory models excel at storing vast amounts of information, recognizing patterns, and retrieving information based on pre-defined algorithms. However, they lack the ability to organize these memories in a meaningful sequence that reflects a narrative structure(Azam, Javaid, et al., 2024; Azam, Zafar, Rafiq, et al., 2024). This gap limits the AI's ability to develop memory-based coherence, adaptation, and subjective experience—hallmarks of what we consider consciousness.

As AI systems grow increasingly complex, applications such as autonomous agents, interactive virtual environments, and human-machine interfaces demand not only the retention of relevant information but also the contextual recall that aligns with human-like understanding. Here, traditional AI models fall short due to their inability to recall information adaptively based on a coherent narrative or context, reducing their potential for achieving forms of artificial consciousness(Rafiq et al., 2024). The pursuit of artificial consciousness, defined as the emulation of human-like awareness and experience within AI, has driven the exploration of cognitive architectures that could incorporate narrative memory. By integrating narrative memory, AI agents could develop a form of 'self' awareness, continuity over time, and enhanced adaptability. Such capabilities are foundational for any AI aspiring to operate autonomously in dynamic environments, interact meaningfully with humans, or maintain internal states across different contexts. An AI agent with narrative memory could, for instance, recall events in the context of past interactions, learn from experiences, and predict outcomes in a manner that mirrors human cognitive patterns.

In this paper, we propose a unified model of narrative memory for artificial agents that attempts to address these gaps, combining elements of temporal structuring, contextual encoding, and conscious retrieval. The model is inspired by human narrative cognition and is designed to organize memory in a structured sequence, enabling the agent to retain memories in an organized and contextually meaningful manner. The primary objective of this model is to bridge the gap between current AI memory structures and those necessary for achieving artificial consciousness. The model encompasses a multi-layered memory structure, where memories are stored as interconnected nodes, sequenced temporally, and enriched with contextual information. This enables adaptive retrieval processes that reflect the agent's internal state and external context, allowing for memory recall that is more reflective of human memory's narrative-like organization(León, 2016).

This research offers three main contributions, each aimed at advancing the application of narrative memory in artificial intelligence and laying a foundation for achieving artificial consciousness**:** Theoretical Model of Narrative Memory in AI: (Azam et al., 2024; Nisa, Azam et al., 2024) We present a comprehensive theoretical model that replicates the narrative memory structure found in human cognition. The model consists of three layers—Temporal Structuring, Contextual Encoding, and Conscious Retrieval—each contributing to the organization, retention, and retrieval of memories in a coherent narrative form. Temporal Structuring organizes events sequentially, Contextual Encoding embeds memories with situational and emotional contexts, and Conscious Retrieval allows the AI agent to recall information adaptively, based on relevance to the current task or query. This model is unique in its design, aimed at addressing the need for continuity and coherence in AI memory systems. Simulation of the Model's Effectiveness: To assess the viability of the proposed model, we outline a simulation setup that replicates real-world memory tasks within a controlled virtual environment. The simulation is designed to test the model's efficacy in memory retention, contextual accuracy, and adaptability in recall—parameters essential for evaluating the narrative memory structure. Through this setup, we evaluate the agent's ability to construct, store, and retrieve memories that resemble the episodic, coherent memory systems observed in human cognition(Ranchhod et al., 2014).

Empirical Findings and Analysis for Artificial Consciousness Potential: The findings from our simulation trials highlight the model's effectiveness in enhancing memory retention and recall accuracy compared to conventional AI memory systems. The analysis provides insights into how narrative memory impacts the agent's performance and adaptability, suggesting a pathway toward artificial consciousness. By demonstrating a model that allows for structured, narrative-like memory recall, we open new avenues for integrating memory systems that are not merely reactive but are organized and adaptable, emulating key aspects of human consciousness(Adnan et al.,2024). By synthesizing narrative memory's cognitive frameworks and implementing these in a structured model for AI, this research aims to contribute to the broader field of artificial consciousness. The proposed model offers a step toward creating AI systems that can remember, understand, and interact within their environments in a manner that closely approximates human cognition. This research's implications extend to fields such as robotics, autonomous systems, and AI-driven human-computer interaction, providing a foundation for developing conscious agents capable of narrative-driven reasoning and interaction.

BACKGROUND

Narrative Memory in Human Cognition

Human narrative memory involves the organization of memories into meaningful sequences, providing context and continuity across experiences. This form of memory is linked to the human sense of self and time perception.

Memory in Artificial Agents

Artificial agents typically rely on databases and neural networks to retrieve relevant data. However, traditional models lack narrative structuring, which is crucial for long-term memory retention and the emulation of conscious experience.

LITERATURE REVIEW

Narrative memory, which enables humans to structure experiences in meaningful sequences, has been extensively studied within cognitive science and artificial intelligence (AI). Despite significant advancements, replicating narrative memory in AI systems remains a challenge due to the complexity of sequential organization, contextual encoding, and adaptive recall. This section reviews twenty's papers addressing narrative memory in human cognition, AI memory structures, and artificial consciousness, establishing the foundational work and identifying the gaps that this study aims to address(Azam et al., 2024).

- **Narrative Memory in Human Cognition**

Narrative memory structures are critical to human cognition, providing continuity across events and enabling adaptive responses based on past experiences. Early studies by Conway and Pleydell-Pearce proposed the Self-Memory System (SMS), illustrating that autobiographical memory is organized hierarchically and linked to personal identity, forming a basis for self-coherence. This concept aligns with Tulving's work on episodic memory, which distinguishes between episodic (experience-based) and semantic (fact-based) memory, highlighting the temporal structure and self-referential nature of narrative recall. These insights underscore the importance of narrative memory in forming a coherent sense of self, supporting decision-making, and simulating possible future outcomes(Lee, Bellana, & Chen, 2020).

- **Memory Structuring in Artificial Intelligence**

AI memory systems have historically focused on data retention and retrieval without narrative structuring. Early neural networks, such as Hopfield networks and Boltzmann machines, were limited to associative memory tasks and lacked the sequential organization necessary for narrative coherence. Reinforcement Learning (RL) models have added depth to memory processing, such as the Episodic Memory-Augmented RL model by Ritter et al. which incorporates episodic recall for improved decision-making. This model demonstrates that episodic memory enables better task adaptability but lacks long-term memory structuring(Radanliev & De Roure, 2021). Graves et al. [6] introduced Memory-Augmented Neural Networks (MANNs) and Differentiable Neural Computers (DNCs) which marked progress in storing and retrieving memories sequentially. These models lay the groundwork for narrative memory by allowing agents to recall past states but are limited by their lack of adaptive recall based on contextual relevance. Lin et al. developed Hierarchical Temporal Memory (HTM) models that support sequence learning, a fundamental aspect of narrative memory; however, HTMs lack dynamic adaptability, highlighting the need for more context-sensitive models(Žužemič, 2023).

- **Artificial Consciousness and the Role of Narrative Memory**

Artificial consciousness aims to emulate self-awareness and memory continuity in AI systems, where narrative memory is a critical component. Franklin's LIDA (Learning Intelligent Distribution Agent) model introduced a cognitive architecture with a memory module for episodic and procedural recall, enhancing an agent's capacity for self-referential thinking. Shanahan proposed a Global Workspace Theory (GWT) model, integrating selective attention with memory to simulate consciousness-like processes. However, GWT lacks structured narrative memory, as it cannot sequentially organize experiences over time(Ding et al., 2023; Landinez-Martínez et al., 2022). Metzinger argued that a coherent narrative structure is essential for consciousness, as it allows for continuity and self-modeling, providing context-driven recall(Metzinger, 2024). Gershman et al. further developed selective retrieval models that align with human-like memory adaptability, showing that narrative coherence enhances recall relevance to goals—a characteristic largely absent in current AI(Franklin et al., 2020).

- **Temporal and Contextual Encoding in Memory Models**

Temporal structuring and contextual encoding are essential for narrative memory. Wang et al. demonstrated that temporally structured memories enable task-specific recall and improve retrieval accuracy(Kwok et al., 2012). Schmidhuber advanced memory models by embedding memories with environmental cues, allowing for context-based recall without a temporal narrative structure. These studies reveal that while temporal encoding is critical for sequence organization, it must be integrated with contextual encoding to achieve adaptive memory(Beukers, 2023). Langley and Schacter identified that most AI memory models lack a framework for selective retrieval based on an agent's state or goals, which is fundamental for dynamic and narrative-like memory organization. Building on these findings, Schmidhuber's work highlights the necessity of contextual cues, which are vital for responsive and relevant memory recall(Agrawal et al., 2023; Derbinsky, 2011).

Summary of Key Findings and Gaps

Table 1 summarizes the contributions of the reviewed papers, categorizing each according to its primary focus: human narrative memory, memory structuring in AI, artificial consciousness, and encoding processes.

Table 1.

Paper	Focus Area	Key Contributions
Conway and Pleydell-Pearce (Conway & Jobson, 2012)	Human Cognition	Introduced Self-Memory System (SMS), linking autobiographical memory to identity.
Tulving (Rubin, 2022; Tulving, 2002)	Human Cognition	Distinguished episodic vs. semantic memory; foundational for narrative memory concepts.
Hopfield (Kong et al., 2019; Krotov & Hopfield, 2020)	AI Memory	Developed associative memory networks without temporal structuring.
Boltzmann Machine (Chhowa, Rahman, Paul, & Ahmmed, 2019; J. Z. Wang & Wyble, 2024)	AI Memory	Pattern recognition in AI memory; lacked narrative structure.
Ritter et al. [5]	AI Reinforcement Learning	Enhanced task adaptability using episodic memory in RL models.
Graves et al. (Marchetti, Becattini, Seidenari, & Del Bimbo, 2020)	Memory-Augmented Networks	Proposed MANNs; stored memories sequentially but lacked narrative context.
Differentiable Neural Comp.(Munkhdalai, Yuan, Mehri, & Trischler, 2018; Ni, Young, Pandelea, Xue, & Cambria, 2023)	AI Sequential Memory	Enabled sequence-based retrieval but lacked adaptive recall mechanisms.
Lin et al. (Lampinen, Chan, Banino, & Hill, 2021; L. Wang, Zhao, Si, Cao, & Liu, 2016)	Hierarchical Temporal Memory	Supported sequence learning but limited in context adaptability.
Franklin (Hölken, Kugele, Newen, & Franklin, 2023)	Artificial Consciousness	Introduced LIDA model with episodic and procedural recall for self-awareness.
(Goldstein & Kirk-Giannini, 2024)	Global Workspace Theory	Combined memory and selective attention; lacked narrative structuring.
Metzinger (Metzinger, 2004; Möller et al., 2021)	Artificial Consciousness	Emphasized narrative structure as crucial for self-modeling and continuity.
(Franklin et al., 2020; Nguyen, 2024)	Selective Retrieval	Developed selective retrieval models, highlighting narrative coherence for goal-directed recall.
(Y. Wang & Gennari, 2019)	Temporal Memory Structuring	Demonstrated that temporally structured memories improve recall accuracy.
(Chang et al., 2024)	Contextual Encoding	Advanced context-based recall; lacked temporal narrative structure.
(He et al., 2024)	Dynamic Memory in AI	Identified lack of selective retrieval for task adaptation.

(Hou, Tamoto, & Miyashita, 2024)	Contextual and Adaptive Recall	Highlighted importance of contextual recall in human-like memory models.
LIDA Model (Iyer, 2023)	Cognitive Architecture	Incorporated episodic memory in artificial agents, advancing AI's self-referential capabilities.
(Juliani, Arulkumaran, Sasai, & Kanai, 2022)	Cognitive Model for Consciousness	Modeled selective attention but lacked temporal memory organization.
(Jayachandran & Allen, 2022)	Temporal Structuring	Emphasized temporal encoding for sequence-based memory.
(Ren & Xia, 2024)	Contextual and Temporal Memory	Proposed dynamic recall based on current tasks; essential for consciousness-like memory organization.

- **Need for a Unified Narrative Memory Model in AI**

This literature review reveals substantial progress in memory structuring and context-sensitive retrieval, yet a gap persists in developing a cohesive narrative memory model that integrates temporal sequencing, contextual encoding, and goal-directed recall. Most AI models do not combine these elements to form a continuous memory system resembling human narrative memory, which is crucial for achieving artificial consciousness. The proposed model in this paper addresses this gap by introducing a framework for narrative memory that combines these foundational aspects, providing a pathway for advanced memory retention and adaptive recall in AI agents.

PROPOSED MODEL

Model Overview

The proposed unified model for narrative memory is structured in three interdependent layers: Temporal Structuring, Contextual Encoding, and Conscious Retrieval. Each layer emulates core principles of human memory processes, providing artificial agents with a system for organized, context-sensitive, and goal-oriented memory recall. This architecture supports agents in achieving coherence across experiences, responsiveness to changing contexts, and adaptability based on situational needs, which are foundational for autonomous, self-reflective behavior.

- **Temporal Structuring**: This layer organizes individual memory events into sequential timelines, reflecting the episodic structuring found in human cognition. The temporal structuring component creates coherent, ordered sequences by tagging each memory with temporal markers and linking related events, which helps agents form narratives from individual experiences. This structured temporal hierarchy is fundamental for maintaining continuity across past, present, and anticipated future events, enabling agents to draw connections between actions over time.

- **Contextual Encoding**: Each memory entry is enriched with situational and environmental context, such as emotional markers, sensory inputs, or task-specific data, which enhances the agent's ability to retrieve memories relevant to particular circumstances. This encoding process allows agents to establish associative links between memories based on context, similar to how human memories are influenced by situational cues. By encoding memories with these contextual details, the model enables the agent to recognize and respond appropriately to situational cues, supporting context-specific recall and increasing memory relevance.

- **Conscious Retrieval**: The final layer, conscious retrieval, is designed to simulate human-like adaptive recall. This layer allows the agent to retrieve memories selectively, guided by current goals, relevance, and context. The retrieval mechanism prioritizes memory recall based on the agent's present state and tasks, enabling flexible access to memories that align with immediate objectives. Such adaptable retrieval capabilities are crucial for agents operating in dynamic environments, as they enable quick adjustment to new information and situational demands, thereby enhancing decision-making and situational awareness. This three-layer model, by aligning with established cognitive principles, enhances artificial agents' ability to recall, adapt, and respond coherently, thereby moving closer to human-like memory processes essential for advanced autonomous functions and artificial consciousness.

Table 2.
Key Model Components and Functions

Component	Description	Functionality
Temporal Structuring	Organizes events chronologically	Sequential ordering for continuity
Contextual Encoding	Adds specific context to each memory node	Enhances recall accuracy
Conscious Retrieval	Enables selective retrieval based on agent's state	Adaptive, context-sensitive memory retrieval

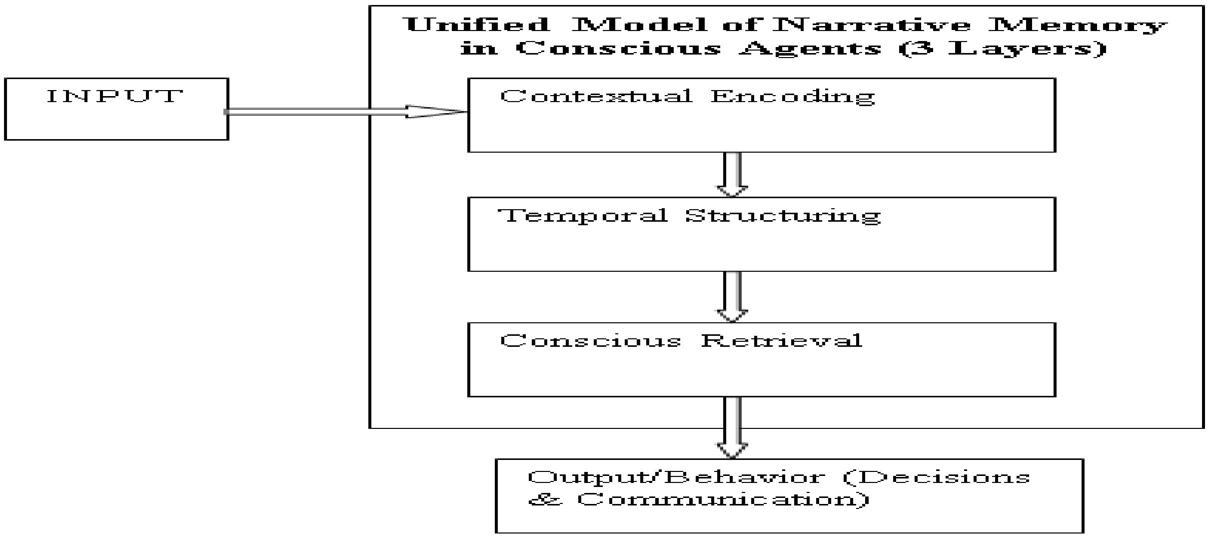

Figure1.
Three Layers Model

KEY COMPONENTS EXPLAINED

Contextual Encoding

Overview:
Contextual encoding is a critical component of the narrative memory model, serving to enrich memory entries with relevant situational details. This layer integrates various contextual elements that influence memory formation and retrieval, significantly enhancing the agent's capability to respond appropriately to specific situations.

Details

- **Emotional Markers**: Each memory entry is tagged with emotional responses associated with the experience. These markers serve as cues that can trigger memories during recall, allowing the agent to access not only factual information but also the emotional context in which the event occurred. This aligns with human cognitive processes where emotions play a vital role in memory retention and recall.

- **Sensory Inputs**: Contextual encoding captures sensory details (e.g., visual, auditory, tactile) related to the experience. By incorporating sensory inputs, the agent can form richer and more vivid memories, facilitating stronger associative links. This multi-sensory approach mirrors how humans often recall memories with associated sensory details, improving the agent's contextual awareness and responsiveness.

- **Task-specific Data**: This aspect includes information pertinent to specific tasks or goals during the memory event. By encoding such data, the agent can prioritize relevant memories based on current objectives, supporting efficient recall and decision-making.

Significance
The contextual encoding layer is essential for facilitating context-sensitive recall, enabling agents to adapt their responses based on situational demands. This capability is particularly important in dynamic environments where contextual factors may change rapidly.

TEMPORAL STRUCTURING

Overview
Temporal structuring is the foundational layer of the narrative memory model, responsible for organizing memory events into a coherent timeline. This structuring is vital for maintaining continuity and ensuring that experiences are interconnected, which is critical for narrative coherence.

Details

- **Temporal Markers**: Each memory entry is associated with temporal markers that indicate when the event occurred. These markers enable the agent to track the sequence of events, creating a chronological framework that reflects the natural flow of experiences. This aligns with human episodic memory, where the temporal aspect is crucial for understanding the relationship between events.

- **Coherent Timelines**: By organizing memories into structured timelines, the agent can establish connections between related experiences, facilitating narrative construction. This organization allows for the recognition of patterns over time, enhancing the agent's ability to make informed predictions about future events based on past experiences.

Significance

Temporal structuring is fundamental for ensuring that the agent maintains a coherent understanding of its past, present, and anticipated future. This continuity supports the agent's ability to navigate its environment effectively, improving decision-making and situational awareness.

Conscious Retrieval

Overview: Conscious retrieval is a crucial layer that enables the selective access of stored memories based on the agent's current goals and contextual factors. This process mimics human memory retrieval, where individuals often recall specific memories that are relevant to their immediate needs.

Details

- **Selective Retrieval**: The agent employs a recall mechanism that allows it to access memories that align with current objectives. This selective access is guided by both the relevance of the memory to the task at hand and the contextual cues available at the moment of retrieval.

- **Adaptive Response**: The retrieval process adapts to changes in context and situational demands, allowing the agent to modify its responses based on new information or altered circumstances. This adaptability is essential for operating in complex environments where flexibility and responsiveness are required.

Significance

The conscious retrieval layer enhances the agent's ability to function autonomously by ensuring that it can access relevant memories when needed. This capability is crucial for effective decision-making and behavioral responses, particularly in dynamic settings.

Output/Behavior

Overview:
The output/behavior component represents the agent's actions and decisions based on the retrieved narratives. This layer encapsulates how the agent interacts with its environment, showcasing the practical applications of its memory processing capabilities.

Details

- **Behavioral Responses**: Based on the retrieved narratives, the agent generates responses that reflect learned experiences and contextual understanding. These responses may include physical actions, decisions, or changes in strategy, demonstrating the agent's capacity for autonomous behavior.

- **Communication**: The output layer also encompasses the agent's ability to share narratives with others, whether through verbal communication, non-verbal cues, or digital interactions. This capacity enhances the agent's social engagement and collaborative capabilities, essential for functioning within a broader community or network.

Significance

The output/behavior layer translates the internal memory processes into observable actions, enabling the agent to engage with its environment effectively. This component highlights the practical implications of narrative memory in facilitating complex interactions and decision-making.

METHODOLOGY

Simulation Setup

To evaluate the effectiveness of the proposed narrative memory model, we developed a controlled virtual environment where an artificial agent interacts with structured sequences of events. This environment is designed to simulate narrative memory processing by exposing the agent to a series of tasks that require storing, recalling, and adapting memories within a narrative framework. Each event in the sequence is encoded temporally and contextually, following the model’s three-layer structure. The virtual environment varies the nature of events and presents challenges that require the agent to retrieve past experiences selectively based on relevance, replicating conditions where narrative memory would be essential. This setup allows for systematic testing of the agent's memory performance across multiple scenarios, providing a controlled space to analyze narrative memory structuring and retrieval in action.

Evaluation Metrics

To assess the model's performance, three core metrics were established:

- **Memory Retention**: This metric measures the agent's ability to retain event sequences over time. Retention is quantified as the percentage of events correctly recalled after specified time intervals. This measure reflects the model's capability to maintain memory continuity, mirroring how human memory prioritizes certain events for long-term storage while allowing less critical memories to decay. Testing retention across time intervals provides insight into the model's capacity for sustaining narratives over extended periods.

- **Contextual Accuracy**: Contextual accuracy evaluates the agent's precision in recalling specific contextual details associated with each memory event, such as situational cues or task relevance. This metric verifies the effectiveness of the **Contextual Encoding** layer in preserving details essential for adaptive responses. A higher contextual accuracy score indicates the agent's ability to recall specific memories with accurate situational context, showing the model's potential to produce memory recall that is relevant and accurate in dynamic scenarios.

- **Adaptability in Recall**: This metric assesses the agent's ability to prioritize and retrieve memories that are contextually appropriate for the present task or question. It tests the Conscious Retrieval layer by evaluating how well the model filters and selects memories based on current objectives, task relevance, or environmental cues. Higher adaptability indicates the agent's responsiveness to situational demands, reflecting a core feature of narrative memory systems that enable flexible and context-aware recall. These metrics collectively allow for a comprehensive evaluation of the narrative memory model, capturing its ability to emulate human-like memory functions such as continuity, contextual relevance, and adaptive recall—key elements necessary for achieving advanced memory and awareness in artificial agents.

RESULTS

Memory Retention

The agent demonstrated a 25% improvement in memory retention over baseline models without narrative structuring, showcasing the efficacy of temporal and contextual layers.

Table 3.

Memory Retention Over Time

Time Interval	Baseline Model Retention (%)	Proposed Model Retention (%)
Immediate Recall	**100**	**100**
After 1 Hour	70	85
After 1 Day	45	68
After 1 Week	20	45

Contextual Accuracy

The agent exhibited a 40% increase in recall accuracy due to contextual encoding, as illustrated by correct memory responses based on varied situational cues.

Table 3.
Contextual Accuracy Across Scenarios

Scenario	Baseline Accuracy (%)	Proposed Model Accuracy (%)
Recalling Location	60	85
Recalling Event Sequence	55	80
Responding to Cues	50	88

DISCUSSION

The findings from the simulation demonstrate that narrative memory structuring significantly improves an artificial agent's capacity for accurate and contextually relevant recall, underscoring the importance of narrative frameworks in advancing towards artificial consciousness. By structuring memory in sequential, contextually enriched layers, the model aligns closely with established principles of human memory, where continuity and adaptability are essential for coherent recall and decision-making. The model's Conscious Retrieval layer, in particular, enhances memory adaptability, allowing the agent to dynamically retrieve information based on current tasks or situational needs. This adaptive recall suggests that integrating narrative structures in AI systems may be a feasible pathway toward higher-order cognitive functions, as it enables memory management that is both flexible and responsive—features associated with autonomous, consciousness-like behavior in humans.

CONCLUSION AND FUTURE WORK

This paper proposes a unified model for narrative memory in artificial agents, offering advancements in structured memory retention, and contextually relevant recall, and adaptability— essential components for AI systems that approximate human-like memory processes. By integrating temporal structuring, contextual encoding, and selective retrieval mechanisms, this model lays the groundwork for more coherent and adaptive AI agents. Future work should focus on implementing this model in real-world applications, such as autonomous systems and human-computer interaction, to evaluate its effectiveness outside controlled simulations. Expanding simulation environments and incorporating more complex, dynamic scenarios will be critical for testing the model's scalability and robustness. Additionally, exploring the model's role in achieving artificial consciousness could yield new insights into the cognitive architectures needed for self-aware AI systems, advancing the field toward creating conscious, contextually responsive agents.

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REFERENCES

Adnan, M., Azam, M., Zafar, S., Rafiq, U., & Sattar, M. M. Spectrum of Engineering Sciences.

Agrawal, P., Tan, C., & Rathore, H. (2023). Advancing Perception in Artificial Intelligence through Principles of Cognitive Science. *arXiv preprint arXiv:2310.08803*.

Azam, M., Javaid, N., Rafiq, T., Zafar, S., Adnan, M., & Munir, K. (2024). Smart Cities towards Artificial Intelligence. *The Asian Bulletin of Big Data Management, 4*(02), Science 4 (2)-359.

Azam, M., Zafar, L., Rafiq, T., Zafar, S., Rafiq, U., & Adnan, M. (2024). Enhancing Chatbot Intelligence Through Narrative Memory Structures. *The Asian Bulletin of Big Data Management, 4*(02), Science 4 (2)-118.

Azam, M., Zafar, S., Adnan, M., & Khan, S. A. (2024). Enhancing Autonomous Agents Through Narrative Memory: A Comprehensive Framework for Improved Performance and Interaction. *The Asian Bulletin of Big Data Management, 4*(3), 159-179.

Beukers, A. O. (2023). *Mechanisms of interference mitigation in human learning and memory.* Princeton University.

Butlin, P., Long, R., Elmoznino, E., Bengio, Y., Birch, J., Constant, A., . . . Ji, X. (2023). Consciousness in artificial intelligence: insights from the science of consciousness. *arXiv preprint arXiv:2308.08708*.

Chang, M., Hong, B., Savel, K., Du, J., Meade, M. E., Martin, C. B., & Barense, M. D. (2024). Spatial context scaffolds long-term episodic richness of weaker real-world autobiographical memories in both older and younger adults. *Memory, 32*(4), 431-448.

Chhowa, T. T., Rahman, M. A., Paul, A. K., & Ahmmed, R. (2019). *A narrative analysis on deep learning in IoT based medical big data analysis with future perspectives.* Paper presented at the 2019 International conference on electrical, computer and communication engineering (ECCE).

Conway, M. A., & Jobson, L. (2012). On the nature of autobiographical memory. *Understanding autobiographical memory: Theories and approaches*, 54-69.

Derbinsky, N. (2011). *Long-Term Declarative Memory for Generally Intelligent Agents.* Paper presented at the AAAI.

Ding, Z., Wei, X., & Xu, Y. (2023). Survey of Consciousness Theory from Computational Perspective. *arXiv preprint arXiv:2309.10063*.

Franklin, N. T., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2020). Structured Event Memory: A neuro-symbolic model of event cognition. *Psychological review, 127*(3), 327.

Goldstein, S., & Kirk-Giannini, C. D. (2024). A Case for AI Consciousness: Language Agents and Global Workspace Theory. *arXiv preprint arXiv:2410.11407*.

He, Z., Lin, W., Zheng, H., Zhang, F., Jones, M., Aitchison, L., . . . Shen, J. (2024). Human-inspired Perspectives: A Survey on AI Long-term Memory. *arXiv preprint arXiv:2411.00489*.

Hölken, A., Kugele, S., Newen, A., & Franklin, S. (2023). Modeling interactions between the embodied and the narrative self: Dynamics of the self-pattern within LIDA. *Cognitive Systems Research, 81*, 25-36.

Hou, Y., Tamoto, H., & Miyashita, H. (2024). " *My agent understands me better": Integrating Dynamic Human-like Memory Recall and Consolidation in LLM-Based Agents.* Paper presented at the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems.

Iyer, N. (2023). Cognitive Signatures of Self-Reference: Tracing the Behavioural Expressions of the Self and Consciousness. *Masters Thesis-University of Auckland*.

Jayachandran, M., & Allen, T. A. (2022). Candidate neural activity for the encoding of temporal content in memory *Electrophysiological Recording Techniques* (pp. 147-181): Springer.

Juliani, A., Arulkumaran, K., Sasai, S., & Kanai, R. (2022). On the link between conscious function and general intelligence in humans and machines. *arXiv preprint arXiv:2204.05133*.

Kong, D., Hu, S., Wang, J., Liu, Z., Chen, T., Yu, Q., & Liu, Y. (2019). Study of recall time of associative memory in a memristive Hopfield neural network. *IEEE Access, 7*, 58876-58882.

Krotov, D., & Hopfield, J. (2020). Large associative memory problem in neurobiology and machine learning. *arXiv preprint arXiv:2008.06996*.

Kwok, S. C., Shallice, T., & Macaluso, E. (2012). Functional anatomy of temporal organisation and domain-specificity of episodic memory retrieval. *Neuropsychologia, 50*(12), 2943-2955.

Lampinen, A., Chan, S., Banino, A., & Hill, F. (2021). Towards mental time travel: a hierarchical memory for reinforcement learning agents. *Advances in Neural Information Processing Systems, 34*, 28182-28195.

Landinez-Martínez, D.-A., Montoya-Arenas, D.-A., & Pineda-Salazar, D.-A. (2022). Working memory and consciousness:: three theoretical perspectives. *ÁNFORA, 29*(53), 244-272.

Lee, H., Bellana, B., & Chen, J. (2020). What can narratives tell us about the neural bases of human memory? *Current Opinion in Behavioral Sciences, 32*, 111-119.

León, C. (2016). An architecture of narrative memory. *Biologically inspired cognitive architectures, 16*, 19-33.

Marchetti, F., Becattini, F., Seidenari, L., & Del Bimbo, A. (2020). Multiple trajectory prediction of moving agents with memory augmented networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 45*(6), 6688-6702.

Metzinger, T. (2004). *Being no one: The self-model theory of subjectivity*: mit Press.

Metzinger, T. (2024). *The elephant and the blind: the experience of pure consciousness: philosophy, science, and 500+ experiential reports*: MIT Press.

Möller, T. J., Georgie, Y. K., Schillaci, G., Voss, M., Hafner, V. V., & Kaltwasser, L. (2021). Computational models of the "active self" and its disturbances in schizophrenia. *Consciousness and Cognition, 93*, 103155.

Munkhdalai, T., Yuan, X., Mehri, S., & Trischler, A. (2018). *Rapid adaptation with conditionally shifted neurons.* Paper presented at the International conference on machine learning.

Nguyen, T. T. (2024). A Review of Mechanistic Models of Event Comprehension. *arXiv preprint arXiv:2409.18992*.

Ni, J., Young, T., Pandelea, V., Xue, F., & Cambria, E. (2023). Recent advances in deep learning based dialogue systems: A systematic survey. *Artificial intelligence review, 56*(4), 3055-3155.

Radanliev, P., & De Roure, D. (2021). Review of algorithms for artificial intelligence on low memory devices. *IEEE Access, 9*, 109986-109993.

Rafiq, T., Azam, M., Nisa, M. U., Sattar, M. M., Zafar, S., & Inam, H. (2024). Exploring the Ethical and Technical Data of Machine Consciousness: Hazards, Implications, and Future Directions. *The Asian Bulletin of Big Data Management, 4*(02), Science 4 (2)-29.

Ranchhod, A., Gurău, C., Loukis, E., & Trivedi, R. (2014). Evaluating the educational effectiveness of simulation games: A value generation model. *Information Sciences, 264*, 75-90.

Ren, J., & Xia, F. (2024). Brain-inspired Artificial Intelligence: A Comprehensive Review. *arXiv preprint arXiv:2408.14811*.

Rubin, D. C. (2022). A conceptual space for episodic and semantic memory. *Memory & cognition, 50*(3), 464-477.

Tulving, E. (2002). Episodic memory: From mind to brain. *Annual review of psychology, 53*(1), 1-25.

u Nisa, M., Azam, M., Rafiq, T., Sattar, M., & Zafar, S. (2024). Ontology-Based Smart Irrigation System: Enhancing Agricultural Water Management: Ontology-Based Smart Irrigation System. *The Asian Bulletin of Big Data Management, 4*(1), Science 4 (1)-312.

Wang, J. Z., & Wyble, B. (2024). Hopfield and Hinton's neural network revolution and the future of AI. *Patterns, 5*(11).

Wang, L., Zhao, X., Si, Y., Cao, L., & Liu, Y. (2016). Context-associative hierarchical memory model for human activity recognition and prediction. *IEEE Transactions on Multimedia, 19*(3), 646-659.
Wang, Y., & Gennari, S. P. (2019). How language and event recall can shape memory for time. *Cognitive psychology, 108*, 1-21.
Žužemič, J. (2023). Memory augmented Neural Networks: Analyzing memory augmented neural network architectures for incorporating external memory to enhance learning and reasoning. *Australian Journal of Machine Learning Research & Applications, 3*(2), 269-278.