# A Comparative Analysis of Episodic Memory between Humans and AI Agents with Context Correlation

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***Abstract*—This study delves into a comparative analysis of episodic memory, examining both human cognition and Artificial Intelligence (AI) agents. Through an in-depth exploration, the research focuses on the nuanced aspects of episodic memory encoding, retrieval, and associative capabilities in humans and AI systems. The investigation incorporates Electroencephalography (EEG) as a fundamental tool to comprehend and compare the underlying neural mechanisms associated with episodic memory in humans while drawing parallels to memory processes in AI agents. The findings illuminate similarities and disparities, shedding light on the cognitive frameworks and technological advancements shaping episodic memory across biological and artificial entities. This exploration provides valuable insights into the convergence and divergence of memory mechanisms, potentially influencing future AI developments and understanding human cognition.**

***Index Terms*—EEG-Electroencephalography, Episodic Memory, Human Cognition, Artificial Intelligence (AI) Agents, Comparative Analysis, Memory Retrieval, Context.**

## I. Introduction

Episodic memory stands as a pivotal facet of human cognition, representing the ability to recall specific past events, experiences, and their contextual details within a personal timeline. It encompasses the richness of autobiographical memory, allowing individuals to mentally travel back in time and relive moments while integrating sensory perceptions, emotions, and spatial-temporal context. This unique cognitive ability enables humans to navigate daily life, learn from past experiences, and project themselves into the future, forming the cornerstone of our identity and decision-making processes.

Concomitant with advancements in AI, the emergence of AI agents equipped with memory systems presents a paradigm shift in technological capabilities. These agents, ranging from sophisticated chatbots to complex neural networks, are designed to mimic cognitive processes, including memory encoding, retrieval, and learning. AI memory frameworks, though algorithmically driven and fundamentally distinct from human cognition, are pivotal in enabling these agents to retain and utilize information, make decisions, and perform tasks across various domains.

This paper aims to undertake a comparative analysis of episodic memory, focusing on the influence of contextual factors on memory encoding, retrieval, and associative processes in both humans and AI agents. It delineates the impact of context on memory mechanisms, leveraging EEG as a tool to probe neural correlates associated with episodic memory in humans and explore parallels or distinctions in AI memory frameworks. The paper is structured to first delve into the nuances of episodic memory in humans, subsequently transitioning to the emerging landscape of AI memory systems. Through a comparative lens, it examines context-mediated memory effects and EEG correlations, ultimately aiming to elucidate the convergence and divergence between human cognition and AI memory mechanisms.

## II. Episodic Memory in Humans

### *A. Memory Encoding and Context Effects*

Memory encoding in humans involves the initial processing of sensory information into a form that can be stored and later retrieved. This process occurs through various stages, including attention, perception, and consolidation, where information is integrated into existing memory networks.

Contextual cues, encompassing environmental, emotional, and situational factors, play a pivotal role in memory formation. The encoding specificity principle posits that retrieval of information is most effective when the context at encoding matches the context at retrieval. This principle underscores the significance of contextual congruence in memory formation and recall.

Several studies employing EEG have revealed insights into context effects on human episodic memory. For instance, research [3], showcased increased neural synchrony in specific brain regions during memory encoding when contextual cues were present, emphasizing the influence of context on neural patterns associated with memory formation.

### *B. Memory Retrieval and Contextual Influences*

Memory retrieval involves accessing stored information from memory networks. Context plays a pivotal role in triggering recall by acting as retrieval cues [1], [2], facilitating the retrieval of associated memories when the context at recall aligns with the context at encoding.

 ISBN: 978-1-68558-127-5 

Studies investigating context-dependent memory retrieval in humans have consistently demonstrated the impact of context on recall. EEG studies revealed distinct neural signatures during context-induced memory retrieval, highlighting the role of neural oscillations and synchronization in retrieving context-linked memories.

### C. Associative Memory and Contextual Linkages

Associative memory involves forming connections between different pieces of information. Contextual information acts as a binding factor, strengthening associations between items encoded within a similar context.

EEG studies exploring neural correlates of associative memory in context-rich environments have unveiled patterns of neural activation in specific brain regions, elucidating the neural mechanisms underlying the influence of context on associative memory processes. For instance, research has revealed increased coherence between brain regions associated with contextual processing and memory association tasks.

## III. Episodic Memory in AI Agents

### A. Memory Encoding Mechanisms

Memory Encoding mechanisms in AI agents primarily rely on structured databases and algorithms. Databases store information in a structured format, enabling efficient retrieval and manipulation. Algorithms manage the Encoding, organization, and retrieval of data, utilizing various techniques such as indexing, hashing, and neural network architectures for memory representation.

Integrating contextual information into AI memory frameworks poses significant challenges. AI agents traditionally process information based on predefined patterns and lack the inherent contextual understanding characteristic of human cognition. Challenges include contextual ambiguity, dynamic context changes, and the computational complexity of incorporating multifaceted contextual cues. However, integrating contextual information offers potential benefits, enhancing the adaptability, relevance, and decision-making capabilities of AI systems.

### B. Memory Retrieval and Contextual Integration

The AI agents retrieve information from stored data using algorithms tailored for efficient search and retrieval. Context plays a crucial role in retrieval algorithms, aiding in narrowing down search results or providing relevant cues for retrieving associated information. Contextual integration involves algorithms that utilize contextual cues to refine retrieval processes, akin to humans using context as retrieval cues.

Ongoing research and developments aim to imbue AI memory systems with contextual awareness. For instance, advancements in Natural Language Processing (NLP) incorporate contextual embeddings or attention mechanisms, allowing AI models to consider contextual information in text-based tasks. Additionally, research in machine vision explores contextual understanding in image recognition tasks by leveraging spatial and semantic context to improve object recognition and scene understanding in AI systems.

For our experimentation, we use a TransformerXL backbone by [6] and modify its sequential memory buffer with Automatic Chunking [7] to enable the transformer to apply attention to only relevant parts of memory depending on the current context that might not always be sequential. The model architecture is described in Section VI.

## IV. EEG Data Collection and Analysis

EEG data was collected using an Emotiv FLEX EEG cap, which features 32 channels for recording neural activity during encoding and retrieval phases in human participants. This cap was equipped with monopolar gel-based electrodes strategically positioned across the scalp to capture electrical signals emanating from various regions of the brain. The electrode positions were determined according to the 10-20 international system for EEG electrode placement (Figure 1), ensuring standardized and precise positioning for data acquisition.

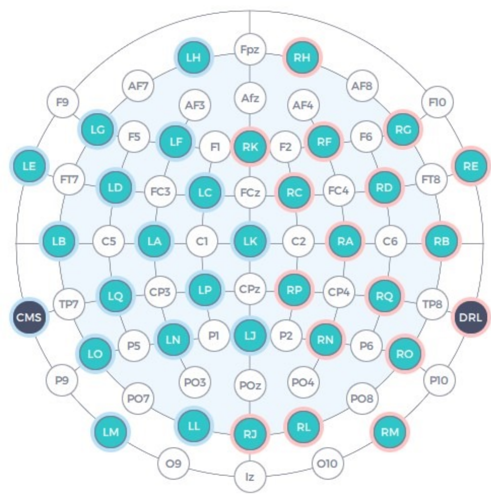


Fig. 1: EEG Electrode Placement.

### A. Captured EEG Data

The EEG data was captured using the CyKit software [11] during the encoding and retrieval phases of the experiment. To provide a comprehensive understanding of the analyzed brain activity, this section details crucial information regarding the data acquisition process. The recording duration for encoding phase was 60-70 seconds while for decoding phase the subjects were not bound for time intervals, allowing for analysis of the temporal dynamics of brain activity. Additionally, a high-pass filter with a cutoff frequency of around 0.16 Hz and notch filters at 50 Hz and 60 Hz to remove power line noise interference was applied to the data using CyKIT, focusing on the specific frequency band of interest. Moreover, the data is downsampled to 128 Hz before transmission. Finally, the analysis incorporates data from a single trial from the encoding and retrieval phases, enhancing the generalizability of the findings.

 ISBN: 978-1-68558-127-5 

### B. Topographical Brain Mapping

The topographical brain activity maps were generated for EEG data obtained from the participants using resources from [10] as a baseline. This code repository offered tools and utilities specifically designed for EEG data processing in Python, facilitating the creation of detailed and informative brain activity maps. The generated maps serve as valuable tools for analyzing and interpreting the complex patterns of brain activity observed during the experiment, enabling us to gain deeper insights into memory-related cognitive processes. The graphs were generated such that the top data points correspond with the front of the scalp. Please refer to Appendix A and B for the EEG maps plotted during all our experimentation. The graph was rendered to provide a top-down perspective of the head, where the upper regions of the graph represent the front of the head, the left sections correspond to the left-hand side, and the right sections depict the right-hand side. This approach ensured that the spatial orientation of the depicted neural activity aligned appropriately with anatomical references, facilitating a clear and intuitive interpretation of the topographical brain mapping results.

### C. Encoding Phase Analysis

During the encoding phase, EEG data analysis involved assessing neural correlates linked to the processing of contextual cues (such as wall colours) and memory encoding. The topographical brain maps derived from this phase showcased neural activation patterns specific to encoding information within distinct contextual contexts.

### D. Retrieval Phase Analysis

Similarly, during the retrieval phase, EEG data analysis focused on discerning neural signatures associated with memory retrieval and decision-making while navigating the game. The topographical brain maps generated during retrieval indicated neural activity patterns corresponding to successful memory recall and decision-making processes influenced by contextual cues.

### E. Integration of Topographical Maps

The topographical brain maps were generated using the Akima interpolation method, which was chosen due to its effectiveness in facilitating a smoother visualization of spatial distribution. No parameter tuning was performed as default settings were deemed sufficient for the analysis. The time window used for calculating brain activity represented in each topographical map corresponds to the encoding or retrieval phase of the memory task. Specifically, the observation interval spans from the onset of the memory task to the offset of the task period. The topographical brain maps provided visual representations of the neural activation patterns across different scalp regions. Areas exhibiting heightened or suppressed electrical activity were depicted, aiding in the identification of brain regions implicated in context-mediated memory encoding and retrieval [4] [5]. Variations in neural activity across scalp regions were indicative of the brain's response to contextual cues during memory-related tasks. The transformation from 2D matrices of channels by samples to 2D spatial maps involved several key steps in topographical brain mapping. Initially, each channel within the EEG data corresponded to a specific electrode position on the scalp, known from a standardized electrode montage such as the 10-20 system. Subsequently, contour plotting techniques were applied to visualize the spatial distribution of this interpolated activity, creating a 2D map where different colors or shading indicated varying levels of neural activity across scalp regions. This process enabled us to gain insights into the spatial dynamics of brain function during cognitive tasks or experimental conditions.

### F. Integration with Behavioral Performance

These EEG-derived topographical brain maps were correlated with participants' behavioral performance during the game-based task. The association between neural activation patterns depicted in the maps and the accuracy/speed of memory-related decisions offered insights into the neural mechanisms underlying context-induced effects on episodic memory.

## V. EXPERIMENTS: CONTEXT EFFECTS ON EPISODIC MEMORY IN HUMANS AND AI AGENTS

### A. Experimental Design 1

*a) Objective:* The objective of this experiment was to investigate and compare the impact of contextual cues on episodic memory encoding and retrieval in both human participants and an AI agent model. The study aimed to explore EEG correlations to identify neural signatures associated with context-mediated memory processes in humans and simulate analogous processes within an AI system.

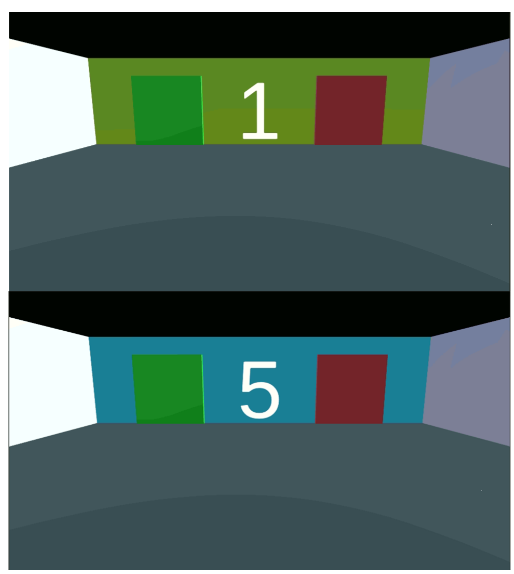



Fig. 2: Experiment 1 Game environment.

*b) Methodology:* Four individuals (aged 20-30) without any neurological disorders participated in this experiment. We utilized a neural network-based AI model that simulates memory processes akin to episodic memory for comparison with human subjects.

*c) Task design:* Participants engaged in a game involving 20 rooms, each containing numbers (1-20) and distinct wall colours (see Figure 2). In each room, there was a red and a green door. Participants had to select one door, aiming to choose the correct door to progress to the next room. Correct door selection allowed advancement to the next room, while an incorrect choice led to a shift back to the previous room.

*d) Encoding Phase:* Participants were explicitly instructed to remember the correct door in each room during the game as part of the encoding phase. They were told the correct door and played through the environment a few times till they felt they had memorized all the doors. The EEG plots of participant A and B were collected to see which regions of the brain would should high activation during encoding (see Figure 9).

*e) Retrieval Phase:* During the retrieval phase, participants replayed the game without explicit instructions, relying on their memory for choosing the correct door in each room. The EEG plots of participant A and B were also collected to see which regions of the brain would should high activation during decoding (see Figure 10).

*f) Contextual Manipulation:* The distinct wall colours in each room served as contextual cues.

### B. Experimental Design 2

*a) Objective:* The objective of the second experiment was to explore the influence of diverse contextual cues on context-dependent memory retrieval and episodic memory association. Participants engaged in a game-based task involving various contextual environments to examine the influence of these contexts on memory recall and associative processes.

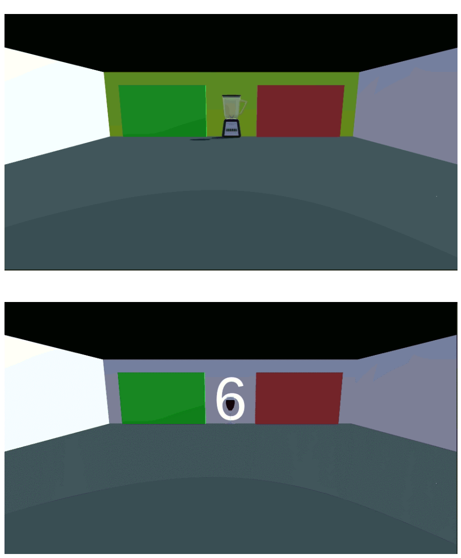



Fig. 3: Game Environment for Experiment 1 containing objects.

*b) Methodology:* The experiment involved two individuals familiar with the game environment from a prior session.

*c) Task Design with Diverse Contextual cues:* Participants navigated through 30 rooms similar to Experiment 1, each designed with specific contextual cues:

- 10 rooms with numbers (1-10).
- 10 rooms with distinct wall colours.
- 10 rooms with attached scenery (no wall colours).

Each room contained 20 random objects and two doors (red and green), requiring participants to choose one to progress (see Figure 3).

*d) Encoding Phase:* During the encoding phase, participants played the game twice while being exposed to varied contextual environments, once with rooms in normal series and once with all rooms shuffled. The objective was to encourage the association of contextual cues with the correct door choice in each room. The EEG plots of both subjects were plotted during encoding (see Figure 11).

*e) Retrieval Phase:* In the retrieval phase, participants were presented with rooms lacking contextual cues (no wall colours, numbers, or scenery). Participants were tasked with recalling the context associated with each room and selecting the correct door choice based solely on their episodic memory. Recall was tested and EEG data measured right after encoding (see Figure 12), 6 hours after encoding (see Figure 13) and 24 hours after encoding (see Figure 14).

## VI. Model Architecture

### A. TransformerXL

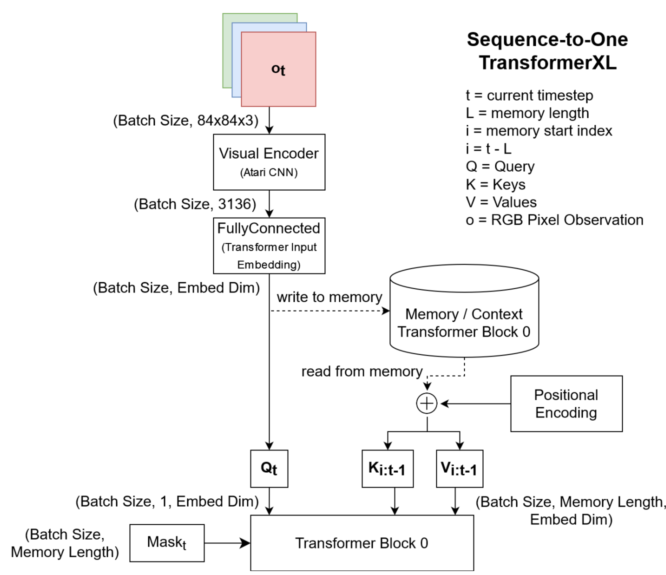



Fig. 4: TransformerXL Architecture [6].

We use a modified decoder-only TransformerXL architecture for testing the performance of AI agents with episodic memory. Ego-centric visual observations are used which are encoded into an embedded representation using a 3-layer Convolutional encoder. The encoded observation is saved in the memory buffer and used as the query in the Transformer decoder where attention is performed inside the encoder between the memory buffer and the query. A categorical action probability is calculated for each action by applying a linear layer to the output of the decoder. The model weights are trained using Proximal Policy Optimization 2 (PPO2) based on [12] and mini-batch training and the model learns to predict a suitable action given the current observation and the past context. Adam optimizer from [12] is used to decay the learning rate and other PPO2 parameters. Multiple instances of the environments are used to create larger batched data for training.

The memory buffer used in TransformerXL is a simple sequential buffer that stores the encoded observations every timestep. Using all the memories in the buffer during attention in the layer is computationally intensive and scales with the buffer length. All past observations might also not be appropriate in the current context. To combat this, we use Automatic Chunking before the memory buffer is passed to the decoder. This is similar to how human episodic memory is chunked based on certain groups of events that are correlated as discussed previously.

### *B. Automatic Chunking Mechanism*

Automatic Chunking works on the memory buffer and divides the buffer into chunks of constant size. A summary value is calculated for each chunk using mean pooling. Top-level attention is performed between the summary values and the current observation, and the Top-k chunks are chosen with the highest correlation values. These chunks are then concatenated and used as the summarised memory buffer which is used by the decoder. The summarised memory buffer includes memories that are most relevant in the current context thus leading to better action calculation by the transformer decoder. With Automatic chunking, the TransformerXL memory buffer is modified to act like an Episodic memory buffer due to the fact that it includes egocentric sequences of past events and can recall the most appropriate sequences from it. We can thus compare the TransformerXL model with Automatic chunking with the episodic memory of human subjects.

### *C. Tasks*

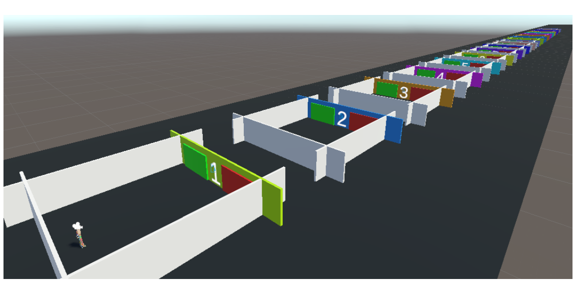



Fig. 5: Game Environment for Experiment 1.

The game environments used in our experimentation are created using Unity MLAgents [10]. Our reinforcement learning models are trained using the Gym API [11] for MLAgents while the games can be directly played by the human subjects. The AI models were trained until they achieved the maximum reward in the task.

We created two variations of the Experiment 1 game environment used for human testing and AI testing as described later. The observation space of the agent includes the agent's visual observations of size 40x40x3, the agent's position and the current room number of the agent. The rewards were set such that the agent got a positive reward proportional to the room number in each room. If it made a mistake in a room, a negative reward proportional to the room number was given and the agent was teleported back two rooms.

The two variations of the task were:

- The Unshuffled variant: Here, the rooms were in numerical order from 1 to 20 and the correct door colours were fixed (see Figure 5). This variant tested the agent's and player's ability to remember long sequences of information.
- The Shuffled variant: Here, the order of rooms was shuffled during training and testing for every episode. The correct doors for each individual room were fixed. Thus, here, the agent and player needed to learn the correlation between the context i.e., the number of the room and wall colour and the correct door and recall this information during testing non-sequentially.

We trained TransformerXL with and without Automatic Chunking using the same parameters on both variants of the task. The memory length was set to the length of each episode at 500 while the Automatic Chunking parameters used were 10 chunks of size 30. We used default PPO2 parameters except for a changed initial learning rate of 5 e-5. The parameters for Automatic Chunking were decided based on the experimentation by [7] where it was found that chunking the memory and only using around 60% of the memory in the transformer gave the best results in most tasks. Keeping a small chunk size helps in this task as well as the model can access smaller sequences in further apart sections of the memory which is required in this task due to the amount of time spent in a single room is short compared to the total episode length.

The trained models were tested on the same environments for 50 episodes to test whether the model had learnt the proper sequences or mapping in the tasks.

### *D. Training Results*

*a) Unshuffled Variant:* In Figure 6, we plot the average rewards over the multiple instances of the environments versus the episode number for both models. Both models achieve the maximum reward of 100 in the environment in 400 episodes.

*b) Shuffled Variant:* In Figure 7, we plot the average rewards over the multiple instances of the environments versus the episode number for both models. Both models achieve the maximum reward of 100 in the environment in around 800 episodes.

 ISBN: 978-1-68558-127-5 


Fig. 6: Average Training Rewards v/s Episode Number for Unshuffled Task.

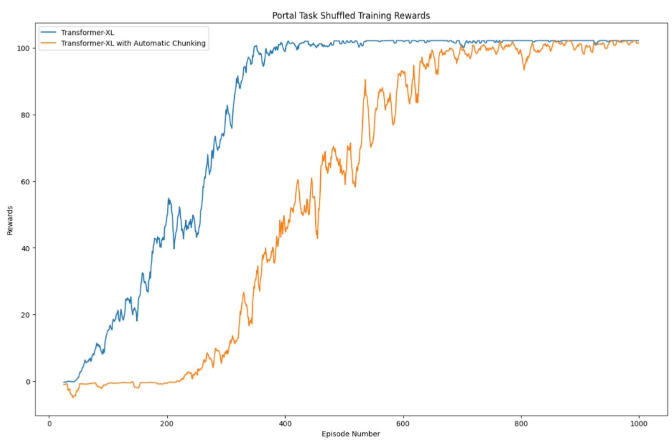



Fig. 7: Average Training Rewards v/s Episode Number for Shuffled Task.

### E. Testing Results

Both models successfully reached the final room and completed the task in the Unshuffled variant with a success rate of 98%Ṫhis proved that the model had learnt the long sequence well and achieved a higher success rate than the human subjects. Both models successfully completed the shuffled variant as well with a success rate of 100%Ṫhis proved that the models learned the correlation between the context and the goal correctly. The models also proved their generalizability by learning the random environment with shuffling which proved difficult for the human subjects.

TABLE I: TESTING RESULTS OF MODEL.

| Task | Model | Success rate | Failure rate |
|---|---|---|---|
| Unshuffled Portal Task | TransformerXL | 49/50 (98%) | 1/50 (2%) |
| | TransformerXL with Automatic Chunking | 49/50 (98%) | 1/50 (2%) |
| Shuffled Portal Task | TransformerXL | 50/50 (100%) | 0/50 (0%) |
| | TransformerXL with Automatic Chunking | 50/50 (100%) | 0/50 (0%) |

## VII. Results

### A. Experiment 1: Context Effects on Game Performance

The findings from the first experiment revealed variations in in-game performance and completion among participants:

*a) Subject A Performance:* They successfully completed the game with 8 mistakes. They demonstrated efficient memory recall and decision-making, navigating through the rooms and completing the task.

*b) Subject B Performance:* They experienced difficulty progressing through the game, halting at the 17th room.They made 12 mistakes, indicating challenges in memory recall or decision-making during the task.

These outcomes suggest individual differences in memory retrieval and game performance, highlighting varying abilities to recall contextual cues and make accurate decisions during the game.

### B. Experiment 2: Contextual Recall and Episodic Memory Association

In the second experiment, participants' performance in recalling context and associating it with the correct door choice was analyzed:

*a) Subject C Contextual Recall:* They recalled only 6 correct contexts associated with the rooms.They made 3 mistakes, indicating limitations in episodic memory recall and association with contextual cues.

*b) Subject D Contextual Recall:* They successfully recalled 15 correct contexts associated with the rooms. They made 3 mistakes during the recall phase, showcasing robust episodic memory association with contextual cues.

These results indicate significant differences in participants' abilities to recall and associate contextual cues with correct door choices, highlighting varying levels of episodic memory recall between individuals.

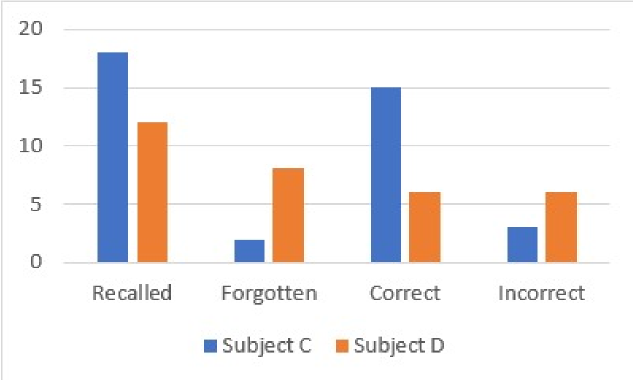
### C. Overall Insights

The results from both experiments underscore the impact of contextual cues on memory recall and decision-making during the game-based tasks. Individual variations in memory retrieval abilities and the influence of contextual cues on episodic memory association were evident, showcasing the significance of vivid contextual cues in enhancing memory recall and performance.

## VIII. Conclusion

### A. Human Memory Limitations and AI Advantages

The limitations of human memory capacity, as observed in the experiments, underscore the potential advantages of AI systems in memory-related tasks. While humans exhibited varying degrees of memory recall and performance limitations,




| | Recalled | Forgotten | Correct | Incorrect |
|---|---|---|---|---|
| **Subject C** | 18 | 2 | 15 | 3 |
| **Subject D** | 12 | 8 | 6 | 6 |

Fig. 8: Subject performance in Experiment 2.

AI models showcased consistent memory retrieval capabilities. This suggests that AI systems, being devoid of cognitive constraints, possess the ability to store and retrieve vast amounts of information more reliably than human memory.

### *B. Neural Activation Patterns During Encoding and Retrieval*

The observed neural activation patterns during the encoding and retrieval phases provide insights into the underlying neural mechanisms associated with episodic memory processes. Activation in the prefrontal lobe during encoding aligns with previous research highlighting its role in memory encoding and organization of information. Contrastingly, the predominant activation in the right hemisphere, particularly in the temporal and prefrontal lobes, during retrieval resonates with studies emphasizing the involvement of these brain regions in memory retrieval and associative processes.

### *C. Time-Dependent Memory Fading and Contextual Complexity*

The experiments revealed nuances regarding the influence of time and contextual complexity on memory retention. Human memory demonstrated susceptibility to memory fading over time, impacting the accuracy and completeness of memory recall. Moreover, the complexity of contextual cues played a pivotal role in memory association and retrieval. Clear and distinct contextual cues facilitated better memory recall and association, while vague or complex contexts led to limitations in memory retrieval and decision-making, underscoring the importance of context clarity in enhancing memory performance.

### *D. Implications and Future Directions*

Understanding the interplay between human memory limitations, neural activation patterns, temporal effects on memory, and contextual complexity holds implications for both cognitive research and AI development. Further investigations could delve into strategies to optimize human memory recall, leveraging insights from AI memory frameworks to enhance human cognitive processes. Additionally, refining AI memory systems to mimic or adapt to human-like memory constraints in varied contexts could revolutionize AI applications in memory-intensive tasks. Adding abilities such as Future imagination and forgetting could are a step towards emulating human-like cognition in robots and we are exploring these in our future work.

AI surpasses human memory in several aspects, primarily in Encoding capacity, retrieval speed, and consistency. Unlike human memory prone to forgetting and capacity limitations, AI systems retain vast amounts of information without degradation or inaccuracies. They retrieve data rapidly and consistently, handling multiple tasks simultaneously, a feat challenging for human memory. AI's adaptability, immunity to cognitive biases, and continual learning surpass human memory's limitations, making it resilient, precise, and constantly improving. Its applications across diverse domains further underscore its potential to revolutionize memory-intensive tasks, offering unparalleled advantages over human memory capabilities.

Since our current experimentation was a preliminary study, we plan to increase the number of subjects in future trials. By expanding our sample size, we aim to enhance the robustness and generalizability of our findings by sampling larger variations in brain activity patterns and responses.

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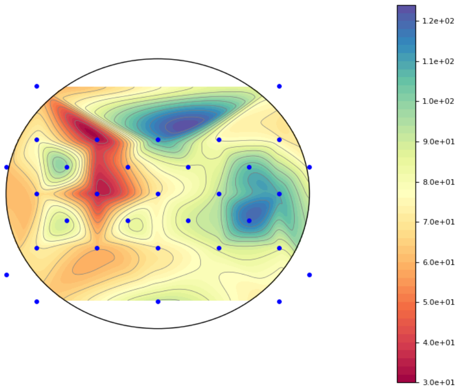
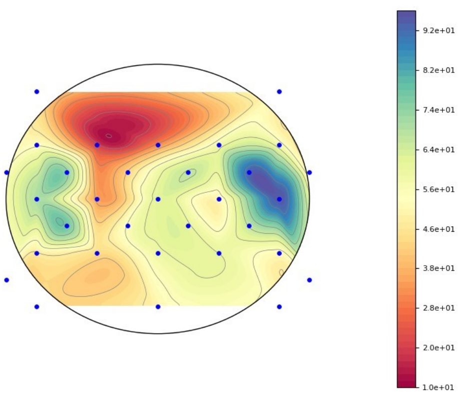
# APPENDIX

## A. Experiment 1 EEG Plots

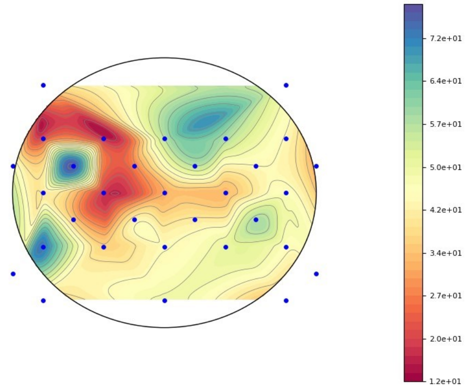



(a) Subject A.

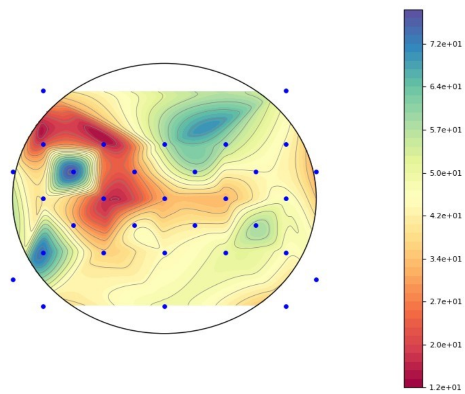



(b) Subject B.

Fig. 9: Experiment 1: Topographical Map During Encoding for Subjects A and B.



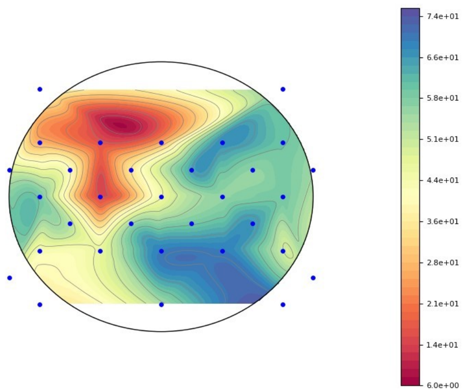

(a) Subject A.



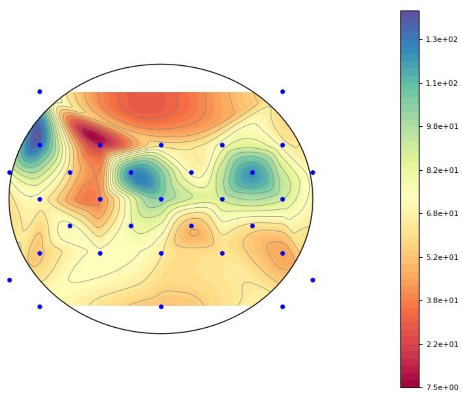

(b) Subject B.

Fig. 10: Experiment 1: Topographical Map During Retrieval for Subjects A and B.

## *B. Experiment 2 EEG Plots*

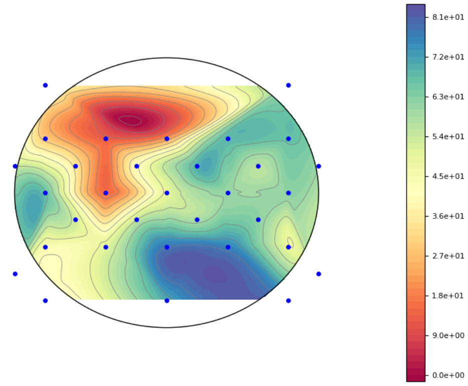



(a) Subject C.

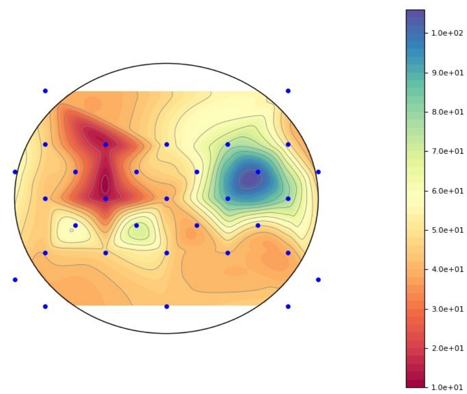



(b) Subject D.

Fig. 11: Experiment 2: Topographical Map During Encoding for Subjects C and D.



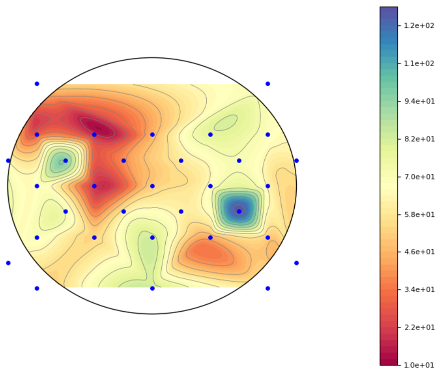

(a) Subject C.



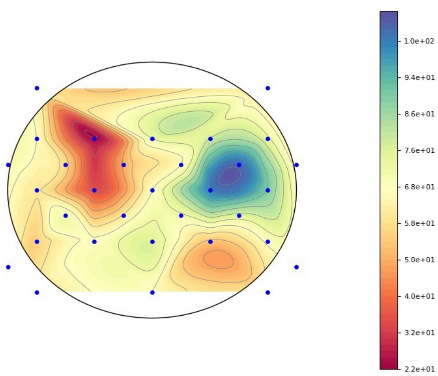

(b) Subject D.

Fig. 12: Experiment 2: Topographical Map During Retrieval for Subjects C and D (after encoding).

 ISBN: 978-1-68558-127-5 

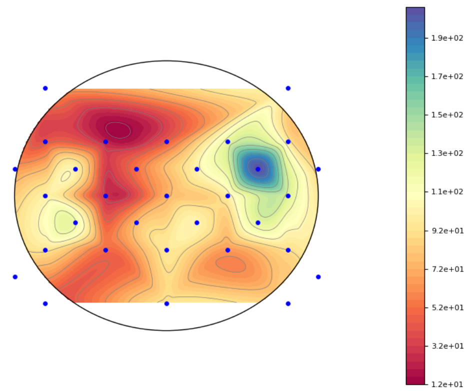



(a) Subject C.

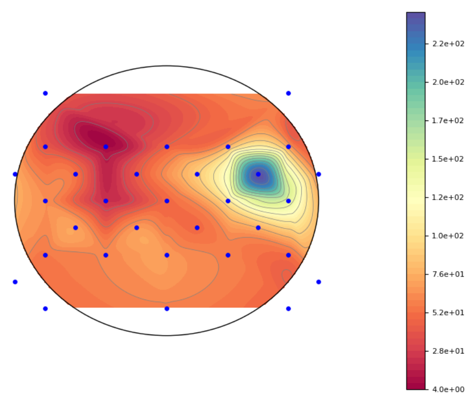



(b) Subject D.

Fig. 13: Experiment 2: Topographical Map During Retrieval for Subjects C and D (after 6 hours).




(a) Subject C.




(b) Subject D.

Fig. 14: Experiment 2: Topographical Map During Retrieval for Subjects C and D (after 24 hours).