Encoding of Memories for the Near and Far Future

Michelle Yael Coppes

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S3712591
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Department of Psychology
University of Groningen
Examiner/Daily supervisor:
Wouter Kruijne

Abstract

Memory is an essential cognitive process in our daily lives, as it influences how we perceive the world and make decisions. Nevertheless, the nature of information stored in memory varies in terms of its flexibility. Some information needs frequent updates or is easily forgotten shortly after encoding, while other types of information exhibit greater resilience and endurance over extended periods. This study aimed to explore whether the expectation of when a memory would be tested influences its retention over time. Forty-one participants performed a continuous recognition task with unfamiliar American city names, where the color and position of the text indicated whether a word was likely to be encountered again early or late in the trial sequence. Some of these cues were intentionally invalid, allowing us to investigate their impact on memory encoding and retention. Hit rate (HR) analysis revealed a higher HR for early tested items, indicating better memory retention, without any significant modulation by cue type. However, reaction time (RT) analysis showed an effect of cue type, as participants responded slower to early cued items. Test type, however, did not significantly affect RT, and responses were equally fast regardless of whether items were tested early or late. The EZ-diffusion model, combining RT and HR data in a single model, showed that cue type influenced the nondecision time, suggesting differences in the cognitive processes preceding or following the decision-making stage. The study offers insights into the timing aspect of memory control, indicating potential strategic control over memory encoding guided by expectations on when the information is needed. Additional research and incorporation of additional measures may help further to understand the underlying mechanisms and potential applications in enhancing cognitive functions of memory.

Keywords: memory, encoding, continuous recognition task, cognitive control, memory cues

Introduction

Memory, is a fundamental cognitive process which plays a crucial role in our daily lives by enabling us to encode, store, and retrieve information. It allows us to retain experiences, knowledge, and skills, shaping our perception of the world and influencing our behavior. However, not all memories are maintained equally well. The brain's ability to retain and recall information can vary based on various factors such as attention, emotional significance, and repetition (Muzzio et al., 2019; LaBar & Cabeza, 2009; Karpicke & Roediger, 2007). By understanding the intricacies of memory retention, researchers may be able to develop strategies to optimize learning and memory performance in a wide variety of settings, from educational contexts (Sense et al., 2021) to clinical interventions for memory-related disorders (Cotelli et al., 2012).

The modulation of memory strength initiates with the process of encoding. This represents the primary phase in which information is transformed into a form which allows it to be effectively stored within the network of the brain for retrieval at a later stage. This makes encoding a crucial aspect of memory research. Numerous studies have examined the mechanisms underlying the process of encoding memories, indicating that encoding is a dynamic and flexible process. One important finding is that the encoding of long-term memories appears to be greatly influenced by the strength of brain activity in certain brain areas during encoding, for example in the hippocampus, the perirhinal cortex, the posterior cingulate cortex, and the left inferior frontal gyrus (Carr et al., 2010; Liu et al., 2014). In support of this notion, Kim (2011) observed that heightened activity in these areas during encoding can serve as a reliable predictor of successful recall later on. Sneve et al. (2015) also demonstrated the crucial role played by the hippocampus and its connectivity with the neocortical regions in predicting a more enduring status of recollection. On the contrary, relatively higher activity in the default-mode network is associated with poorer memory performance. Similarly, in electrophysiology, it has been observed that the enhancement of brain oscillations, specifically in the theta frequency range (4 – 8 Hz) and gamma frequency range (28 – 64 Hz), serves as an indicator for predicting effective memory formation (Sederberg et al., 2003). Such phenomena where patterns in neurophysiological measures are related to successful subsequent retrieval are commonly referred to as the "subsequent memory effect" (Rypma & D'Esposito, 2003).

Another such psychological measure that shows a subsequent memory effect is the size of an individual's pupil. Numerous studies have provided evidence indicating that the amplitude of pupillary responses elicited during the encoding of information correlates with the probability of subsequent recognition or later memory retrieval (Bergt et al., 2019; Kucewicz et al., 2018; Miller et al., 2019; Papesh et al., 2012). An increased pupillary response has been related to an elevated level of attentional processing or resource allocation during the memory processing (Miller et al., 2019). This suggests that spending more mental effort toward the item that is to be remembered facilitates encoding. Pupil dilation has been established as an indicator of emotional arousal as well (Bergt et al., 2018; Lempert et al., 2015). The association between emotional arousal and its impact on the increased pupillary response, may potentially foster a reciprocal relationship with attention, subsequently leading to improved memory retention.

It is worth considering that heightened memory strength, allowing for more easy retrieval, which could result from better encoding, may not always be advantageous. In fact, the opposite process of forgetting also plays a crucial role in a properly functioning memory system. Nørby (2015) suggests that forgetting serves as an adaptive mechanism enabling individuals to prioritize and efficiently retrieve relevant information for various purposes. It plays an essential role in emotion regulation by limiting access to negative memories, in orienting information processing to the present and the future, and in facilitating knowledge acquisition. The latter occurs through the filtering and structuring of knowledge, since an excessive amount of retained information can lead to problems in other cognitive domains. For instance, individuals with extraordinary memory abilities often exhibit significant impairments in areas such as social functioning (Boucher & Bowler, 2008).

Additionally, just because a particular piece of information is not remembered at a given point in time, does not necessarily mean that it won't be remembered in the future (Green et al., 2008). Not all memories require the same level of flexibility and immediate retrieval. Consider, for instance, the distinction between remembering the location of your keys versus the storage place of your ice skates, which are primarily utilized during winter periods. The keys need frequent and swift recollection, updating and forgetting, while the ice skates might not demand such flexibility. This purpose of forgetting or not needing a memory at that moment in time aligns with Anderson's inhibition theory (2003), which proposes that the memory system utilizes a probability assessment to determine the necessity of a memory and anticipates which memories are likely to be relevant in the near future. The brain then actively inhibits any competing or irrelevant information to facilitate retrieval of the relevant information. The inhibition theory could suggest that retained information that is currently irrelevant, but may be required in a later stage, is inhibited by the retrieval of information that is required currently. Consequently, as the anticipated moment of recall approaches, the inhibited information may become more accessible, potentially enhancing the efficiency of the retrieval process.

To what degree do the mechanisms outlined above give us the ability to regulate the encoding and retrieval of our memories, and to what extent is this regulation under voluntary control? Several previous studies have demonstrated the significant influence of a cue preceding an event on the subsequent recall of that event i.e., on encoding (Otten et al., 2006, 2010; Guderian et al., 2009). On top of that, Gruber and Otten (2010) conducted an EEG-based study that provided compelling evidence supporting the notion of individuals possessing some voluntary control over memory encoding, and potentially enhancing the encoding process. They did this by conducting an experiment where a cue was presented before a word with either a high or low monetary reward. In their study the electrical brain activity evoked by a cue preceding a word was a predictor of the subsequent memory of the word. However, this was only evident when the cue indicated a high monetary reward. Indicating some kind of control by the participants to successfully encode the information following the high value cue compared to the low value cue. Furthermore, Schneider and Rose (2016) discovered that the intention to encode something in the long-term memory influences the brain activity right before the onset of a stimulus. Participants who were aware of the necessity to encode stimuli exhibited distinct preparatory processes compared to those who were not aware of this. Therefore, participants' awareness seems to influence their preparatory strategies, further supporting the notion of voluntary control over memory encoding.

These studies reveal various processes and neural signatures that can affect the memory strength and ease of retrieval of stored information. However, there is still a lot to discover about the extent to which these are under voluntary control, and what the effects are of such control. In line with the inhibition theory, not all memories are immediately relevant and necessary at the same time. Therefore, it may be useful to have some control over how persistent memories are and how quickly they are forgotten, to maximize their strength at the moment that it is most useful and least intrusive. By investigating whether individuals possess voluntary control over when memories are easiest to retrieve, we gain insight into the extent of this personal control over memory retrieval. In the current study we aimed to explore whether the expectation of when a memory will be tested affects how well it is retained over time.

Materials and Methods

Participants

Forty-five students from the University of Groningen took part in the experiment (ages ranging from: 18 – 27, mean age: 21; 28 female, one identified as neither male or female; 38 were right-handed). They received study credit or a monetary reward (7 euros) in exchange for their participation. All participants reported normal or corrected-to-normal vision. The study was exempt from ethical review based on a set of criteria outlined by the Ethics Committee of Psychology at the University of Groningen (study code: PSY-2223-S-0423). Each participant provided informed consent before participating, and the experiment was conducted in accordance with the NETHICS code for ethical experimentation.

The sample size was determined based on a power calculation using a separate pilot sample of 15 participants (reduced to 10 participants after filtering on performance). This power analysis was conducted using the simr package (Green & MacLeod, 2016) for the effects on hit rate. The analysis focused on the interaction effect between whether an item was cued to be tested early or late (cue type, see below) and whether the city name was actually tested early or late (test type).

Procedure

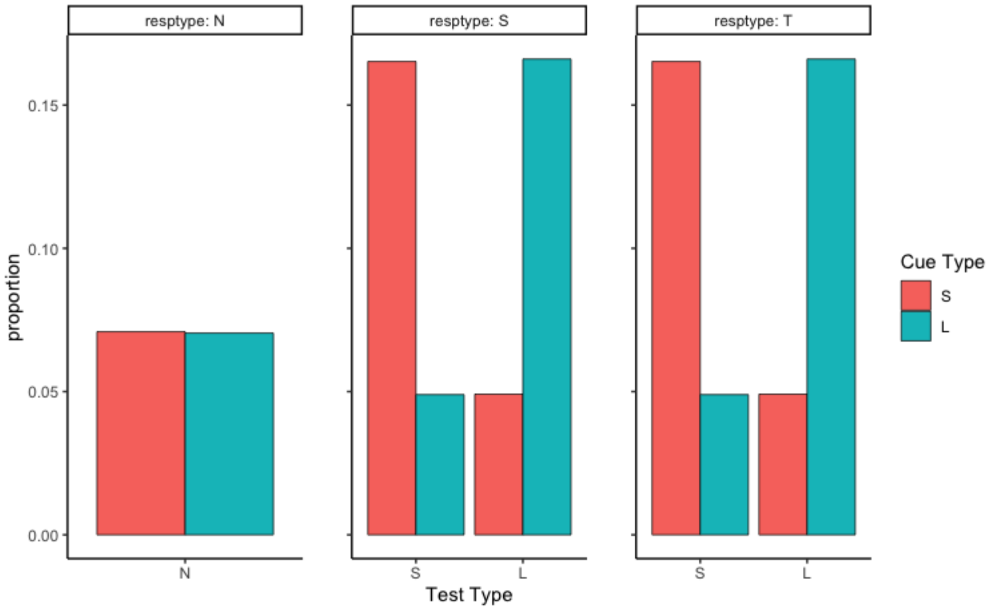
Participants were seated at approximately 70 cm viewing distance from the screen in a softly lit sound-attenuated cubicle. Task instructions were displayed on the screen before starting the experiment. The participants performed a continuous recognition task where items were drawn from a set of American city names. During the task, participants were shown a continuous sequence of cities, split into 10 blocks of 100 trials each, separated by breaks. Embedded in the sequence were multiple trial types. By means of the color and position of the cities, they were cued to be repeated early (after 8 – 13 trials) or late (after 20 – 25 trials), hereafter called the ‘cue type’ of each item (detailed further below under ‘stimuli’). This cue was usually valid, though a proportion of items was cued early but tested late, and vice versa. In addition to this, cities of either cue type were presented that were never tested. The trial sequences were built iteratively, by placing trials of different types at different positions in the sequence until the experiment was filled. Figure 1 shows the probabilities of every condition averaged over all participants. Due to the stochastic nature of item placement, not all trial types occurred equally often for each participant. On average, 331 city names (*SD* = 3.19) were cued early and tested early, 332 city names (*SD* = 3.09) were cued late and tested late, 71 city names (*SD* = 1.83) were cued early and tested never, 71 city names (*SD* = 2.24) were cued late and tested never, 98 city names (*SD* = 1.78) were cued early and tested late, 98 city names (*SD* = 1.73) were cued late and tested early.

On each trial, participants were instructed to indicate whether it was either a ‘new’ city that was presented for the first time (study item), or an ‘old’ city that they had seen before (test item). ‘Old’ and ‘New’ responses were given with the Z or M key, counterbalanced across participants. Participants were instructed to respond as fast as possible as well as accurately as possible. In between blocks, participants had a break and were shown a screen containing information about their accuracy and their average response time (RT).

To familiarize themselves with the task, each participant completed a practice block prior to the start of the actual task, comprising a predetermined sequence of 25 more widely recognized city names. In the practice block no distinction was made for the conditions, the cities were presented in black in the center of the screen.

Figure 1

Condition Probabilities



Note. Depiction of the probabilities of different trial types, averaged over all the participants. For cue type and test type, S and L reflect a short or long retention period respectively. Resptype reflects the type of trials: N are study items that are never tested, S are study items ('new' items) and T are test items, which are study items repeated later in the sequence ('old' items).

Stimuli

The continuous recognition task that the participants performed involved a dataset of American city names pulled from a US Cities Database (https://simplemaps.com/data/us-cities). These city names were filtered on population (higher than 10), no non-alphabetic characters in their name, and consisting of five to ten alphabetic characters (e.g., no spaces or hyphens). Out of the resulting list, the 25 cities with the highest populations were used for the practice block, and the 1200 cities with the lowest population counts were used for the experimental blocks. For both block types, city names were randomly sampled separately across participants.

The city names were presented on a 768 x 1024 LCD screen, with a dark grey background. Figure 2 illustrates the trial sequence. At the start of each trial, participants looked at a black fixation dot in the center of the screen. After 500 milliseconds, the city name appeared. Text was presented in mono font at an 18p font size. Stimuli would have either a dark red or dark blue color, and would be positioned above or below the fixation dot. The position and color of the word were always consistently coupled, and could indicate an 'early' or 'late' cue respectively in a manner that was counterbalanced across participants. Repeated words were always presented in the same color and position as their first presentation.

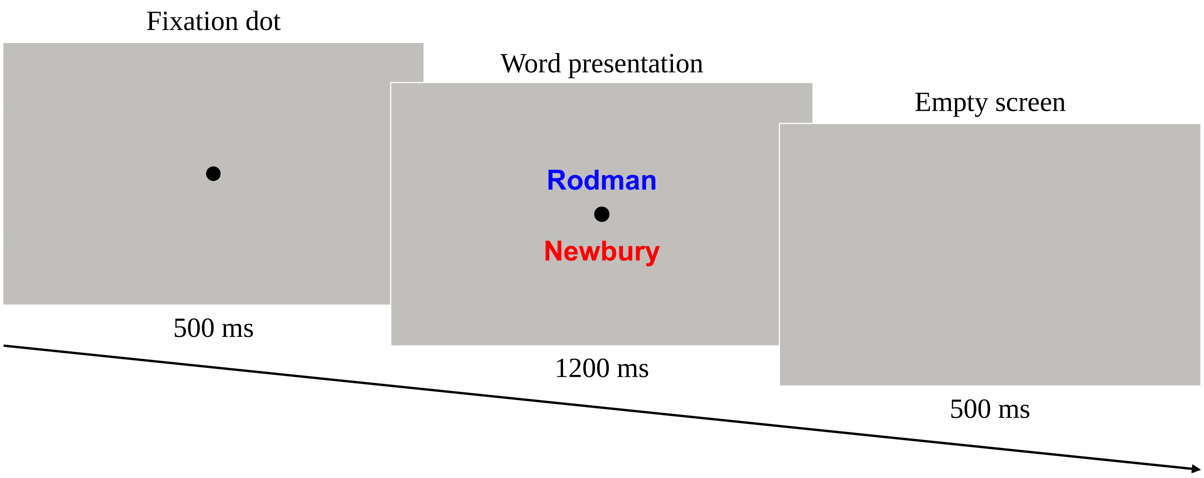
The city name was on the screen for 1200 milliseconds, after which an empty screen appeared for 500 milliseconds. Participants were asked to respond as fast and accurate as possible whether the item was old or new using the Z and M key on the keyboard. The meaning of these keys was also counterbalanced across participants. They had to provide their response withing the response window of 1700 milliseconds following stimulus onset. After this interval, a fixation dot was presented indicating the start of a new trial.

Trial and Participant Filtering

Participants were excluded from data analysis if they had outlier responses on more than 15% of the trials. To identify these outliers, we used a per-participant cutoff defined by log(RT)'s that were 3 median absolute deviations (MADs) away from the median. This procedure resulted in the exclusion of two participants. Furthermore, participants whose hit rate fell below the expected rate of 43% (based on pure guessing) were also excluded from the analysis, in order to establish a minimum level of performance from the participants. As a result, an additional two participants were discarded from the analysis, resulting in a final sample size of 41 for the subsequent analysis. Among the remaining participants outlier responses were discarded, which resulted in discarding 2.85% of the trials.

Figure 2

Trial Sequence



Note. Each trial involved presenting the participant with a word positioned either above or below the fixation dot. The word was displayed in either red or blue, serving as the cue type.

Results

Accuracy

The overall average hit rate (HR) in the experiment was 0.79 with a false alarm (FA) rate of 0.19 resulting in a *d'* of approximately 1.83. Figure 3 provides the HRs and correct rejections (CR) for each condition. Notable is that the CR rate can only be calculated for different cue types, since the factor test type does not have any meaning: these are all 'study' trials with no retention interval.

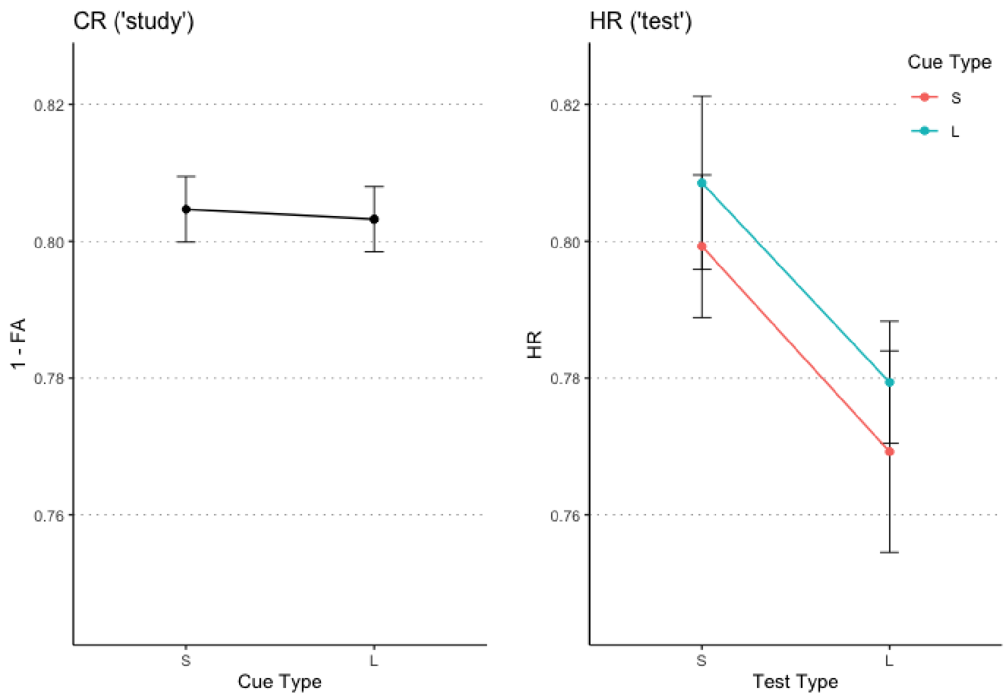
For hit rate, a generalized linear mixed model analysis was conducted to examine the effects on HR. This model predicted whether a response was correct using a logistic regression on the effects of cue type, test type, and their interaction. Based on a chi-square likelihood ratio test between an intercept-only model and a model including a fixed effect of test type, we conclude that test type significantly impacted hit rates ($\chi 2(1) = 17.22$, $p < .001$). This indicates a difference in hit rate between early and late tested items, with a higher hit rate for early tested items, possibly due to the recency of the early items. In contrast, cue type did not have a significant effect on HR ($\chi 2(1) = 1.25$, $p = .264$) when compared to the intercept-only model. Adding cue type to the model including only an effect of test type did not significantly improve the model ($\chi 2(1) = 1.85$, $p = .174$), nor did a full model which included an interaction between the two terms ($\chi 2(1) = 1.85$, $p = .396$).

As a complementary statistical analysis, we calculated the Bayesian Information Criterion (BIC) for four models: the full model including all main effects and the interaction, the model including the additive effect of cue type and test type, the model only including cue type as an effect, the model only including test type as an effect, and a model with no effect at all. Of these, the model only including test type as an effect had the lowest BIC compared to the other models (All ΔBIC > 7.9), which is consistent with the effects found in the generalized linear mixed model analysis.

We also conducted a generalized linear model analysis to examine the effects on the correct rejections. This gave us no significant effect of cue type compared to the intercept-only model ($\chi2(1) = 0.06$, $p = .803$).

Figure 3

Depiction of the hit rate (HR) and the correct rejections (CR) for each condition



Note. The ‘S’ in cue and test type refers to a short memory interval, indicating the early condition. The ‘L’ similarly refers to long memory interval (late condition). In these and all subsequent plots, error bars indicate within-subject 95% confidence intervals (Morey, 2008; Cousineau, 2005).

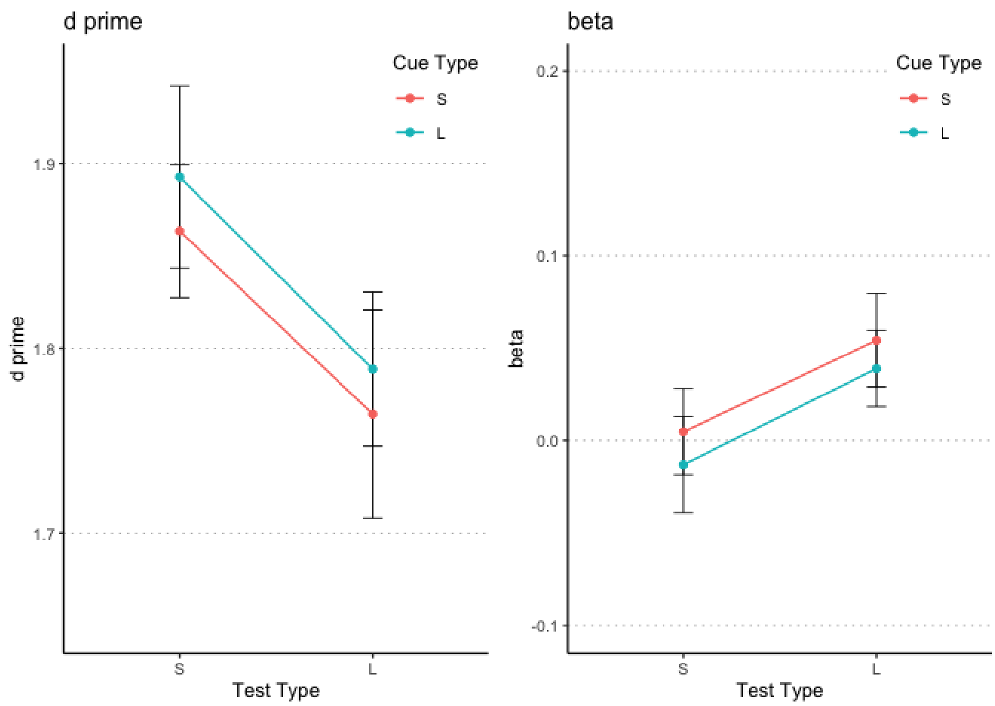
Signal Detection Theory

Based on accuracies, it appears that cue type does not strongly impact memory performance. While its effect on response rates during study is not substantial, similarly lacks a pronounced impacted on hit rates during retrieval, particularly when compared to the effects of test type, which effectively represents the impact of time/spacing. These findings imply that cue type exerts little to no discernible influence on memory, contradicts the initial hypothesis. Recognizing that accuracy measurements can potentially encapsulate response biases that underlie participants' decision-making, we used the signal detection theory (SDT) as an additional theoretical framework to disentangle and refine the accuracy assessment.

The above findings are reflected in the measures of the SDT. The results indicate barely any effects on false alarm (FA) rate due to cue type during the study phase, which meant that any variation in the SDT parameters *d'* and beta was driven by fluctuations in HR. The results of repeated measures ANOVAs showed that early-tested items exhibit a significantly improved *d'* ($F(1,40) = 9.13$, $p = .004$), while early cued items show a slight enhancement in *d'*; however this is not significant ($F(1,40) = 0.67$, $p = .420$). Similarly, the criterion (beta) is slightly lower for early tested items ($F(1,40) = 9.13$, $p = .004$) and a lower criterion for late cued items; however this is not significant ($F(1,40) = 0.86$, $p = .360$). There are no indications of interactions for *d'* and beta ($F(1,40) < 0.01$). Figure 4 provides the values of *d'* and beta for each condition.

Figure 4

Depiction of d prime (d') and beta for each condition



Note that although we did not find significant accuracy-effects of cue type, it is worth highlighting that there is nevertheless a tendency for test items to have more accurate responses when they are cued to be tested late. This suggests that there might actually be an effect of cue type on memory representations, but that accuracy of these responses maybe is not sensitive enough to detect this. Therefore, we turn to RT, which is potentially a more sensitive measure of how cue type affects responses in this task.

Reaction Time

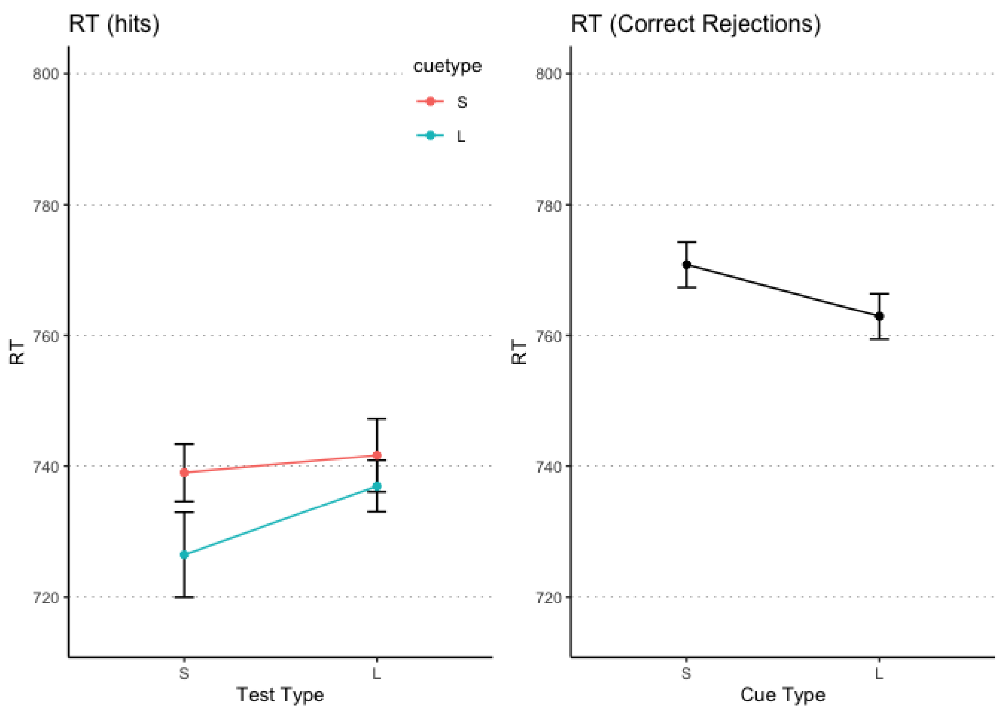
The average RT in the experiment was 733 milliseconds (*SD* = 155.38). Figure 5 provides the reaction times for all correct responses across different conditions. For the correctly identified test items (hits), we conducted a linear mixed model analysis to examine the effects of cue type and test type on RT and their interaction. The model included random intercepts for different participants and was fitted to log(RT) to account for skewed RT distributions. The main effect of cue type was found to be significant ($F(1, 13551) = 8.97$, $p = .003$), indicating that there was a difference in RT between items that were cued early versus late cued items, and participants responded slower to early cued items. Interestingly, the main effect of test type was not significant ($F(1, 13552) = 3.65$, $p = .056$), suggesting that there were no differences in RT between early tested items and late tested items. However, a trend was observed for the main effect of test type, indicating longer RTs for late tested items compared to early tested items. The interaction between cue type and test type was not significant ($F(1, 13551) = 0.49$, $p = .483$), indicating that the effect of cue type on RT did not differ significantly across test type conditions. The BIC value for the model containing only the main effect of cue type was the lowest compared to the other models (All $\Delta BIC > 5.4$).

These results show contrasting findings between HR and RT. Our initial expectation was for the pattern of results in reaction time (RT) to mirror that of accuracy. Surprisingly, we find that cue type influences RT, whereas test type does not.

We also conducted a linear mixed model analysis on the RT of the correct rejections (Figure 5). Interestingly, we also found a significant effect of cue type on the RT of the correct rejections ($F(1,18276) = 13.21$, $p < .001$). The correct rejections pertain to study items, where responses are not based on memory. This potentially suggests that cue type exerts a distinct impact compared to the influence of test type on memory.

Figure 5

Depiction of the RT for the hits and for the correct rejections

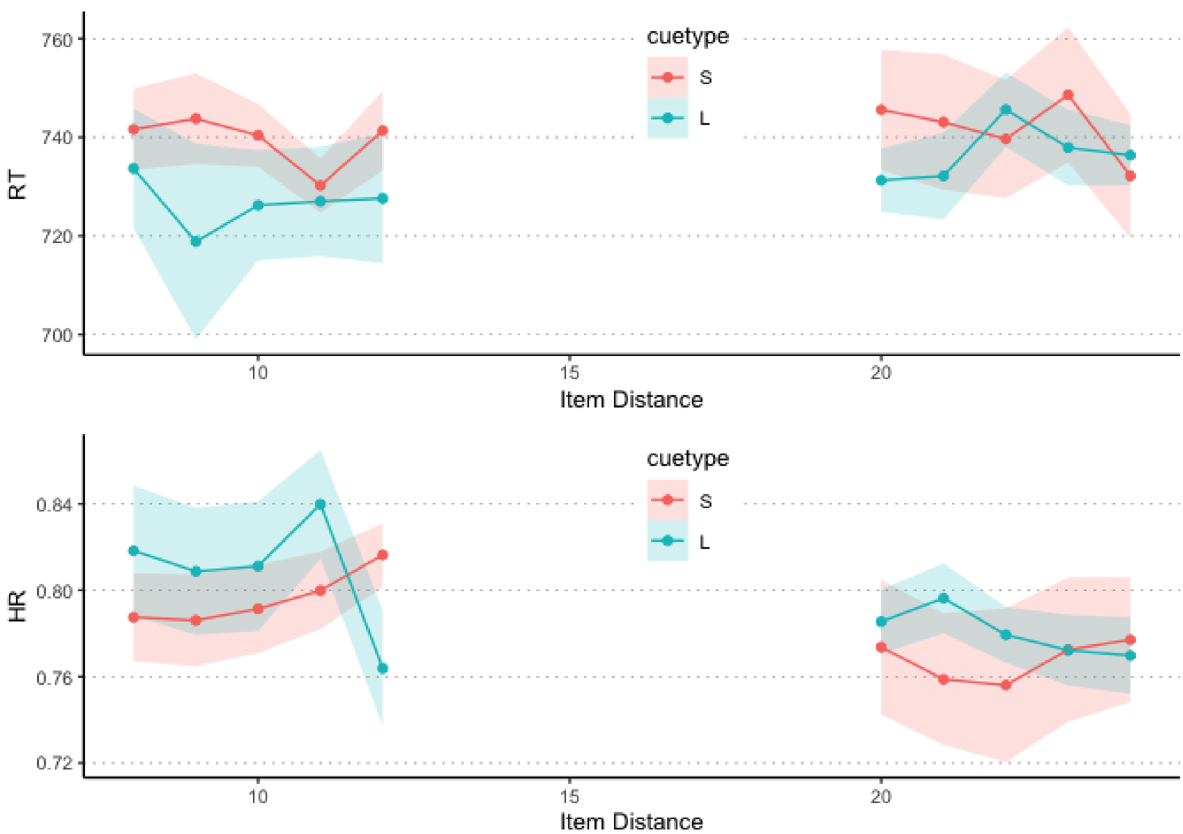


Item Distance

In order to assess whether we could observe and assess the time course of forgetting for items that were cued or tested early or late, we looked at RT and HR as a function of the number of items between study and test (item distance). Figure 6 illustrates RTs for each item distance, separated by cue type. No clear effect or pattern corresponding to item distance, such as decay of memory, was observed. Figure 6 also illustrates the hit rates for each item distance, separated by cue type. Similarly, no apparent discernible pattern or trend was evident. Worth noting is that the cued early tested late and cued late tested early conditions have higher error bars compared to the cued early tested early and cued late tested late conditions. This is due to the lower frequency of those conditions, as could be seen in Figure 1. Drawing meaningful conclusions about the relationship between item distance and RT/HR is challenging here, due to the low number of trials per condition, which resulted in not enough power.

Figure 6

RT and HR as a function of the item distance



EZ-Diffusion Model

That RT seems to be affected by cue type, while HR results show an effect of test type only, is a contradicting aspect of our results. It suggests that both these behavioral measures possibly tap into different cognitive mechanisms. To gain a more comprehensive understanding of the combined effects of RT and HR, we analyzed our data using the EZ-diffusion model (Wagenmakers et al., 2007). This model accounts for decision-making as a process of accumulating evidence over time until a certain threshold is reached, at which point a decision is made (Ratcliff & McKoon, 2008; Myers et al., 2022). In this model, accuracy and RTs are combined to extract different parameters with different cognitive meaning. The EZ-diffusion model calculates the nondecision time (T_{er}), the boundary separation (a), and drift rate (v). We calculate these parameters separately for study and test trials, and try to find whether cue type and test type perhaps affect different cognitive stages in this task.

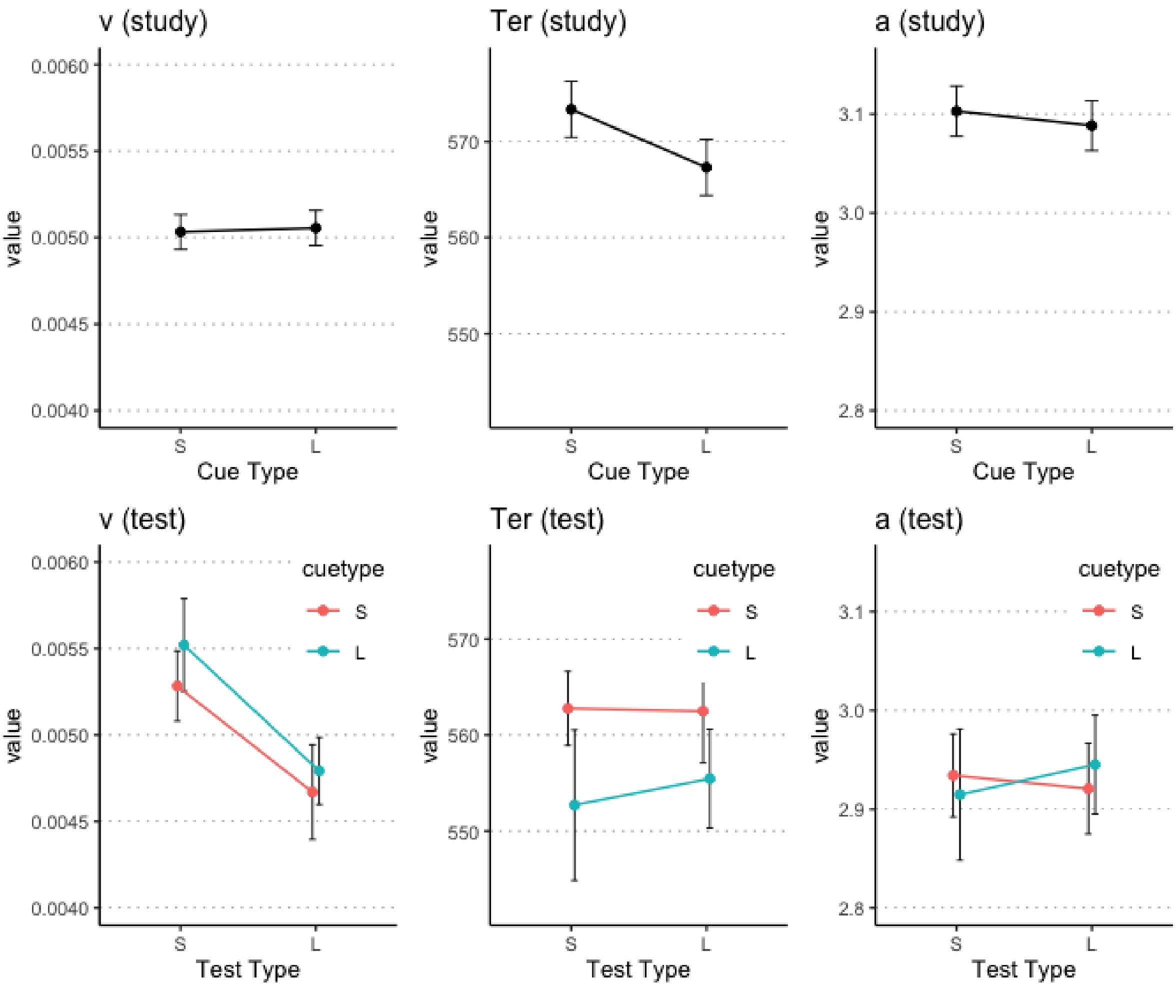
The calculated parameters are depicted in Figure 7. For the parameters of test trials, we found no significant effects of cue type, test type, or their interaction on boundary separation (all $F(1,40) < 0.24$), indicating that the same amount of information was necessary to make a decision across conditions, signifying a uniform response caution. However, we observed a significant main effect of cue type on the nondecision time ($F(1,40) = 5.00$, $p = .031$), with the early condition having a longer nondecision time. Test type did not affect nondecision time, nor did it interact with cue type ($F(1,40) < 0.13$). For the drift rate, we found a significant main effect of test type ($F(1,40) = 12.20$, $p = 0.001$), with higher drift rates for early tested items. Since drift rate influences both RT as HR, this suggests that early tested items resulted in faster and more accurate decisions. These results are in line with what we observed in the behavioural data. Cue type appears to have a minimal effect on the drift rate which was not significant ($F(1,40) = 1.48$, $p = 0.232$). This suggests that the RT effects of cue type (see Figure 5) are mostly due to modulations of nondecision time, and not due to differences in drift rate.

We also fit the EZ-diffusion model to data from the study trials. This analysis revealed no effects on boundary separation or drift rate ($F(1,40) < 0.34$). However, we again observed an effect of cue type on the nondecision time ($F(1, 40) = 4.38$, $p = .043$), suggesting that this was modulated by cue type even when the word is completely new. This may explain the cue type effect on RT for correct rejection trials. It suggests that this does not reflect a difference in the actual decision time but rather in some preceding or executing process. Regardless of what answer people give and regardless of whether the word is a study or a test item, people respond faster when cue type is late.

These results of our continuous recognition task indicate that cue type and test type exert distinct influences on behavior. As expected, drift rate, which can be related to memory strength (Starns et al., 2012), is dependent on the test type (i.e., the retention interval). Although there appears to be a tendency for cue type to impact memory strength, this effect is not significant. The RT effects that were observed for cue type effects seem to largely originate from a difference in nondecision time. The precise implication of this finding in the context of memory remains uncertain. However, the similar effect observed for study items indicates that it may be unrelated to memory representations.

Figure 7

Parameters of the EZ-diffusion model



Discussion

The present study aimed to explore whether expectation of when a memory will be needed will impact how it is encoded or maintained. To look into this, we performed a continuous recognition task that consisted of city names that could either be cued early or late and tested early or late. In terms of the accuracy, we observed a significant main effect of test type on HR, indicating a higher HR for early tested items compared to late tested items. This finding suggests that memories that are tested earlier are more readily accessible and accurately recognized. This is in line with the general idea that memories decay over time, where items are more difficult to recall when time passes (Ebbinghaus, 1885). An analysis of HR showed no significant effects of cue type. Moreover, analysis of the proportion of correct rejections showed no significant effects of cue type as well, indicating that there was no difference between how often early and late cued items were correct rejected. Taken together these results suggest that cue type does not impact memory performance when looking at accuracy. The same findings were reflected in an analysis of signal detection theory parameters, *d'* and beta. These showed significant effects of test type, whereas differences in cue type were not significant.

To look at a more sensitive measure of how cue type affects responses in the continuous recognition task, we looked at RT. In terms of RT, we did observe a significant main effect of cue type on RT, indicating that participants responded slower to items that were cued to be tested early, compared to late cued items. However, statistically it seemed that RT results were contradictory with that of accuracies, with the former showing significant effects of cue type only, and the latter only showing test type effect. The results regarding RT have added to the complexity to our findings. Since it contrasts with our expectation that the effects on RT would mirror the effects on accuracy. However, as described, we found the opposite.

To give us a more comprehensive understanding of the trade-off between reaction time and accuracy we turned to the EZ-diffusion model. When looking at the combined effect of RT and HR, the drift rate, which affects both the speed and accuracy of decision-making, was significantly affected by test type. Early-tested items exhibited faster and more accurate decisions, indicating that the retention interval influenced the quality of the decision-making processes. This could still just be an effect of early tested items that are fresher in participants their memory than late tested items are, which again reflects the decay of memory over time.

Additionally, the EZ-diffusion model revealed a significant effect of cue type on the nondecision time. This indicates that the time taken for nondecision processes, such as stimulus encoding, responding, or anything not being the decision-making process itself, differed between early and late cued items. Early cued items have a longer nondecision time than the late cued items. This finding may suggest that participants encode words in a color and position belonging to early cued items in a different way than words in a color and position belonging to late cued items, which influenced cognitive processes preceding or following the decision-making stage. It is unlikely that these low-level stimulus features themselves affected RT, because they were counterbalanced across participants. This could be attributed to varying expectation of when the memory will be needed, which subsequently influences the process during which encoding of the information happens. However, it is difficult to say what this exactly means, in the context of memory. The fact that a similar effect is observed for study items indicates that maybe this has very little to do with memory representations. One explanation might be that participants respond faster to late cued items, as this will give them more time to study the item. This effect could be masked by the decay of memory strength over time, and consequently not show any effect in the accuracy.

An additional explanation could be drawn from the discoveries of Bright et al. (2022). Their study revealed a dependency of RT on the recency of item presentation in a continuous recognition task. They propose that individuals engage in a retrograde ‘scanning’, which they term as the “recovery of temporal context”, withing their memory. This process involves seeking evidence indicating the presence of information within their memory and subsequently initiate the decision-making process to validate their certainty. This line of reasoning could align well with our results. If participants indeed require a recovery of temporal context, and if this time is evident in the nondecision time, it could imply that participants might do this faster if it contains a late cued item compared to an early cued item. A possible explanation for this is that it might not be deemed as worthwhile to search one’s memory for recent occurrences if there is already a strong belief that those events transpired in the distant past.

Our investigation into the relationship regarding the effect of item distances to RT and HR did not yield any discernible patterns or effect. This outcome may be attributed, at least in part, to the relatively high error terms observed in the cued early tested late and cued late tested early conditions. To gain deeper insights in the effects of item distance, future experiments could be designed to include a higher number of trials per item distance, which may reveal a clearer pattern of how items are forgotten over time. Moreover, it is possible that the item distances were too close to one another to reveal any clear effects of item distance. Since within the test type groups, we don’t see any clear patterns. However, between test type groups, we do see a clear forgetting effect (see Figure 3). Therefore, it might be interesting to conduct a version of the experiment were early and late items are spanned at a larger range of items so that the effects of item distance are visible even with the limited power that we have, and subsequently provide us with a better understanding of their impact on memory performance.

Despite some valuable insights provided with our study, some limitations should be acknowledged. There were some city names included in the American cities database that were words that may have already had pre-existing meaning for the participants. Examples of such cities include “Interior”, “Rivers”, “Dinosaur”, and “Windmill”. These familiar words among city names would presumably stand out, and would potentially interfere with the memory processes of interest. It is worth noting that these instances were relatively few in number, and would still be randomly assigned to different conditions. While their inclusion might have introduced additional noise to the results, it would not have formed a confounding factor. However, in future research, it would be advisable to exclude such words that already carry meaning in participants’ daily lives to minimize potential interference with the memory process.

In this study, we have focused on investigating whether expectation of when a memory will be needed will impact how it is encoded or maintained. However, to gain a comprehensive understanding of this, it is essential to explore additional research dimensions. Therefore, further investigations in terms of measurements beyond behavioural data and adaptations to the current experiment should be made to shed more light on the effects found in this study. For instance, measurement of pupil size could provide valuable insights into whether the cue type manipulation in this experiment affected the mental effort participants put into memory encoding on study trials, and whether this relates to subsequent changes in HR or RT (Bergt et al., 2019). The use of fMRI could offer a clearer understanding of the effects of time cues on how memory is encoded as well, as previous research has demonstrated that successful memory retention is associated with heightened brain activity in the hippocampus, the perirhinal cortex, the posterior cingulate cortex, and the left inferior frontal gyrus, during memory encoding (Carr et al., 2010; Liu et al., 2014). The brain activity in combination with the HRs could tell us more about the differences of each condition during encoding. Additionally, employing EEG to measure changes in theta and gamma brain oscillations during memory encoding, as demonstrated by Sederberg et al. (2003), could offer valuable information about how time related cued are processed differently. Exploring these supplementary measures may offer valuable insights into the neural underpinnings of nondecision time differences observes for early cued and late cued items, and drift rate differences observed for early tested and late tested items. Furthermore, exploring the effect that we found of cue type on RT, which appears distinct from memory strength manipulation, presents something that can explore using neurophysiological measures. Since these metrics have predominantly centered around memory strength effects, such as the subsequent memory effect (Rypma & D'Esposito, 2003).

Future research could delve further into investigating the voluntary impact of participants expectations of when a memory will be needed and how this is then encoded or maintained in memory. To gain deeper insights into this, explicit instructions regarding the color and position association with the cues could be removed. By doing so, researchers can assess whether participants can learn to discern that a particular color/position corresponds to items cued either early or late. This comparison would shed light on whether explicit knowledge of the color and position produces the same recall patterns as when participants lack such explicit information.

The continuous recognition task might not be optimal for investigating the effect of early and late cues on memory strength. The integration of encoding and retrieval in each trial creates challenges in interpreting the data. A possibly more effective alternative would involve adopting a study-test design with a similar setup. In this approach, participants would learn a list of words, consisting of novel items which are marked in either red or blue. Subsequently, they would get tested on a list of words, a mix of old and new items, where early cued items are more likely to appear early in the list, and long-cued items are more likely to be tested later in the list. By clearly separating study and test, it might become clearer whether the present results are a result of encoding and retrieval, or whether they are an artefact of the dual-task nature of continuous recognition. This may answer and perhaps be a possible explanation for the questions drawn by the current study.

To conclude, our study provides interesting findings into memory encoding and retrieval. Early tested items were found to have more accurate responses compared to late tested items, indicating that people do forget over time. Additionally, the contradicting aspects of the current study are the results regarding cue type on RT and test type on HR. Since early cued items led to longer nondecision times possibly indicating different encoding processes for these items. These effects of cue type may go beyond just a memory effect, in that participants might just create a strategy and respond faster to late cued items to gain more time to encode items that they will encounter later than early cued items. An alternative explanation might involve a pre-decision scanning process of the temporal context performed by the participants. Therefore, the RT might be shorter for late cued items, possibly due to a reduced search for the most recent items, because they have a strong belief these items are further in the past. These results definitely need more investigating to fully elucidate the exact meaning of the cue type effect on nondecision time. Additionally, more research needs to be done to fully understand the underlying mechanisms and the extent to which individuals can voluntarily control how they encode memories based on the expectation of when they will need that memory again. However, the current study serves well as a starting point. As understanding the complexities of memory modulation and control is crucial for various applications and contexts in daily life. This study contributes to the growing body of research on memory processes and the interplay between time, memory encoding, and retrieval. Its results call for further exploration to unravel the full extent of voluntary control over memory and its potential applications in enhancing cognitive functions. Understanding how we encode memories based on our anticipation of when we will need that memory again can be beneficial in certain settings. For instance, by perhaps providing specific cues to essential information we could potentially facilitate more effective encoding, and in turn enhance the learning process, which might create pathways that lead to more efficient memory retrieval. Knowledge of memory encoding also equips learners to optimize their learning strategies, and intentionally shaping the cues that stimulate successful memory recall. This could be beneficial in educational settings, but also in other contexts like clinical interventions in memory-related disorders. By knowing how memories are encoded, we may also discover a way to restore it.

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