Correlating Spatial Massive Memory and Temporal Massive Memory

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Abstract

Humans have a massive capacity for remembering images and related information, such as the location or time an object appeared. Previous research has found that humans possess both spatial massive memory (SMM) and temporal massive memory (TMM), but the extent to which they are correlated or limited in capacity remains unclear. Therefore, our study aims to uncover the correlation between SMM and TMM by measuring the automaticity, or the cost-free encoding of irrelevant tasks. In each of our four distinct trials, participants were given different sets of instructions that altered the information they encoded consciously. Despite the differing instructions, all of them were tested on the same information: spatial, temporal, and identity—where, when, and if the image had been shown at all. Participants then underwent a second round that provided a complete set of instructions to compare the first round with for more statistically robust results. We found that temporal information is partially automatic, as participants performed significantly well on temporal tasks in trials where it was task-*irrelevant* but did not when it was task-*relevant*. In addition, we found a significant correlation between spatial and time error in the trials where we provided Full and Spatial instructions but not in the Identity or Temporal trials, showing that TMM relies on SMM but not necessarily vice versa.

Summary

Many of us underestimate our memory in significant yet understandable ways. Studies have shown that humans can accurately determine familiarity with tens of thousands of images. Furthermore, we can very accurately remember the location and time of appearance of images, but we do not entirely understand why and if the two are related. Notably, we do not know if focusing on, for example, the order of a deck of cards, might mean we forget what hand the magician was holding it in. This possible correlation between the spatial and temporal information was focus of our research, allowing us to learn more about how humans integrate real-world memories where both space and time play a significant role, and the mechanics—and limits—of our fabulous data collection skills. Somewhat surprisingly, we found that humans encode temporal information well when instructed to memorize spatial information or both spatial and temporal, but do not necessarily do well when instructed to memorize only temporal information or the familiarity of images. We also found that temporal memory relies on spatial memory, but not necessarily vice versa.

1 Introduction

What we retain and what we do not is a thorny question. An observer watching a movie trailer will surely see much more than what they report later on and this is the result of the complicated way information is absorbed and encoded in the brain. Memory decay occurs as the information absorbed from the outside world passes from sensory memory, where it resides for a few hundred milliseconds, to short-term memory, where it stays for only a few seconds, to its final resting point, the long-term memory, from which the observer can only report sparse details [1]. But, though the long-term memory of the movie trailer may not be as vibrant and complete as the original production, it can live alongside a huge collection of other long-term memories; this is the phenomenon known as *massive memory*.

While all the information from the movie trailer was not actively encoded, much of the impression it left and the properties of the image are recorded unconsciously in a process known as *automaticity*. This is in contrast to task-relevant memory, a more active form of recall in which an observer is prompted to deploy their attention to a specific stimulus feature, such as the color of an apple or the movement of a car. Take the example of an apple: if an observer is told to find a red apple, the color, and shape of the objects perceived are relevant [2]. While searching for the red apple, the observer unconsciously begins to memorize the colors of various other objects to speed up the visual search, as shown in previous studies by Vo et al. [3]. But more information may be accidentally or unintentionally encoded. While the observer looking for an apple might be paying attention to the location of the objects they are shown, they may also pick up task-irrelevant information like the orientation of the object [4].

Since the proposal of free encoding of information, researchers have found that information may also be encoded with partial automaticity. This may mean unintentional memory in a certain fraction of trials and no memory in the rest, or possibly a limit to how much information is automatically memorized [4]. These limits and our own limitations in finding, recognizing, and measuring partial automaticity form the foundation of this research, in which partial automaticity within two specific categories of information encoding is explored for the first time.

Our research focuses on Spacial Massive Memory (SMM) and Temporal Massive Memory (TMM), two subsets of Massive Memory that deal in part with the fantastic capacity humans have for visual memory and recognizing a large number of previously viewed scenes and/or objects [5, 6]. Over the years, we have come to learn much more about what information is stored in Massive Memory. In 1967, Shepard showed observers a series of 600 stimuli and tested them on their ability to recognize "old" stimuli in a pair of "old" and "new" stimuli [7]. Observers were able to recognize the "old" stimuli in forms of words, sentences, or pictures in 90%, 88%, or 98% of test pairs, respectively. A more recent study by Brady et al. found that observers can remember thousands of images and recall if they are familiar with a similar accuracy ranging from 92% to 87% depending on the conditions of the old/new pair. Notably, the pairs were sorted into three conditions of increasing difficulty as seen in Figure 1, but participants still did well [1].

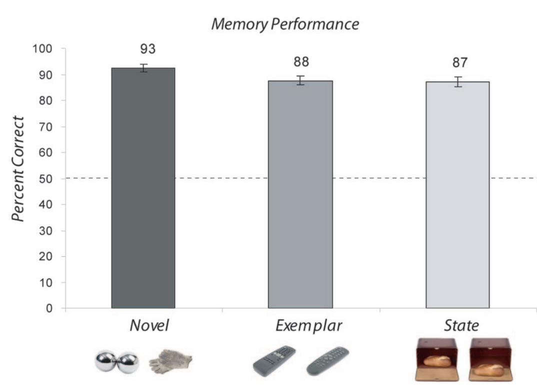

Figure 1: Brady et al.'s experiment showed how good human brains are at differentiating between and remember new vs. old stimuli. In novel, exemplar, and even the trickier state changes, the participants' accuracy were notably high.

But SMM and TMM go a step further than basic familiarity. By remembering *where* an object was, we are storing it into our SMM, which can also be referred to as visual long-term memory [8]. Previous research has found that humans are able to remember the location of approximately 16.6% of images after being shown an array of objects for 2-3 seconds [9]. Similarly, by remembering *when* an object appeared, we store it into TMM. Despite the importance of this information in performing tasks like visual search, there is little known about the extent of TMM and even less about the correlation between TMM and SMM. Understanding how performance is related in spatial and temporal tasks allows us to measure the extent of automaticity in each of these tasks and learn more about how the brain chooses what it remembers.

In this new experiment, we combine aspects of two previous experiments to test the hypothesis that SMM and TMM are correlated with each other. By limiting which form of information is task-relevant, we can measure the performance of the other forms of information and see if the difference in performance is significant, while ensuring any possible distractions are accounted for. For example, if participants are told to only focus on spatial, or location, information, then temporal information becomes task-*irrelevant*. Therefore, if participants still perform just as good on the temporal task than they do in the trial where temporal information is task-*relevant*, we can determine that temporal information is somewhat automatic.

We expected observers to show similar old/new image memory capacity (accuracy around 90% as reported in Brady et al. 2008) [1]. In similar previous SMM experiments, observers remembered the location of 50+ of the 300 objects during testing. We also expected that, by paying attention to one form of specialized information (either spatial or temporal), observers will naturally collect the other form of information without putting in active effort, essentially automatic encoding [4].

2 Methods

2.1 Experimentation

Each participant experiment consisted of two rounds, with each round consisting of a training and testing portion.

During training, observers were shown 50 images, one by one, on a 7x7 grid, for 3 seconds each. Observers were asked to complete a 2-alternative-forced-choice (2AFC) test and respond using keyboard input if the image on screen was a natural or artificial/manmade object, to which only audio feedback was given to avoid possible distraction (the specific instructions can be found in Figure 12) [10].

Before training, participants were given one of four different sets of instructions. For all four conditions, observers were instructed to judge whether the item was new or if it had been shown before (old). Then, a quarter of participants were told to also pay attention to the location of an object on the 7x7 grid, therefore engaging SMM. Another quarter of participants were told to pay attention to the order of appearance of the objects, measuring TMM. Finally, the last quarter were tasked with remembering position in both time and space (refer to Figure 11 for detailed instructions).

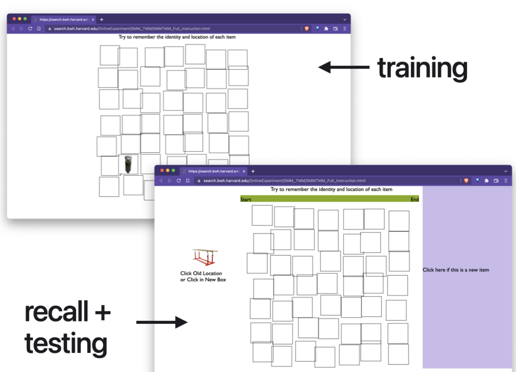

Figure 2: User interface design.

During the testing period, participants were tested on all three parts of information on

100 images (or 2N, where N = the number of training images). If the item shown was new, they were told to click on the purple "New" box on the right of the screen during the testing period. On the other hand, if the item was old, they were instructed to click on the location on the screen where they think they saw it previously (observers are instructed to guess if they need to) as well as the time/order they believe they saw it. They were instructed to respond as fast and accurately as possible, but not time limit was imposed. Notably, participants received no feedback on their spatial or temporal response, but audio feedback was given to their old/new response.

Figure 3: Diagrammatic overview of the four conditions given to participants during training and what they are actually tested on during testing. Half of the images shown in testing will be old, and the rest will be new. In the second round, participants receive the full instructions ("identity + location + time" in this figure).

Finally, in the second round of the experiment, participants were given the full instructions in order to collect control data to compare with the performance of the previous round. Through this experiment, we can measure the extent of spatial and temporal memory is and what the correlation is between spatial and temporal performance, and if these measures differ across different instruction conditions (and therefore what observers actively focus on).

2.2 Data Collection

Participants were hired from Amazon Mechanical Turk, a crowdsourcing data acquisition platform [11]. The experiment was run on a web application developed in JavaScript[1]. Participants of each trial saw a different version of the four Round 1 trials, but all trials directed to the same Round 2 application.

3 Results

A total of 64 participants responded, with 14 participants' data discarded because of either a natural/artificial type response accuracy less than 70% or an old/new response accuracy less than 60%. Participants were informed of this accuracy requirement (in order to be compensated) before the first training section began. After filtering these data, we had 12 participants in each of the Full (identity, spatial, and temporal instructions given) and Identity (only identifying old or new image) trials and 13 participants in each of the Spatial (identity and spatial instructions) and Temporal trials, resulting in 50 valid individuals.

Demographic data was also collected. The average age of participants was 40.44 years old with a standard deviation of 11.97. In terms of race, there were 39 White, 7 Black or African American, and 4 Asian respondents. Of the 64 respondents, 4 were Hispanic of Latino.

3.1 Time and Location Error

Time error was defined as the distance from the proportional location the participants' click on the time bar was. We define spatial error as the euclidean distance from the actual

[1]Find the code and some data analysis here: `github.com/ClaireBookworm/smm-tmm`

x, y coordinate location of the images.

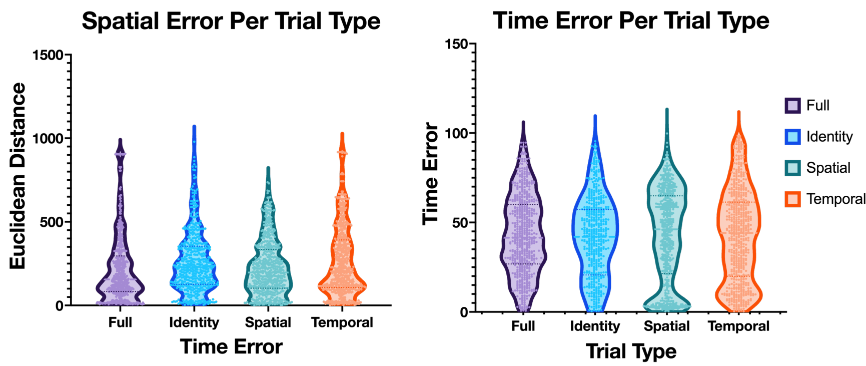

Figure 4: The distribution of error for time and location tasks per trial type. Time error was measured in distance between user click response and proportional order of image appearance. Spatial error was measured as euclidean distance of user click response and original x,y coordinate of image appearance.

As is seen in Figure 4, the error values for some of the trials were not normally distributed, so a parametric t-test would be inaccurate. Thus, Mann-Whitney U-test was performed to compare sets of spatial, temporal, and identity error in order to determine significant difference between trial types.

Within the spatial error tasks in each trial, a significant difference in performance was found between Full vs. Temporal ($p = 0.0168$) and Full vs. Identity ($p = 0.0015$), all with the Full Instructions trial participants performing better. In addition, participants in Spatial trial performed statistically significantly better than Temporal ($p = 0.0353$) and Identity ($p = 0.0045$) trials.

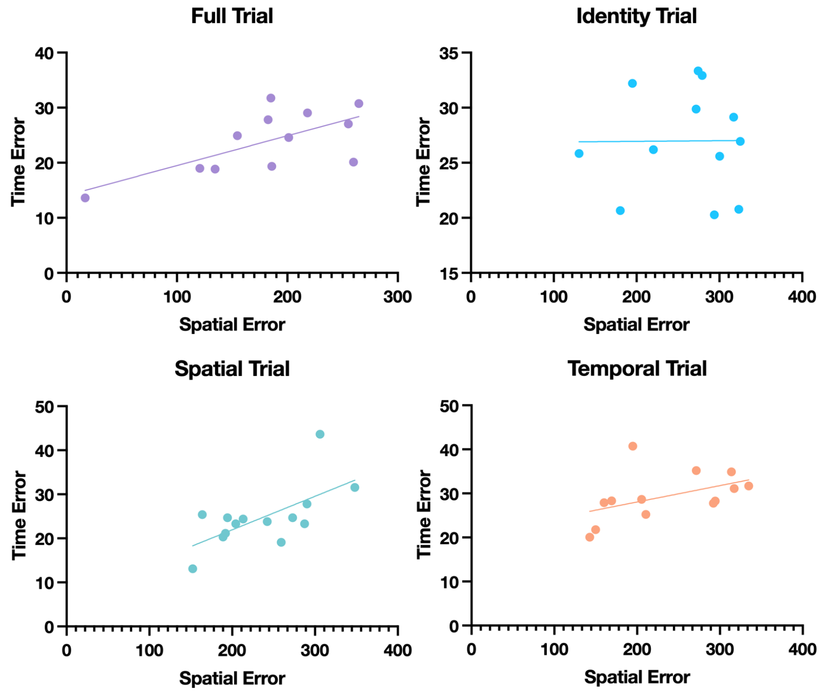

Figure 5: Linear regression analysis of spatial error against time error for each of the four trial conditions. A statistically significant slope was only found in the Full and Spatial trials.

On the other hand, for the time error task, none of the trials were statistically different except that of Identity vs. Spatial ($p = 0.0264$), in which the Identity trial performed better, and Full vs. Identity ($p = 0.0387$), with Identity performing better. Notably, the p-values for Temporal vs. Full ($p = 0.6071$) and Temporal vs. Spatial ($p = 0.8859$) were close to 1, or chance.

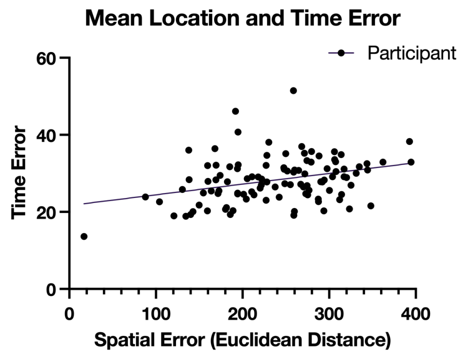

Figure 6: Mean location and time error over all trials.

The mean location and time error over all four trials had a significantly non-zero slope with a p-value of 0.0007. Individually, the slope significance for the Full Instruction trial was $p = 0.0171$, Temporal trial was $p = 0.1037$, Spatial trial was $p = 0.0366$, and Identity trial was $p = 0.9800$.

3.2 Lag Analysis

Nosofsky et al. define the concept of *lag* in memory experiments as a way to normalize against familiarity bias. It is the serial position of an item during training (also known as "study set") relative to the serial position of the same item during testing (probe set) [12]. The lag between encoding of a stimuli and recall of the same stimuli should be roughly random between all images—therefore, if participants seem to show some form of familiarity bias, it may be a sign of partial automaticity or some other limit to temporary memory capacity [13].

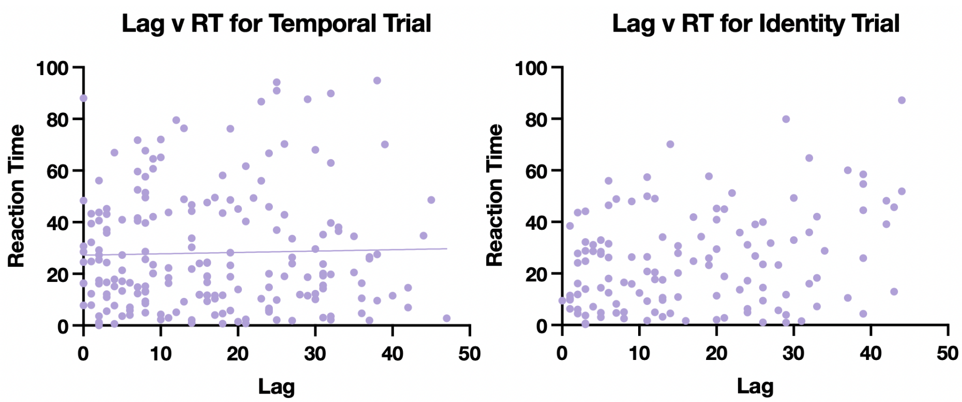

Figure 7: Comparison of capacity of ROIs between spatial and temporal trials within the location task.

As evidenced by the data shown in Figure 7, there is no obvious familiarity bias, and no significant linear regression correlation between reaction time and lag. The experiment had a sufficient amount of training and testing images that were set to appear in a random order to ensure images were encoded into long-term massive memory.

3.3 Regions of Interest and Capacity

It is not representative of true performance if a participant is penalized equally for being slightly off as compared to answering completely incorrectly. We separated, based on previous work, the time (100 ROIs) and spatial error (14 ROIs) data for each trial into specific regions of interest that can be used to categorize [14].

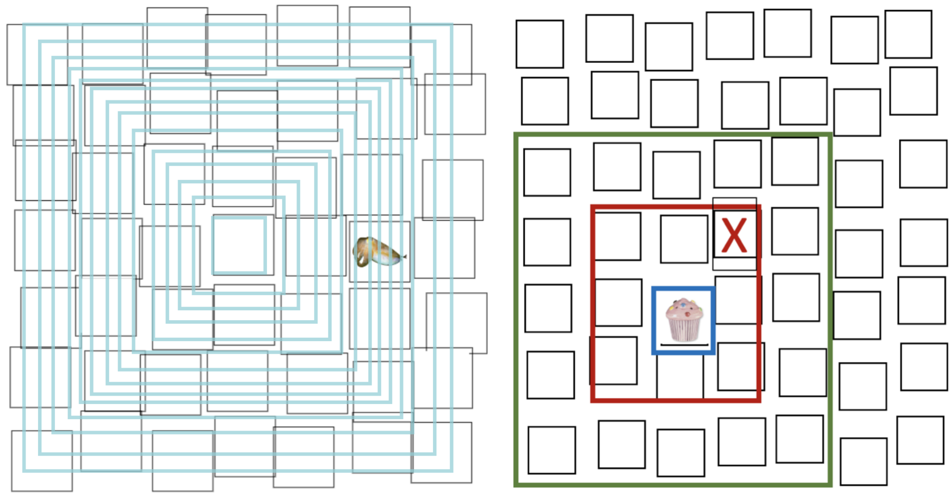

Figure 8: Example of how the grid was separated into 14 ROIs and also how the ROIs incorporate responses that are close to correct.

As seen in Figure 9, the four combinations of Spatial trial + Time task, Spatial trial + Location task, and so on, are plotted with corrections against guessing. We simulated guessing by randomly generating the chance a click may land in the ROI for another object and repeating it for a few thousand pairs [15]. Then, by subtracting the guessing function from participant responses, we obtain a capacity function that indicates the percentage of responses within each ROI.

Within the spatial location task, the peak for the spatial trial experiment was at ROI = 4 and for the temporal trial it was at ROI = 3.

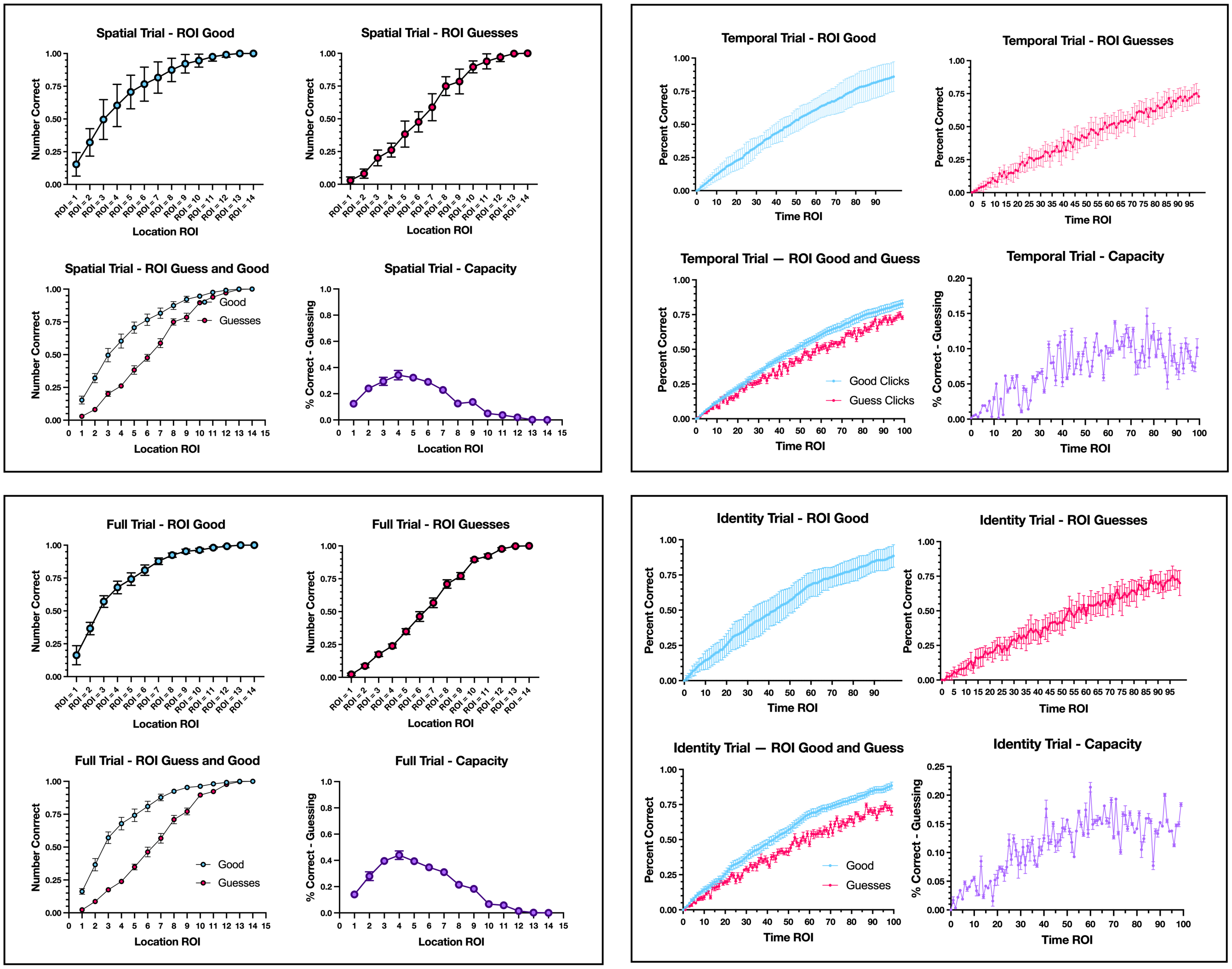

Figure 9: Graphs of participant performance in the spatial (subfigures **a** and **b**) and temporal (subfigures **c** and **d**) trials based on the locational (spatial) and time (temporal) tasks. Responses were separated into regions of interest (ROIs) and were corrected with a guessing function, a semi-random generated series of numbers to remove possibly guessing influence in responses. Capacity is the resulting graph and shows the ROIs a significant number of participants tended to respond in.

The temporal ROI charts are somewhat more complex, with ROIs being defined in a range from 0 to 100. The percentage correct-guessing peaked for the time task in the spatial trial at ROI=76, and it peaked at ROI=77 for the time task in the temporal trial.

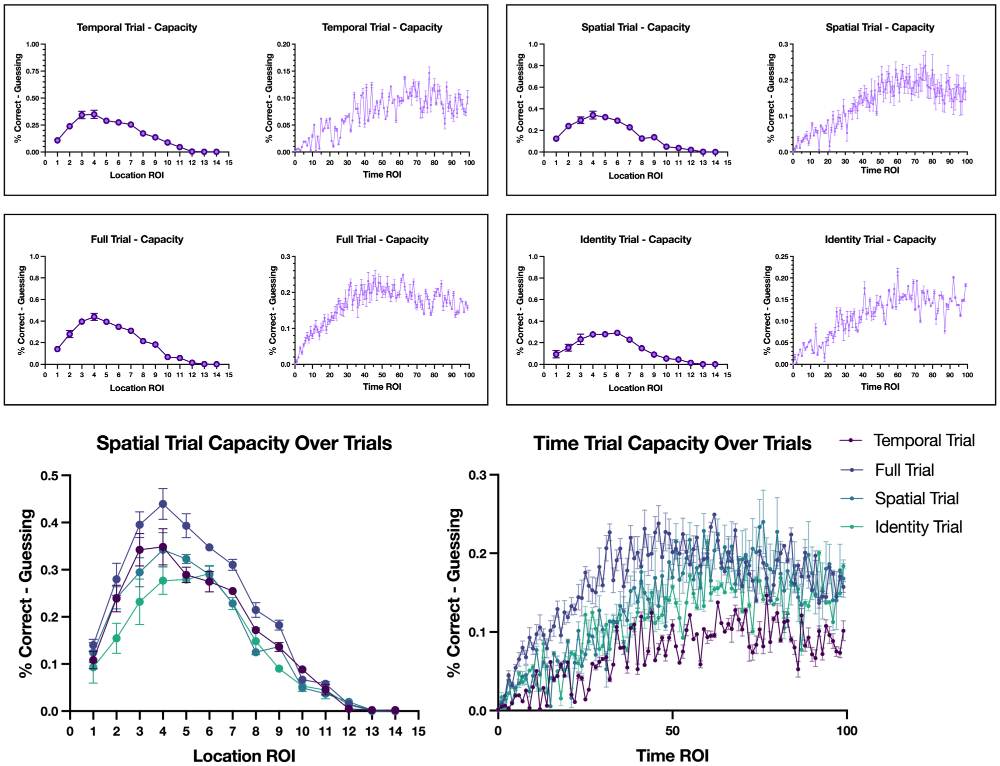

Figure 10: The compiled capacity graphs of each trial type and task and then projected within the same graph to compare capacities.

Through a Mann-Whitney U test, we found that participants in the Full Instructions trial had a significantly greater capacity across all ROIs, than those in the Identity trial, with a p-value of 0.0002. The Full trial also performed better than the Temporal trial ($p = 0.0046$, $\alpha = 0.025$), Identity trial ($p = 0.0012$, $\alpha = 0.0083$), and Spatial trial ($p = 0.0036$, $\alpha = 0.0167$), correcting with Benjamini (False Discovery Rate). Finally, participants in the Identity trial performed statistically significantly better than the Temporal trial with a p-value of 0.01 ($\alpha = 0.033$). These results can also be seen in Figure 10 in the Spatial graph. In comparison, within the time task, the Temporal trial performed statistically worse than every other trial with a p-value of less than 0.0001, using a paired Mann-Whitney U test.

4 Discussion

We ran four independent trials on participants who followed different initial instructions that changed what information was directly task-relevant and therefore consciously encoded, as seen in Appendix 11. In all trials, regardless of whether they were told to do so, participants were tested on the spatial, temporal, and identity of images.

The statistically significant correlation of location and time error in Figure 5 for the Full Instruction trial shows that SMM and TMM are correlated when both are task-relevant. This is further corroborated by the significant correlation between the location and time error in the Spatial Instructions trial. This likely implies that temporal information is correlated with its spatial counterpart, but not the other way around.

Through comparing the capacities of the various trials in spatial and temporal tasks, as seen in Figure 10, we find that temporal information is likely partially automatic—the temporal information must be grounded in another form of information, and there is a solid limit to how much temporal information can be stored. Capacity can either be explained by one of the two current possible models. The first is the *slot model*, which theorizes that there are a limited number of slots in memory. The second is the *response model*, which theorizes that all items are retained, but the memory representations are blurry and imprecise [16].

The same cannot be said about location information. The Full Instructions trial had a significantly higher capacity for such information than the Temporal, Spatial, and Identity trials, but the Spatial trial did not have a significantly higher capacity than the Temporal trial. Given the significant difference between capacity in the Full and Identity trials, especially at the peak ROIs of 3-4, we can see that SMM performs best when it is task-relevant. This holds true when comparing Full trials with Temporal ones, meaning SMM is not fully automatic.

According to Hasher and Zacks, automatic operations are constantly functioning under all circumstances and do not benefit from practice [17]. They defined spatial, temporal, and frequency-of-occurrence information as automatic processes, but recent research has found that this may not be wholly correct [18]. Our study further proves that some types of information memory may not be fully automatic but are still strongly correlated with other forms of memory. This is a significant finding and one that comes as somewhat of a surprise, particularly because it alters our expectation of information encoding processes. Cost-less encoding of data underpins the utility of our long-term memories: if something that may not have been directly relevant at the time later becomes important, we can still train ourselves on past experience because we have retained robust information. But this research shows that information one would expect to be correlated and therefore stored together does not come as a package deal.

The correlation or lack thereof between SMM and TMM is a viewpoint at a much broader question, the one brought up in the first sentence of the Introduction: ”what do we retain, and what do we not?” By understanding more about the interplay of this data encoding, we can better understand the effects of memory impairments and other memory decay [19]. For example, the level of automaticity of TMM can be a marker of aging and degeneration of mental capability that is not necessarily correlated with conscious encoding. This research lays the bedrock for a new portrayal of cost-less encoding and aut

5 Future Work

We hope to work on better understanding the causal relationship between the types of massive memory by altering various elements of the experiment and not just the initial instructions. In addition, it can be helpful to use more realistic scenery in experimentation to simulate real-world scene encoding better to apply better to how human episodic memory works.

Given how unique temporal information is, we also hope to test the extent of TMM in different types of experiments that may make it easier or more challenging to complete. In addition, we require further experimentation to better understand the automaticity of SMM and how SMM correlates to TMM and basic massive memory.

6 Conclusion

The initial aims this experiment were to provide an alternative estimation of the spatial memory capacity, as well as to evaluate the temporal aspect of memory capacity and compare it with the spatial and visual memory capacity. In other words, does temporal memory capacity vary with spatial or old/new image memory capacity? Another aim was to discover if either temporal or spatial information is encoded for free or if, by contrast, they require active effort to be stored.

We found that while SMM is still proven to be massive, TMM may not necessarily be so. Participants performed poorly on the temporal task in all four trials, with the worse being the Temporal trial itself. But, we do find that temporal memory capacity does vary with spatial memory capacity in the Full and Spatial trials, both of which included spatial information as task-relevant. On the other hand, the Identity trial, which did not include either spatial or temporal information as task-relevant, displayed no change in time error as spatial error increased.

In conclusion, We find that Temporal Massive Memory is partially automatic and is strongly correlated to Spatial Massive Memory. Time error was the least in trials where location information was task-relevant, and we found that the capacity for time information was lowest in the Temporal trial compared to all other trials across all ROIs.

7 Practical Takeaways

We base human identity on our autobiographical episodic memories. In addition, we rely on memory to orient ourselves in our daily lives. By understanding the relationship between spatial and temporal information, we can better understand how we encode memories of events and information without usually consciously attempting to do so. Since temporal memory was found to be partially automatic and correlated to spatial memory, we are a step closer to explaining the way we order previous memories and remember the order of previous events.

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A Appendix: Initial Instructions

There are two phases to this experiment: Training and Testing

- In the training phase, we will show you pictures of objects on the screen one at a time for 3 seconds each. You should try to remember the following information (we will be testing you later)
  1. WHAT objects you saw
  2. WHERE on the screen each object was presented
  3. WHEN in the sequence of images each object was presented
- In the testing phase, we will test your memory for the previously seen objects. We will provide you with more instructions immediately before the testing phase begins.

The experiment consists of around ~100 trials. You should be able to complete the experiment in ~45 minutes. You are allotted 60 minutes in total. You will receive $8 per hour for your participation. **You will be compensated only if you complete all the trials, correctly identify objects as natural or artificial/manmade in the training phase, and correctly identify whether an item is old/new at least 60% of the time in the testing phase.**

Figure 11: This image shows the full instructions shown to participants. For the condition only testing spatial information, element 3 under the training section was omitted. Similarly, when only testing for temporal information, element 2 was omitted. Finally, when only testing for familiarity, elements 2 and 3 were omitted.

B Appendix: Reminder Training Instructions

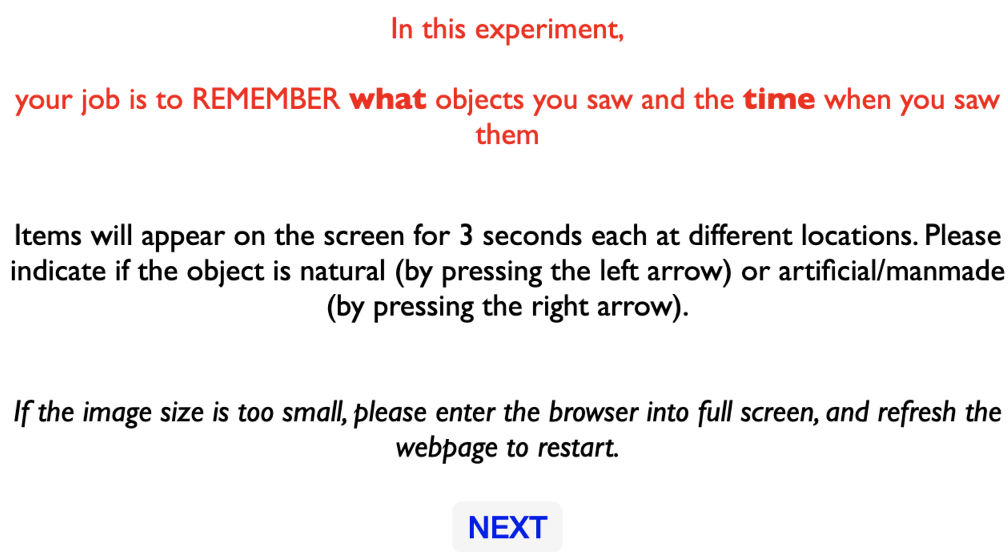


Figure 12: On the second page, participants are reminded of their task and given instructions on how to respond to the 2-alternative-forced-choice (2AFC) test.

C Appendix: Analysis ROI Code

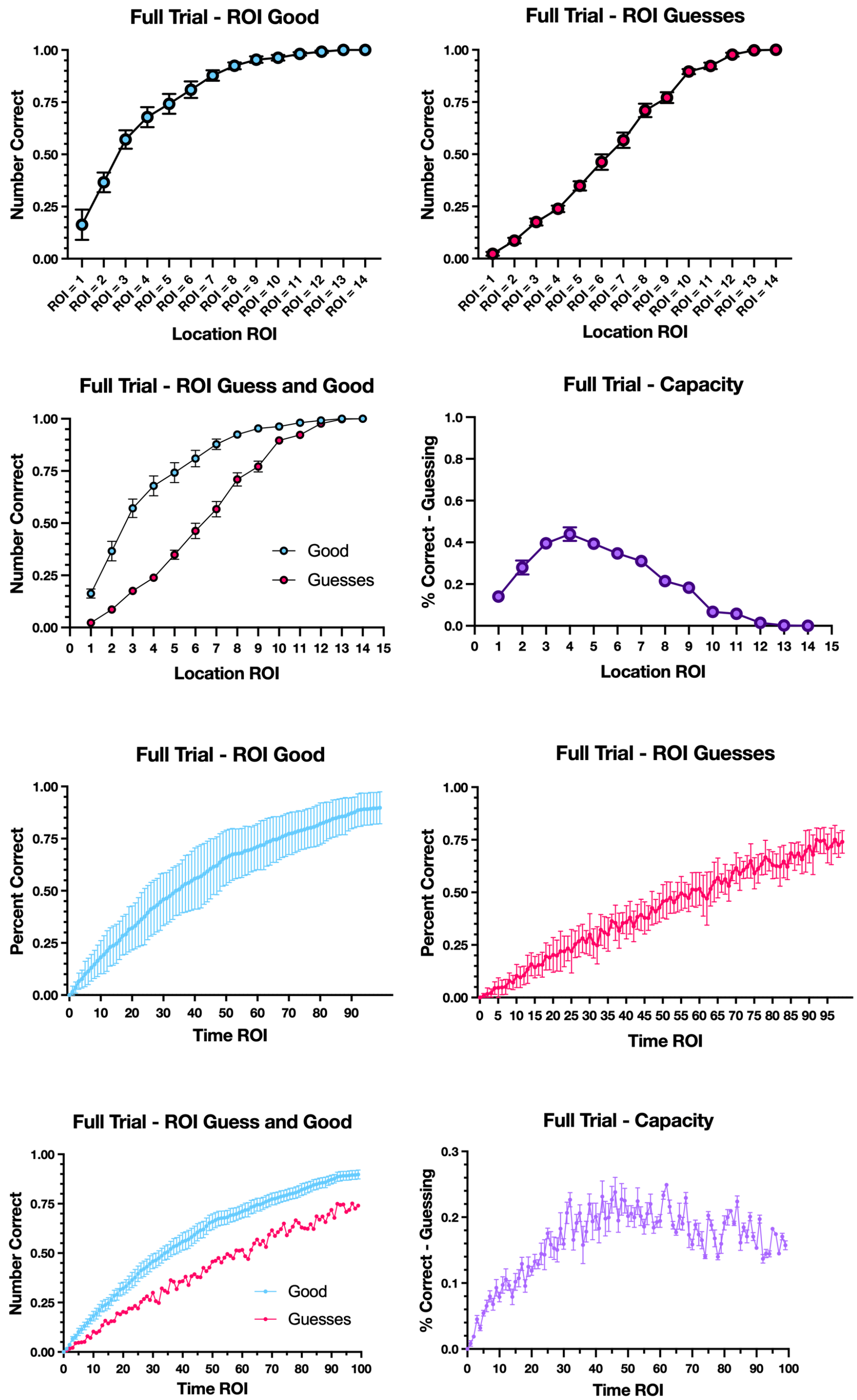
```
files = dir('*.xlsx');
thisData = csvread(files.name);
thisData = csvread('SMMTMM.xlsx');
% GoodOs = [5:7, 9:16, 19:23];

%% Histogram of temporal Error

figure
hold on
HITLines =  find(strcmp(thisData.Message,'HIT'));
histogram(thisData.timeBarErr_RespMinusOld(HITLines),100,'Normalization','
    probability')

title('Temporal Error Distribution','FontSize',18)
ylabel('Response Probability','FontSize',18)
xlabel('Error (ResponseTime - OldItemTime)','FontSize',18)
X = zeros(1,11);
Y = [0:10]/10;
plot(X,Y)
ylim([0,0.14])

%% Simulate Temporal Response Guesses

SimTemporalErr = [];

GuessProportion = 0.5;

for Os = 1:23

```

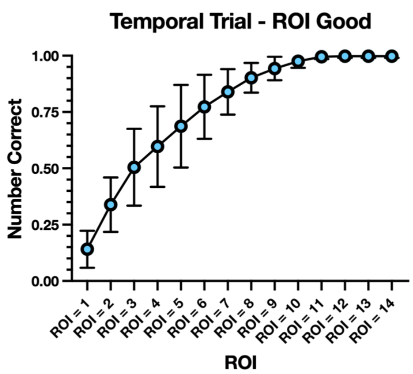
```
    Oslines = find(thisData.Subject == Os);
    OsData = thisData(Oslines,:);

    Testlines = find(strcmp(OsData.blockName,'Test'));
    Oldlines = find(OsData.isOldItem ==1);
    GetLines = intersect(Oldlines,Testlines);

    AllTimePoints = OsData.timeBar_now(GetLines);
    CorrectOldTime = OsData.timeBar_old(GetLines);

    for t = 1:length(AllTimePoints)

        for iteration = 1:200

            if rand< GuessProportion

                %if people tend to guess near the current time
                MinTime = max(0, 0.75*AllTimePoints(t));
                MaxTime = AllTimePoints(t);
                %Guess #1 guess falls onto a normal distribution with mean
    =
                %0.7 * current time
                meanTime = min(MaxTime,MinTime);
                GuessTime = normrnd(meanTime,14);

                thisError = GuessTime - CorrectOldTime(t);
                SimTemporalErr(Os,t,iteration) = thisError;

            else
                r = normrnd(-0.6,3.5) ;

```

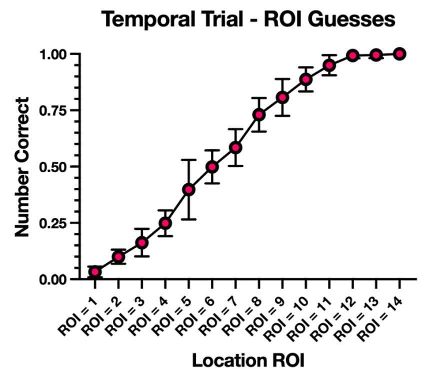
```
                SimTemporalErr(Os,t,iteration) = r;
            end

        end

    end
end
SimTemporalErr = SimTemporalErr(:);
histogram(SimTemporalErr,100,'Normalization','probability')

% Spatial capacity: Pct of good clicks for each ROI size

Guess2TempROIsCorrectCount = nan(23,50);
Guess2TempROIsCorrectPct = nan(23,50);


for Os = 1: 23

    Oslines = find(thisData.Subject == Os);
    OsData = thisData(Oslines,:);
    ScreenWidth = OsData.CanvasWidth_px(1);

    HITlines = find(strcmp(OsData.Message,'HIT'));
    Testlines = find(strcmp(OsData.blockName,'Test'));
    GetLines = intersect(HITlines,Testlines);

    GetData = OsData(GetLines,:);

    for ROI = 1: 100
        InROIcount = 0;

```

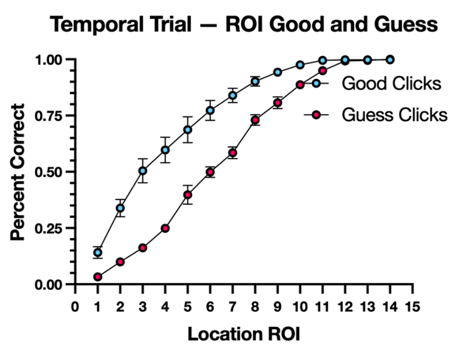
```
        for trial = 1: length(GetLines)

            timebarOld = GetData.timeBar_old(trial);
            timebarNow = GetData.timeBar_now(trial);

            %timebarResp = GetData.timeBar_resp(trial);

            %Guess 1
            RR = 0 + (timebarNow-0).*rand;

            %Guess #2 guess falls onto a normal distribution with mean =
            %0.7 * current time
            %if people tend to guess near the current time
            MinTime = max(0, 0.75*timebarNow);
            MaxTime = timebarNow;
            meanTime = min(MaxTime,MinTime);
            RR = normrnd(meanTime,14);

            if abs(timebarOld-RR)<= (ROI-1+0.01)/2
                InROIcount = InROIcount+1;
            end
        end

        Guess2TempROIsCorrectCount(Os,ROI) = InROIcount;
        Guess2TempROIsCorrectPct(Os,ROI) = InROIcount/length(GetLines);
    end
end
```

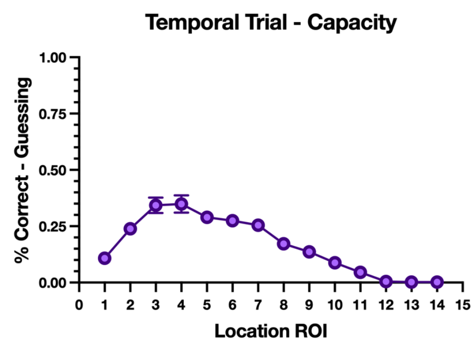
D Appendix: Detailed ROI Graphs

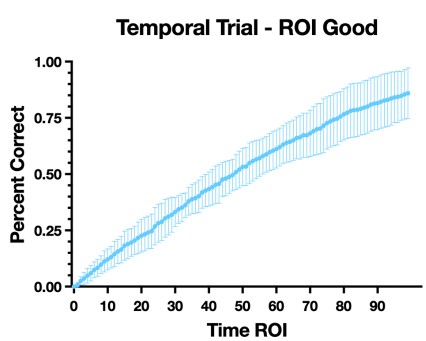


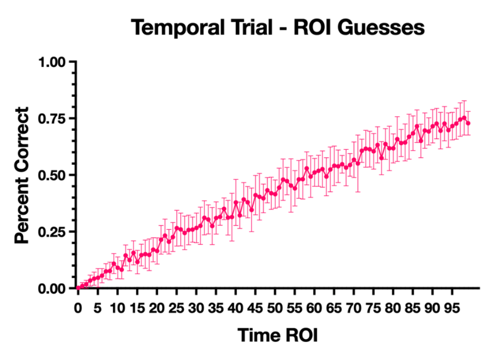

Temporal Trial - ROI Good
Number Correct
ROI

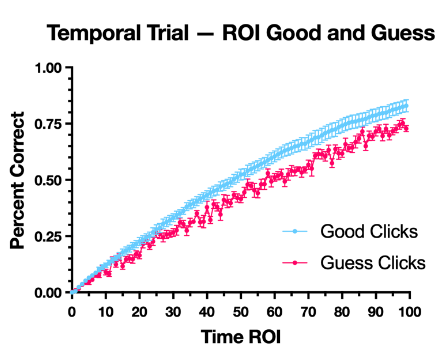

Temporal Trial - ROI Guesses
Number Correct
Location ROI

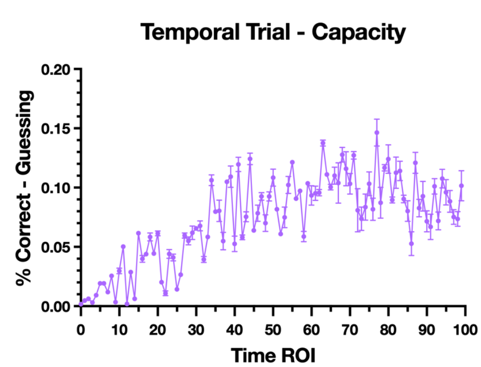

Temporal Trial — ROI Good and Guess
Percent Correct
Good Clicks
Guess Clicks
Location ROI

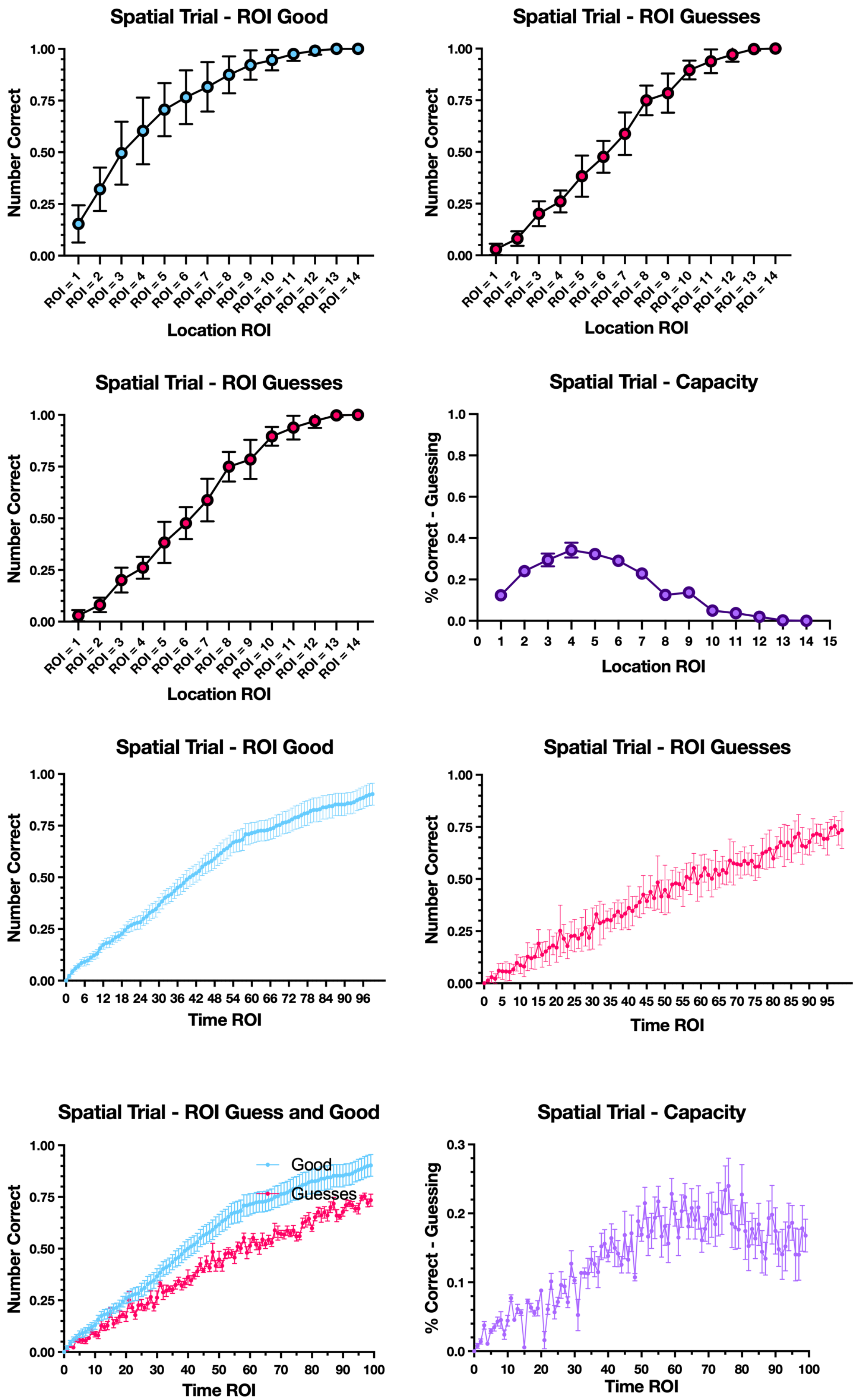

Temporal Trial - Capacity
% Correct - Guessing
Location ROI


Temporal Trial - ROI Good
Percent Correct
Time ROI

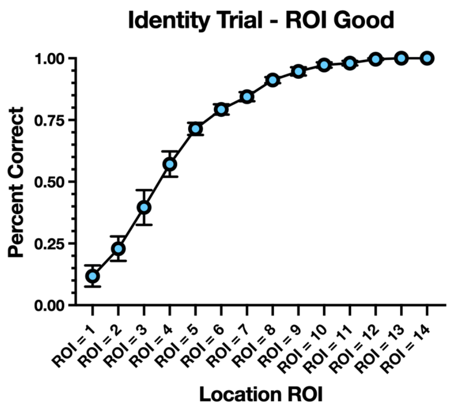

Temporal Trial - ROI Guesses
Percent Correct
Time ROI

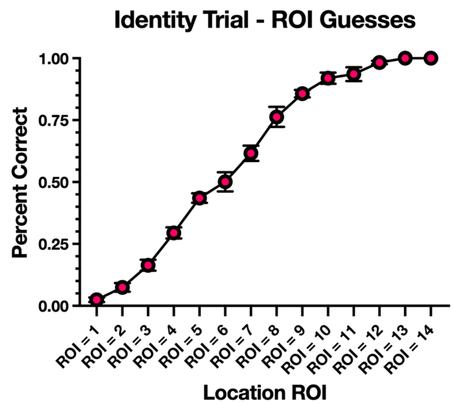

Temporal Trial — ROI Good and Guess
Percent Correct
Good Clicks
Guess Clicks
Time ROI

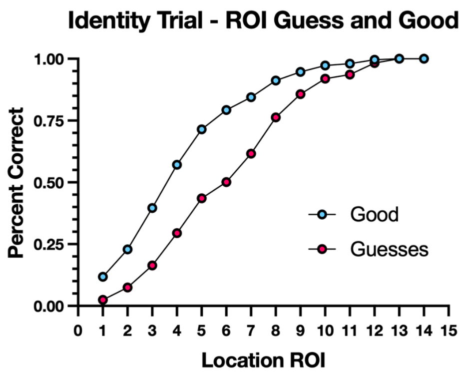

Temporal Trial - Capacity
% Correct - Guessing
Time ROI

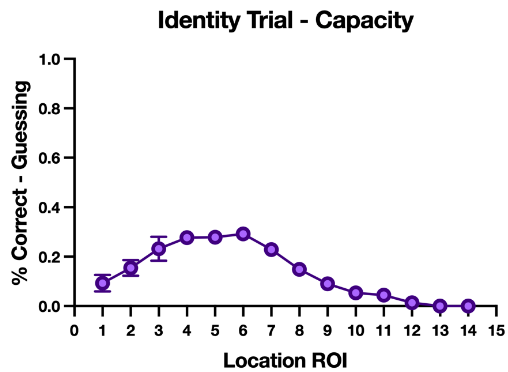


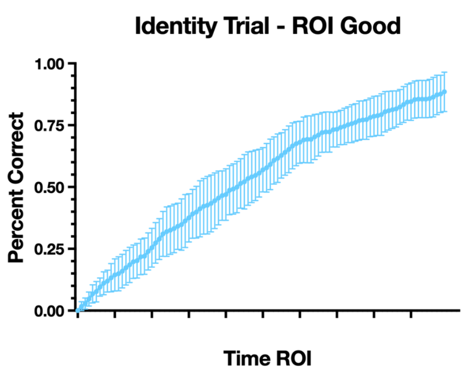
Spatial Trial - ROI Good
Number Correct
Location ROI
Spatial Trial - ROI Guesses
Number Correct
Location ROI
Spatial Trial - ROI Guesses
Number Correct
Location ROI
Spatial Trial - Capacity
% Correct - Guessing
Location ROI
Spatial Trial - ROI Good
Number Correct
Time ROI
Spatial Trial - ROI Guesses
Number Correct
Time ROI
Spatial Trial - ROI Guess and Good
Good
Guesses
Number Correct
Time ROI
Spatial Trial - Capacity
% Correct - Guessing
Time ROI

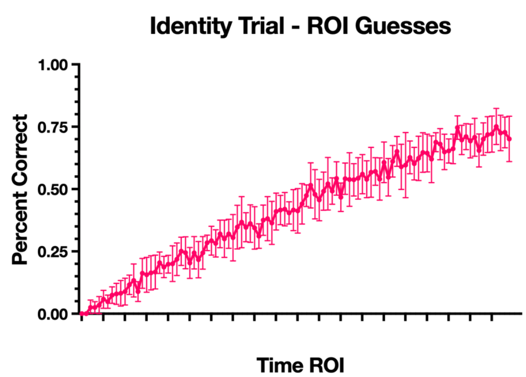

Identity Trial - ROI Good
Percent Correct
1.00
0.75
0.50
0.25
0.00
ROI = 1
ROI = 2
ROI = 3
ROI = 4
ROI = 5
ROI = 6
ROI = 7
ROI = 8
ROI = 9
ROI = 10
ROI = 11
ROI = 12
ROI = 13
ROI = 14
Location ROI

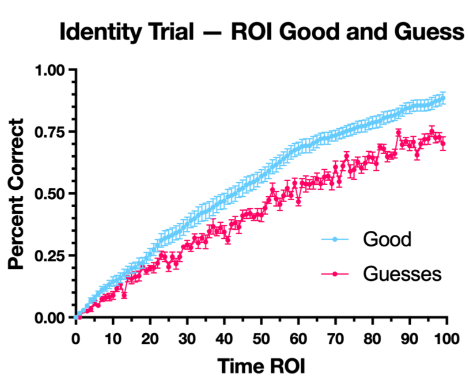

Identity Trial - ROI Guesses
Percent Correct
1.00
0.75
0.50
0.25
0.00
ROI = 1
ROI = 2
ROI = 3
ROI = 4
ROI = 5
ROI = 6
ROI = 7
ROI = 8
ROI = 9
ROI = 10
ROI = 11
ROI = 12
ROI = 13
ROI = 14
Location ROI

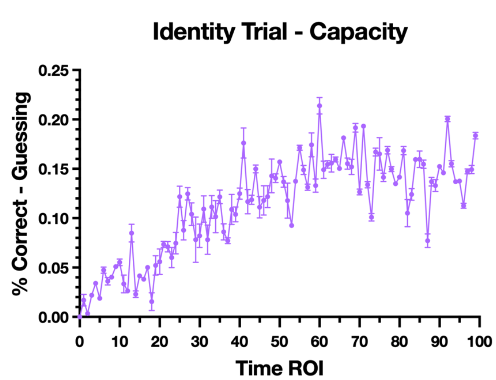

Identity Trial - ROI Guess and Good
Percent Correct
1.00
0.75
0.50
0.25
0.00
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Location ROI
Good
Guesses


Identity Trial - Capacity
% Correct - Guessing
1.0
0.8
0.6
0.4
0.2
0.0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
Location ROI


Identity Trial - ROI Good
Percent Correct
1.00
0.75
0.50
0.25
0.00
Time ROI


Identity Trial - ROI Guesses
Percent Correct
1.00
0.75
0.50
0.25
0.00
Time ROI


Identity Trial — ROI Good and Guess
Percent Correct
1.00
0.75
0.50
0.25
0.00
0 10 20 30 40 50 60 70 80 90 100
Time ROI
Good
Guesses


Identity Trial - Capacity
% Correct - Guessing
0.25
0.20
0.15
0.10
0.05
0.00
0 10 20 30 40 50 60 70 80 90 100
Time ROI