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The Influence of Long-Term Memory on Working Memory Accuracy

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THE INFLUENCE OF LONG-TERM MEMORY ON WORKING MEMORY ACCURACY

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Abstract

The current research examined if representations in LTM necessarily aid working memory (WM) performance and if increasing interference in LTM limits facilitation from LTM on WM. Remembering multiple objects from the same semantic category can create interference in LTM that may decreases the accessibility of LTM representations during a WM task. In two experiments, participants completed an initial study phase in which objects were categorically (i.e., semantically) related or unrelated. Participants then completed a change detection task that included both previously studied and unstudied objects. In Experiment 1, an object changed into another object from a novel category. We found no evidence of facilitation from LTM on WM performance. However, eye-tracking analyses suggested evidence of facilitation on encoding, through shorter dwell times on studied objects compared to unstudied objects. Furthermore, we found no effect of semantic-relatedness on accuracy or dwell times. Change detection was similarly accurate when the studied objects were all from different categories, as when the studied objects were from the same categories, demonstrating that interference in LTM did not affect WM. In Experiment 2, we attempted to increase reliance on LTM representations by increasing difficulty and interference in the WM task. The changed object on the post-change array came from the same category as the pre-change object. Like in Experiment 1, we did not find any evidence of LTM facilitation on WM performance. Once again, we found shorter dwell times on studied objects compared to unstudied objects. Additionally, as in Experiment 1, there was no effect of interference in LTM on WM performance. Change detection accuracy was similar between semantically-related objects and semantically-unrelated objects. Overall, the results from the current study demonstrate that LTM representations were not used to improve WM performance, but may have been used to facilitate the encoding processes.

Introduction

Working memory (WM) is a limited-capacity temporary memory store that is used to actively process and maintain task relevant information (Baddeley, 2000; Baddeley & Hitch, 1974; Cowan, 2008; Miller, Galanter, & Pribram, 1960). Specifically, WM can store about 3-4 objects at a time, allowing sensory information to be manipulated and accessed quickly (Baddeley, 1992, 2003; Fukuda, Awh, & Vogel, 2010; Vogel, Woodman, & Luck, 2001). LTM, however, is an unlimited memory store of representations of previous knowledge and life events (Cowan; 2008; Squire, 2004; Brady et al., 2011). Although the relationship between working memory (WM) and long-term memory (LTM) has been a topic of interest for many years, the relationship between the two is still not fully understood. On the one hand, the classic view is that WM and LTM are considered to be independent systems in that they serve separate functions and have few interactions (Atkinson & Shiffrin, 1968; Baddeley, 1986; Baddeley & Hitch, 1974). One aspect of this classic "separate systems" view is that WM representations are believed to be sheltered from the negative influence of previously stored LTM representations, referred to as proactive interference (PI), that occurs in LTM (Cowan, 2005; Oberauer, 2009). On the other hand, others argue that LTM and WM are not separate systems. According to these models, WM should be considered a temporarily activated subset of LTMs that is vulnerable to PI (Cowan, 1988, 1995; Farrell, 2012; Oberauer, 2009).

Recently, research has moved toward understanding "HOW" these systems interact, rather than debating "IF" they interact. Consider the counterintuitive nature of an isolated and completely independent WM system: WM serves as a system for rapidly updating, maintaining, and creating new representations that must be dissociated from information in LTM. However, WM can be more efficient by relying on previously stored LTM representations (Brady et al.,

2016; Curby, Glazek, & Gauthier, 2009; Xie & Zhang, 2016). In addition, in order to shelter useful WM representations from quick decay, WM transfers representations to LTM for long-term storage (Oberauer, 2009; Oberauer, Awh, & Sutterer, 2017). Therefore, the contents on WM and LTM interact to some degree.

The Influence of LTM on WM Accuracy

Abstract or meaningless objects are typically used in WM tasks in order to acquire a "pure" measure of WM by limiting the contribution of LTM. However, many situations in our day-to-day lives require us to use information for which we have previous knowledge in order to carry out tasks. For example, a greater WM capacity has been observed for nameable objects and for objects that the individual has more expertise or familiarity (Brady et al., 2016; Curby, Glazek, & Gauthier, 2009; Xie & Zhang, 2016). Nameable and familiar real-world objects may activate pre-existing LTM representations that can be used to aid WM maintenance, resulting in larger WM capacity (Brady et al., 2016; Xie & Zhang, 2016). This influence of LTM representations has also been observed in WM studies using lists of words; such that there was an increase in recall performance for repeated but not novel lists of words (Hebb, 1961; Fastame, Flude, & Hitch, 2005; Page, Cumming, Norris, McNeil, & Hitch, 2013). The WM advantage for lists of repeated words may be a result of a more accessible LTM representations for the repeated words. This advantage for repeated stimuli can be compared to the advantage of familiarity and expertise seen in WM studies for visual stimuli. In sum, it seems that WM accuracy may be influenced by the accessibility of task relevant LTM representations.

Although people display impressive LTM for visual stimuli only after a brief presentation (Brady, 2008; Standing, 1973; Standing, Conezio, & Haber, 1970), people often perform poorly in visual WM tasks (Beck, Peterson, & Angelone, 2007; Rensink, 2002; Rensink, O'Regan, &

Clark, 1997; Simons, 2000; Simons & Ambinder, 2005; Simons, Chabris, Schnur & Levin, 2002). If these two memory systems interact and accuracy on WM tasks is influenced by retrieval of relevant LTM representations, then why does this large difference in accuracy between LTM and WM tasks occur? It is possible that people have relevant LTM representations that can be considered useful during a WM task but fail to use or access these representations (Beck & van Lamsweerde, 2011; Brady et al., 2009; Wood & Simons, 2017). WM tasks that require participants to briefly remember objects have provided both behavioral and neural evidence in favor of this account (Beck, Peterson, & Angelone, 2007; Busch, 2013; Hollingworth & Henderson, 2002; Hollingworth, 2005; Varakin & Levin, 2006; Wood & Simons; 2017). It is possible that LTM representations are formed during the encoding (Fukuda & Vogel, 2019) and maintenance phases of WM tasks, but these representations are not necessarily accessible or retrieved to facilitate WM performance. WM performance may be impacted by the accessibility of LTM representations. The overarching goal of the current study is to better understand how and when LTM representations can be used to aid WM performance. Specifically, does the accessibility of LTM representations impact the ability for LTM representations to be used to improve WM performance? Categorical similarity between objects in LTM has been shown to decrease the accessibility of LTM representations (Konkle, Brady, Alvarez, & Oliva, 2010a; Konkle, Brady, Alvarez, & Oliva, 2010b). Therefore, in the current study I tested how the accessibility of LTM representations impacts WM performance by measuring the difference in change detection accuracy when the objects stored in LTM are semantically-related compared to when they are all semantically-unrelated.

Accessibility of LTM Representations

One focus of the current study was to examine if storing multiple semantically-related objects in LTM impacts the accessibility of those representations to WM. Storing multiple objects from the same category in LTM can increase proactive interference (PI) in LTM, which is the tendency of previously stored information to hinder subsequent LTM performance (Baddeley, 1966; Crowder, 1976; Shiffrin & Atkinson, 1968; Shiffrin & Atkinson, 1969). Increasing categorical similarity among objects within LTM has been shown to increase PI in LTM and, in turn, decrease both the accessibility and utility of detailed LTM representations (Konkle et al., 2010a; 2010b). Categorical interference is typically manipulated by increasing the number of objects from the same category in the to-be-remembered set (Baddeley, 1966; Konkle et al., 2010a; 2010b; Vogt & Magnussen, 2007). LTM test accuracy decreases as the number of objects from a single category increases (Konkle et al., 2010a; 2010b). According to the cue-overload hypothesis, the more relevant information there is that is associated with a single cue (e.g., a category label), the less reliable the cue is in allowing accessibility to the LTM representations (Watkins, 1979; Watkins & Watkins, 1975). Categorical distinctiveness between encoded objects may play an important role in maintaining detailed LTM representations with both visual and verbal stimuli (Baddeley, 1966; Konkle et al., 2010a; 2010b). Therefore, encoding multiple objects from the same category increases PI in LTM that impacts the accessibility of these LTM representations, leading to a decrease in LTM test accuracy. The current study manipulated the categorical similarity between objects encoded into LTM in order to determine whether or not categorical similarity impacts the ability for LTM to facilitate WM performance.

The Impact of LTM Representations on WM Accuracy

There have been few studies that have directly examined when previously encoded LTM representations impact performance on a subsequent WM task. Among those few studies, a flexible gate between WM and LTM has been proposed in order to attempt to explain interactions between LTM and WM (Oberauer, 2009; Oberauer et al., 2017). The assumption of this flexible gate hypothesis is that LTM representations can have a facilitatory effect on WM performance if the LTM information can be evaluated as useful to the current WM task. Although, it is important to note that the idea of “evaluated to be useful” is not well defined in this flexible-gate hypothesis. Two ways that people determine whether or not previously stored representations in LTM will be used are described in Oberauer et al. (2017). The first way is that people may initially “assess the goodness” of information in WM on a trial-by-trial basis to determine if information in WM is sufficient to complete the current task. If information in WM is evaluated as insufficient, people then attempt to retrieve accessible representations from LTM. In this view, the gate between LTM and WM remains closed unless information in WM is determined insufficient (Oberauer, 2009; Oberauer et al., 2017). The second way is that people may necessarily access information from both LTM and WM during each trial. This would indicate that the gate between LTM and WM always remains open and that retrieval from LTM is automatic (Oberauer, 2009, Oberauer et al., 2017). Representations from the two memory systems then compete, with the strongest representation determining the response. In most cases, WM representations are evaluated as stronger than representations in LTM and are therefore used. According to this assumption, information about the presence and quality of information in WM is all that is needed to determine the flexible usage of representations in LTM (Oberauer, 2009; Oberauer et al., 2017).

Oberauer et al. (2017) directly examined this flexible-gate hypothesis by using a change detection task that included unique object-color combinations that were previously encoded during a LTM study phase. Participants in their study initially encoded unique object-color combinations for 1s each, followed by a delayed LTM estimation task in which participants were presented with a color wheel and asked to report the color of the presented object. After the LTM estimation task, a WM task was completed that contained some of the objects from the LTM task. For the WM task, a pre-change array was presented containing three objects in unique colors. Importantly, two of the objects were identical to objects that had previously been studied during the LTM encoding phase except one was in the same color (old-match condition) as originally encoded and one was presented in a new color (old-mismatch condition). The third object-color combination was chosen at random and was not previously studied in the LTM encoding phase (new condition). Following this, a post-change array was presented with a single greyscale object along with a color wheel that participants used to report the color of the object from the previous screen. Each of the three objects were tested in a random order. The purpose of the three post-change array conditions was to measure the amount of proactive facilitation (old-match condition) and proactive interference (old-mismatch condition) provided by LTM representations during a WM task. Oberauer et al. (2017) described *proactive facilitation* as helpful influences and *proactive interference* as harmful influences from information previously encoded into LTM.

According to Oberauer et al., (2017), there was evidence for LTM facilitation on WM performance, as displayed by significantly better WM accuracy in the old-match condition compared to the old-mismatch and new conditions. Interestingly, accuracy in the old-mismatch condition was not significantly different from accuracy in the new condition. If accuracy in the

old-mismatch condition had been significantly worse than accuracy in the new condition, then that would be interpreted as evidence of proactive interference. One possible explanation for the similarity in results between the old-mismatch condition and the new condition is that when participants were presented with information that was inconsistent with information in LTM during the WM task (i.e., old-mismatch condition), the facilitatory contribution from LTM was limited. The results provided by Oberauer et al. (2017) suggest that LTM provides a facilitatory effect when representations held in WM are identical to LTM representations (old-match > new). However, LTM representations are not used during the WM task if the information in LTM is not identical to the information in the WM task (old-mismatch = new). When representations in the WM task and LTM are identical, this may provide a strong retrieval cue to retrieve and use relevant information in LTM. LTM representations are used when they are considered to be useful to the task but are not used if they are not considered to be useful (Oberauer et al., 2017). This would suggest that the gate between LTM and WM remains open, allowing information from LTM to aid WM accuracy. The current study aimed to replicate these findings of LTM facilitation on WM performance while using real-world objects in lieu of the unique object-color combinations.

Whereas the study conducted by Oberauer et al. (2017) provides evidence in favor of facilitation from LTM representations on WM performance when using unique object-color combinations, other research using real-world objects has failed to find a facilitatory effect (Schurgin et al., 2018; Wood & Simons, 2017). Is it possible that LTM facilitation on WM performance is not always observed because LTM representations of real-world objects are not always accessible? Schurgin et al. (2018) used EEG to measure contralateral decay activity (CDA) amplitude (a measure of the amount of visual information actively maintained in WM;

see Carlisle, Arita, Pardo, & Woodman, 2011; Vogel, 2004; Williams & Woodman, 2012). CDA was measured as participants completed a WM task with real-world objects that had been previously stored in LTM. Participants initially completed a LTM encoding task in which they encoded real-world objects for 2s each and after a delay, they completed a WM task. During the WM task, participants were presented with pairs of objects on each side of the screen accompanied by a cue directing attention to which object the participant should remember. Half of the time, one of the to-be-remembered objects was an object they had previously studied. This was followed by a 2AFC test including a to-be-remembered object and an exemplar lure that had not been studied (e.g., a coffee mug that was studied and a coffee mug that was not studied). During the WM task in Experiment 1 of their study, there was neural evidence for less active maintenance in WM for objects that had been previously studied. The authors conclude that this means that LTM is being used to maintain the information instead of WM. However, behavioral results suggested that these available LTM representations did not improve WM performance, even when the tested object was cued during the task. One explanation as to why available LTM representations did not improve WM performance is that the WM task required holding only two objects in memory, which is within the capacity of WM. Therefore, it is possible that the use of LTM representations compared to WM representations would not necessarily improve WM performance in this situation. In the current study, participants must encode and maintain four objects in WM, which is close to the capacity of WM, and should therefore be more likely to benefit from LTM maintenance of studied objects.

Similar behavioral results were reported in a study conducted by Wood and Simons (2017). Participants completed an initial LTM encoding phase, followed by a change detection task. In the familiar condition, the change location was cued in the pre-change array by including

in the array an object that was from the same semantic category as an object that was previously studied (e.g., a “curvy road ahead” street sign was presented in the pre-change array when a yield sign had been studied previously). The familiar condition was included in this study in order to determine whether or not previously stored representations in LTM may be used to aid WM performance. On the post-change array, the unstudied semantically-related object was replaced with its semantic category studied counterpart. Therefore, the semantically-related object was always the object to change, and LTM could be used to determine the change location. In the unfamiliar condition, all of the objects in the pre-change array were objects that were not previously studied, and therefore, no change location was cued. The change detection task was followed by a LTM recognition test of objects studied during initial encoding. Results from the LTM recognition test replicated previous research demonstrating that people have detailed LTM representations. However, participants’ change detection accuracy was decreased compared to LTM recognition accuracy, even when cued to the change location. Participants in the study conducted by Wood and Simons (2017) failed to recognize the priming cue of the familiar condition. The change location cued in the pre-change array was only an effective cue when participants had available memory for target categories and were aware of the cue’s benefit. The authors suggested that participants failed to use available LTM representations to improve WM performance (Wood & Simons, 2017). However, these LTM representations may not have been accessed and used if participants did not notice that the category-match pre-change object was meant to cue the object stored in LTM. The current study aimed to better understand the flexible usage of LTM representations to aid WM performance in which the LTM objects were present in the pre-change array and LTM can therefore aid in the storage of information needed for the WM task.

Experiment 1

The overall goal of the current study was to determine if previously encoded LTM representations necessarily facilitate WM performance. When using unique object-color combinations, LTM representations have the ability to aid WM performance when representations in LTM are identical to representations in WM (Oberauer et al., 2017). Furthermore, less active maintenance in WM for previously studied objects compared to unstudied objects suggests that previously stored LTM representations facilitate maintenance processes (Schurgin et al., 2017). However, retrieval from LTM is effortful and therefore may not be considered useful (Kunar, Flusberg, & Wolfe, 2008; Oliva, Wolfe, & Arsenio, 2004; Wolfe, 2000). In order to measure this potential facilitation, a change detection task that included both previously studied and unstudied objects was used. A second question of interest to the current study was whether or not PI in LTM prevents facilitation from LTM on WM performance. Encoding multiple objects from the same category has shown to produce PI in LTM, leading to a decrease in the accessibility and utility of LTM representations (Baddeley, 1966; Konkle et al., 2010a; Konkle et al., 2010b; Watkins, 1979; Watkins & Watkins, 1975). In order to measure the effect of PI in LTM on WM performance, objects encoded into LTM were either semantically-related or semantically-unrelated.

Participants were placed in one of two groups for LTM encoding: semantically-unrelated or semantically-related. Participants initially completed a LTM encoding phase in which they studied a number of objects. Following a delay, a change detection task was administered in which one object (either studied in the LTM encoding stage or not) changed into a new, unstudied object (novel category change) or no change occurred. Finally, after completion of the change detection trials, participants completed a 2AFC test of previously studied objects

including either novel category pairs or exemplar pairs (two objects from the same category). The 2AFC recognition test was used both as a criterion check as well as a measure of the amount of interference within LTM from semantically-related objects. If storing multiple semantically-related objects creates interference in LTM, performance on the 2AFC test should be lower in the semantically-related condition compared to the semantically-unrelated condition. Furthermore, the use of novel category and exemplar pairs in the LTM 2AFC test allowed me to examine the detail of the LTM representations.

Hypotheses and Predictions

The first goal of the current study was to determine whether or not previously encoded LTM representations for real-world objects facilitate WM performance. In WM tasks that have used unique color-object combinations, LTM representations that are identical to the WM task stimuli can aid WM performance (Oberauer et al., 2017). Therefore, I predicted that LTM facilitation would be supported by a main effect of availability of LTM representation due to improved change detection accuracy for studied objects compared to unstudied objects. Alternatively, facilitation from LTM may not be observed because retrieval from LTM may be more effortful than simply using WM (Kunar, Flusberg, & Wolfe, 2008). Alternatively, studies that have examined the effect of LTM representations on WM performance using real-world objects have failed to find evidence in favor of a facilitatory effect from LTM (Schurgin et al., 2018; Wood & Simons, 2017). If the latter was true, then I would expect change detection accuracy to be similar for studied and unstudied objects.

The second goal of the study was to investigate whether or not PI in LTM makes previously encoded LTM representations less accessible, therefore preventing facilitation from LTM on WM performance. Encoding multiple semantically-related objects into LTM can cause

PI in LTM, making LTM representations less accessible (Konkle et al., 2010a; Konkle et al., 2010b). It is possible that LTM facilitation on WM performance may be limited or prevented if LTM representations are not accessible. Therefore, I predicted an interaction between availability of LTM representation and semantic-relatedness for change detection accuracy, driven by a stronger LTM facilitatory effect in the semantically-unrelated condition compared to the related condition.

In Experiment 1 of Schurgin et al.'s (2017) study, previously studied objects produced less active maintenance in WM compared to previously unstudied objects. This suggests that although previously stored LTM representations did not lead to an improvement in performance, these representations may have potentially facilitated the maintenance and encoding processes. The current study examined eye movements during the change detection task in order to explore potential differences in the availability of LTM representations. Eye movement analyses were conducted on the total dwell time on objects on the pre-change (encoding) array during the change detection task. Less time spent dwelling on an object would suggest that LTM representations are more easily available for the fixated object. If previously stored LTM representations facilitate the encoding process in the current study, then I would predict shorter dwell times on objects that had been previously studied compared to unstudied objects. Additionally, if previously stored LTM representations facilitate the comparison and decision process during change detection response, then we would expect faster RTs on previously studied objects compared to unstudied objects.

Experiment 1. Methods

Participants

Participants in the current study were 57 Louisiana State University undergraduates (43 female, average age = 19.6), enrolled in psychology classes. All participants received course credit for their participation, and all participants had normal or corrected-to-normal vision and normal color vision. Using G*Power and assuming a small to moderate effect size (η_2 = .4), 25 participants were required per between-subjects group to achieve an estimated power of .8 to detect any interactions.

Stimuli and Apparatus

The current study used stimuli of real-world objects taken from the Massive Memory database (http://cvcl.mit.edu/MM/). Objects included both categorically distinct objects and objects from the same semantic category (see Figure 1 for example stimuli). Eye tracking was employed using a desktop-mounted Eyelink 1000+ eye tracker. The experiment was programmed in Experiment Builder (SR Research).

Figure 1. Examples of semantic object categories.

Design

Experiment 1 had a 2 x 2 mixed factorial design with availability of LTM representations (studied, unstudied) as a within-subjects factor and semantic-relatedness (unrelated, related) of the LTM encoding stimuli as a between-subjects factor.

Procedure

Participants in Experiment 1 were randomly placed into one of two conditions: semantically-related (29 participants) or semantically-unrelated (28 participants). Participants were presented with either only related or only unrelated objects depending on which condition they were placed.

LTM Encoding Phase. Participants began with a LTM encoding task (see Figure 2a). They completed a total of 420 trials in which they were instructed to detect repetitions in stimuli. Three-hundred and sixty objects were presented and 60 of these were repeated once (shown a total of two times). Each object was shown individually for 2s separated by a 50ms fixation cross. Of the 360 studied objects, 240 were used during the change detection task and 60 were used during the LTM test. The 60 objects that were repeated once during LTM encoding were not used during the change detection task or during the LTM test. In the semantically-unrelated condition, all objects were categorically distinct from one another (i.e., 360 distinct categories of objects). In the semantically-related condition, objects came from 36 real-world object categories with 10 exemplars per category (see Figure 2a for examples of conditions). Participants were explicitly told to remember these objects for a memory test later. In addition to remembering the presented object, participants were required to complete a repetition detection task in which they reported if a presented object was one that they had already seen by pressing a button. Presented

objects were ordered into 6 blocks of 70 objects each. Within each block, 40 objects were used during the change detection task, 10 objects were used during the LTM test, and 10 objects were repeated once (repetition detection task). The order of the 70 objects within each block was randomized. After the presentation of all 420 trials, a 10-minute delay was administered before moving onto the change detection task. During the delay, participants completed simple word-search puzzles.

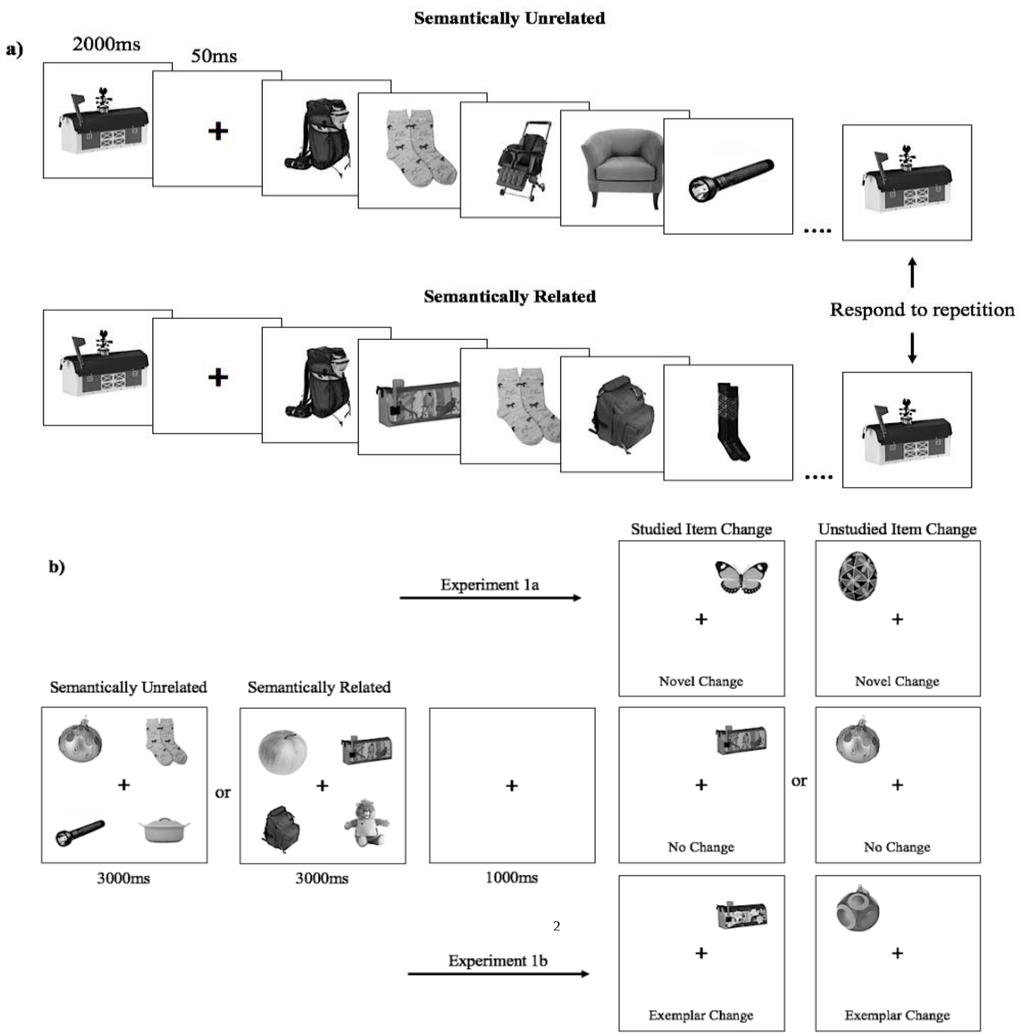

Figure 2. Figure 2 shows and example of the different conditions. Figure (a) displays a typical sequence of events during the LTM encoding phase. Participants were placed in semantically-unrelated (top) or -related conditions (bottom). Figure (b) displays the different conditions during the change detection task. Next, a post-change array was presented with either a studied or unstudied object changing. In Experiment 1 (top), a novel change or no change could occur. In Experiment 2, an exemplar change, or no change could occur.

Change Detection Task. The change detection task included a total of 160 trials. Each trial began with a fixation cross for 200ms (see Figure 2). Following the fixation cross, a pre-change array was displayed with an object in each quadrant of the screen for 800ms. Although an encoding time of 3s was initially proposed, pilot data revealed near ceiling level performance. Therefore, the encoding time of the pre-change array was shortened to 800ms to reduce accuracy below ceiling. The pre-change array included two objects that were studied during the LTM encoding phase and two objects that had never been seen before. Unstudied and studied objects were presented in random locations on each trial. The unstudied objects came from a separate set of categories to ensure that studied and unstudied categories remained distinct from one another. After this, the pre-change array disappeared and was replaced with a fixation cross for 1000ms and then followed by the post-change array. The post-change array contained a single object in a location where an object was previously located. This object location was in the location of an unstudied or studied object on each trial (80 trials each). Half of the trials (80 trials) were no change trials, in which the object in the post-change array was identical to the object in the pre-change array (40 studied and 40 unstudied). The other half of the trials (80 trials) were change trials in which the object in the location of a pre-change object (40 studied and 40 unstudied) was a changed object from a novel category (i.e., an unstudied object from a category that has not been seen before). An additional 36 categories (i.e., separate from studied categories) with 10 objects per category were used as novel category change objects. See Figure 3b for a breakdown of the various change detection trials. Participants were required to respond whether or not a change occurred via button box. The post-change array remained on screen until a response was made.

LTM Recognition Test. Following the 160 change detections trials, participants completed 60 randomly ordered trials of a 2AFC recognition test. One of the objects presented during the recognition test was an object that was initially encoded during the LTM encoding phase (60 trials). The studied object was either paired with an unstudied novel category lure that was categorically distinct from the tested object (30 trials), or an exemplar lure that was categorically similar to the tested object (30 trials). See Figure 3 for an example of the LTM recognition test. Accuracy on the LTM recognition task was used as a manipulation check. It was proposed apriori that participants whose accuracy fell below chance (55% on exemplar pairs) would have their data excluded; however, in the current experiment, all participants scored above 55% on the LTM test. Participants had unlimited time to respond and responded via button box.

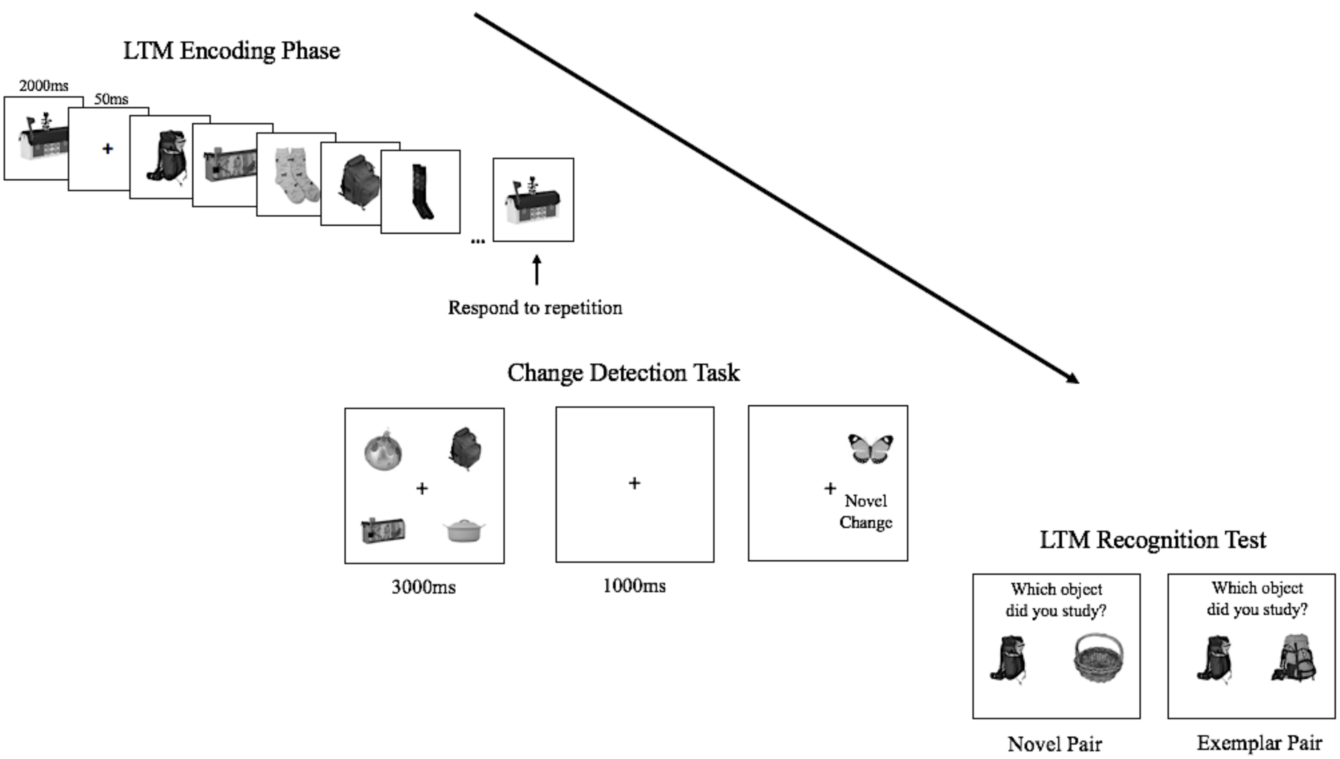

Figure 3. Example of the sequence of events during both experiments. Participants initially completed a LTM encoding phase, followed by a change detection task, and ended with a LTM recognition test.

Experiment 1. Results

Separate 2 x 2 mixed measures ANOVAs were conducted on change detection accuracy, change detection RT, and total time spent dwelling on objects in the pre-change array during change detection. As stated above, semantic-relatedness (unrelated, related) was a between-subjects factor, and availability of LTM representations (unstudied, studied) was a within-subjects factor.

Change Detection Accuracy

The repeated-measures ANOVA for change detection accuracy revealed no main effects for either LTM representation, $F(1,55) = .428$, $p = .516$, $\eta_{p2} = .008$, or semantic-relatedness, $F(1,55) = .897$, $p = .348$, $\eta_{p2} = .016$. Furthermore, there was no interaction between LTM availability and semantic-relatedness, $F(1,55) = 1.91$, $p = .173$, $\eta_{p2} =.034$. Change detection results can be found in Figure 4. Results from the change detection analysis did not reveal any evidence of facilitation from LTM on WM performance, as displayed by similar accuracy for studied and unstudied pictures.

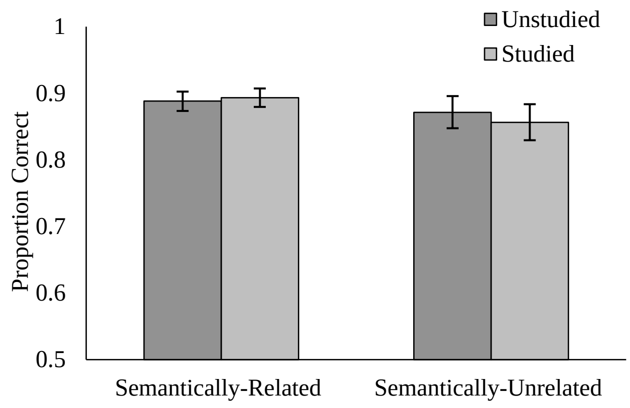

Figure 4. Figure 4 represents average change detection accuracy from Experiment 1, displaying no main effects of LTM availability or semantic-relatedness and no interactions. Error bars represent standard error.

Change Detection Response Time

Separate 2 x 2 repeated-measures ANOVAs were conducted for no-change and change trials with availability of LTM representation (studied, unstudied) as a within-subjects factor and semantic-relatedness (unrelated, related) as a between-subjects factor. RTs were analyzed for correct change detection trials only. When the change detection trial was a no change trial, the post-change object was either a studied or unstudied object that was present on the pre-change array. For no change trials, the repeated measures ANOVA revealed no main effects for either LTM representation, $F(1,55) = .598$, $p = .443$, $n_{p2} = .011$, or semantic-relatedness, $F(1,55) = .035$, $p = .852$, $n_{p2} = .001$. Finally, no interaction between LTM availability and semantic-relatedness was observed $F(1,55) = .346$, $p = .559$, $n_{p2} = .006$. The same pattern of results was displayed for change trials, in which the post-change object was a new unstudied object. No main effects for either availability of LTM representation, $F(1,55) = .673$, $p = .416$, $n_{p2} = .012$, or semantic-relatedness, $F(1,55) = .072$, $p = .79$, $n_{p2} = .001$. Again, no interaction between LTM availability and semantic-relatedness was observed $F(1,55) = .144$, $p = .706$, $n_{p2} = .003$. Neither availability of LTM representation or semantic-relatedness had an effect on the amount of time needed to make a response during the change detection task. RT data are displayed in Figure 5.

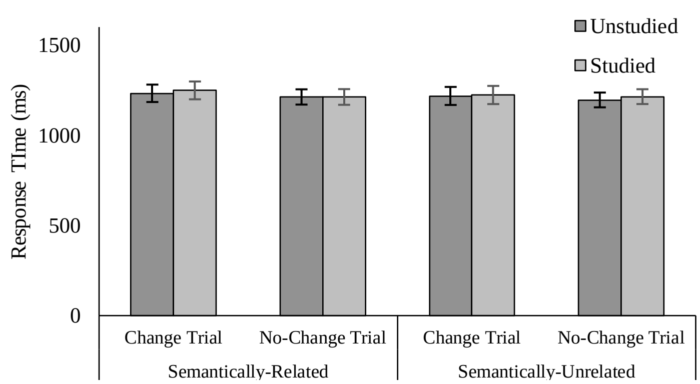

Figure 5. Figure 5 represents change detection RT data, displaying no main effects of LTM availability or semantic-relatedness and no interactions. Error bars represent standard error.

Eye Movement Analysis

Eye-tracking analyses were conducted in order to investigate whether or not there were differences in how studied and unstudied objects were processed during encoding. Eye-tracking data were not recorded for one participant in the semantically-unrelated condition, and therefore that one participant was not included in the analysis. Average total dwell times on each object type (studied, unstudied) are displayed in Figure 6. Dwell times were averaged across both studied and unstudied objects separately. The repeated-measures ANOVA revealed no main effect of semantic-relatedness, $F(1,54) = .046$, $p = .830$, $n_{p2} = .001$. However, a main effect of availability of LTM representation was observed with unstudied objects yielding significantly longer dwell times ($M = 190.86$ms) compared to the studied objects ($M = 183.85$ms), $F(1,54) = 10.15$, $p = .002$, $n_{p2} = .158$. Finally, the interaction between availability of LTM representation and semantic-relatedness was not significant, $F(1,54) = .137$, $p = .713$, $n_{p2} = .003$.

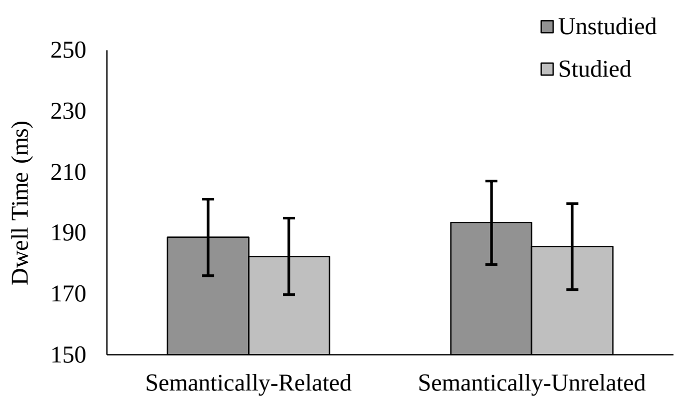

Figure 6. Figure 6 represents average dwell time on objects on the pre-change display during the change detection task. A main effect of LTM availability was found, but no main effect of semantic-relatedness and no interactions were found. Error bars represent standard error.

LTM Test Accuracy

Figure 7 displays average LTM 2AFC accuracy data. Data from two participants were excluded due to a time constraint and not being able to complete the memory test within the allotted time. Two participants were excluded from the related condition. The repeated-measures ANOVA revealed a main effect of lure type with novel lures leading to significantly higher accuracy *(M* = .94) compared to exemplar lures *(M* = .84), $F(1,53) = 93.87$, $p < .001$, $n_{p2} = .639$. However, no main effect of semantic relatedness was observed, $F(1,55) = .006$, $p = .936$, $n_{p2} = 0$. However, the results from the main effect analyses were qualified by an interaction between lure type and semantic relatedness, $F(1,53) = 10.26$, $p = .002$, $n_{p2} = .162$. In order to explore this interaction, difference scores were computed for the difference between exemplar and novel accuracy for the related and unrelated conditions separately. A significant paired-samples t-test revealed that this interaction was driven by a larger difference between exemplar and novel accuracy for the related condition ($M = .135$) compared to the unrelated condition ($M = .067$), $t(26) = 2.96$, $p = .007$. Results from the LTM test reveal that participants had detailed and accessible LTM representations. These results rule out the possibility of no LTM facilitation on WM performance due to a lack of LTM representations.

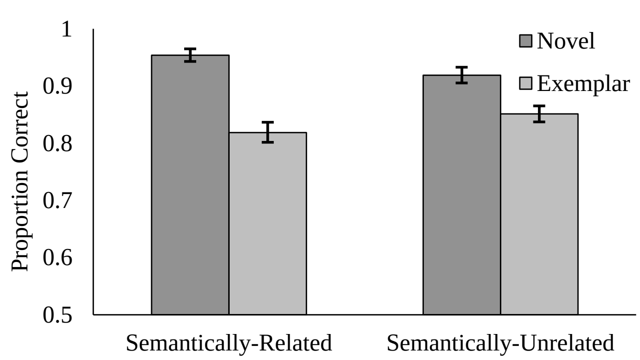

Figure 7. Figure 7 represents accuracy on the LTM 2AFC test, displaying a main effect of lure type and an interaction between semantic-relatedness and lure type. Error bars represent standard error.

Experiment 1. Discussion

The overall goal of Experiment 1 was to determine whether or not previously encoded objects in LTM facilitated WM performance. The change detection results from Experiment 1 did not reveal any evidence of facilitation from LTM on WM performance, as displayed by similar change detection accuracy for previously studied and unstudied objects. The RT analysis supported the change detection results in that there were no significant differences between studied and unstudied objects. However, shorter dwell times were observed on studied compared to unstudied objects on the pre-change array. These shorter encoding times would suggest that participants were relying more on LTM representations when viewing previously studied objects. The results from Experiment 1 of the current study parallel the results from Experiment 1 of Schurgin et al. (2018). In their study, they found differences in active maintenance in WM (i.e., CDA amplitude), but no facilitatory effect on WM performance. Here, we find differences in dwell time for studied compared to unstudied objects, but no differences in change detection performance. The difference in dwell time between studied and unstudied objects suggests that previously encoded LTM representations may have facilitated encoding and maintenance processes, but this facilitation did not lead to an improvement in performance on the WM task.

It is also possible that although there were shorter dwell times on studied objects, these LTM representations were not accessed. Retrieval from LTM may not have been needed and therefore LTM representations were not accessed or used. If retrieval from LTM is more difficult than using other strategies, such as using perceptually-encoded WM representations, then LTM may not be used (Kunar, Flusberg, & Wolfe, 2008). Overall, participants' change detection accuracy was 88%, which means that the task may have been easy enough using perceptually-encoded WM representations and retrieval of LTM representations was not needed to

successfully complete the task. If this is the case, then I cannot conclude that LTM representations were not accessible during the change detection tasks. There are two possible explanations for the possible use of LTM representations. First, it is possible that LTM representations were not used during the task and that only WM representations were used. Second, it is also possible that LTM representations were accessed and used during the task, but that this utilization of LTM representations did not improve WM performance.

In addition, I was also interested in whether or not PI in LTM (manipulated by semantic-relatedness) impacted the accessibility of useful LTM representations. Experiment 1 did not reveal any evidence of an effect of PI on the ability of LTM representations to facilitate WM performance, as displayed by similar change detection accuracy between the semantically-related and unrelated conditions. However, it is important to note that it is possible that our manipulation of PI in LTM was not strong enough to elicit such an effect. The lack of significant differences between the semantically-related and semantically-unrelated conditions in the 2AFC LTM test may suggest that PI was not evident in LTM. Alternatively, the larger difference between novel and exemplar lures for the semantically-related condition compared to the unrelated condition may serve as evidence for PI in LTM. Regardless of the strength of our manipulation of PI in LTM, there was no evidence for an impact of PI on LTM facilitation.

Experiment 2

In Experiment 1, I did not find evidence for facilitation from LTM on WM performance. The lack of a facilitatory effect may have been due to the ease of the WM task. That is, it is possible that the WM representations were sufficient to complete the task, so the LTM representations were not used. Contributing to this point about the ease of the WM task in Experiment 1 is that interference within the WM task was minimized by using only novel category changes. In Experiment 2 I aimed to make the WM representations less sufficient for the task by increasing interference within the WM task.

The goal of Experiment 2 was to determine whether or not interference within the WM task impacts the accessibility of LTM representations and their ability to aid WM performance. There has been significant behavioral and neural data that has demonstrated that the ability to process and maintain multiple stimuli presented at once, as well as observed WM performance, is decreased when objects in the WM task belong to the same semantic category (Brady, Stormer, & Alvarez, 2016; Olsson & Poom, 2005; Szmalec, Verbruggen, & Kemps, 2011; Cohen et al., 2014; Yang, Mo, Wang, & Yu, 2018). When attention is directed towards a new object belonging to the same category, the representation in WM of the previously viewed object is updated with details from the new object. The more this WM representation is updated, the less reliable this representation may become (Oberauer, 2009; Szmalec, Verbruggen, & Kemps, 2011). Exemplar lures have been used in change detection tasks in order to increase the difficulty and interference within the WM task (Schurgin et al., 2018; Wood & Simons, 2017). In Experiment 2 of Schurgin et al.'s (2018) study, they increased interference within the task by requiring participants to remember two objects from the same category during encoding. With increased interference during the encoding stage of the task, there was less reliance on LTM, as

displayed by a similar CDA amplitudes between studied and unstudied objects. Contrary to Schurgin et al.'s (2018) study, Experiment 2 of the current study introduced interference and difficulty during the comparison stage of the task. I increased interference by including exemplar changes in lieu of novel category changes during change detection. By introducing exemplar changes during the change detection task, more detailed representations are required to compare pre- and post-change objects. Thus, it is possible that increasing interference during the comparison stage of the task in the current study will lead to an increase in reliance on LTM representations.

The procedure of Experiment 2 was identical to the procedure in Experiment 1 with the exception of type of change during the change detection task. In Experiment 2, exemplar changes were used in attempt to increase the amount of interference and difficulty within the WM task. It is possible that the novel category changes in the WM task of Experiment 1 made the task easy to complete with WM representations so that LTM representations were not needed to complete the task. Increasing the difficulty of the change detection task in Experiment 2 may encourage more LTM retrieval than in Experiment 1.

Hypotheses and Predictions

The goal of Experiment 2 was to determine if increasing difficulty and interference in the WM task impacts the use of LTM representations to facilitate WM performance. If increasing interference and difficulty within the WM task decreases the ability to use WM representations, then this may increase the tendency to rely on previously stored LTM representations. Therefore, in Experiment 2, I predicted LTM facilitation; there would be a main effect of availability of LTM representation (higher change detection accuracy for studied compared to unstudied objects). First, it is possible that LTM facilitation will be observed in both conditions regardless

of interference within LTM. This facilitation will be observed through a similar main effect of availability of LTM representation in both the semantically-related and unrelated conditions, and no interaction between availability of LTM representation and semantic-relatedness for change detection accuracy. Next, it is also possible that an interaction between availability of LTM representation and semantic-relatedness will be observed. It is possible that the combination of interference within LTM and increased difficulty of the WM task will lead to a lack of accessible LTM representations and therefore a lack of facilitation in the semantically-related condition. That is, I would expect the interaction between LTM and semantic-relatedness to be driven by LTM facilitation on WM performance in the semantically-unrelated condition, but not the related condition.

I also predicted facilitation from LTM on WM encoding efficiency, as supported by eye-tracking data. Like in Experiment 1, I predicted that participants will spend less time dwelling on objects that had been previously studied. If LTM representations are easily available for studied objects, this should lead to shorter dwell times compared to objects that were unstudied. Recall that in Experiment 1 of Schurgin et al.'s (2018) study, participants displayed less active maintenance in WM for objects that had been previously studied, suggesting that LTM facilitated the maintenance process. Therefore, it is possible that LTM could facilitate other processes involved in change detection (encoding or comparison). I predicted that we would find evidence for LTM facilitation on WM encoding.

Experiment 2. Methods

Participants

In Experiment 2, participants were 69 undergrads Louisiana State University undergraduates (57 female, average age = 20.14), all enrolled in psychology classes. Using G*Power and assuming a small to moderate effect size (η_2 = .4), 25 participants were required per between-subjects group to achieve an estimated power of .8 to detect any interactions.

Stimuli and Apparatus

All stimuli and apparatuses used in Experiment 2 were identical to Experiment 1.

Design

Experiment 2 employed a 2 x 2 mixed factorial design with availability of LTM representations (studied, unstudied) as a within-subjects factor and semantic relatedness (unrelated, related) as a between-subjects factor.

Procedure

Thirty-six participants were placed in the semantically-related condition and 33 participants were placed in the semantically-unrelated condition. The procedure in Experiment 2 was identical to the procedure in Experiment 1 (See Figure 3) with the exception of type of change during the change detection task. When a change occurred in Experiment 1, a pre-change object changed to an object from a novel category in the post-change array. In Experiment 2, however, a pre-change object changed to an unstudied object from the same semantic category on the post-change array (e.g., a mailbox changing into a different, unstudied mailbox). See Figure 2b for a breakdown of the change detection procedure.

Experiment 2. Results

Two separate 2 x 2 mixed measures ANOVAs were conducted on total time spent dwelling on objects in the pre-change array during change detection and on change detection accuracy. Semantic-relatedness (unrelated, related) was the only between-subjects factor. Availability of LTM representations during change detection (unstudied, studied) was treated as a within-subjects factor.

Change Detection Accuracy

The repeated-measures ANOVA revealed no main effects for either availability of LTM representation, $F(1,67) = 2.83$, $p = .098$, $n_{p2} = .04$, or semantic-relatedness, $F(1,67) = .370$, $p = .059$, $n_{p2} = .052$. Furthermore, there was no interaction between availability of LTM representation and semantic-relatedness $F(1,67) = .477$, $p = .492$, $n_{p2} = .007$. Figure 8 displays change detection accuracy data.

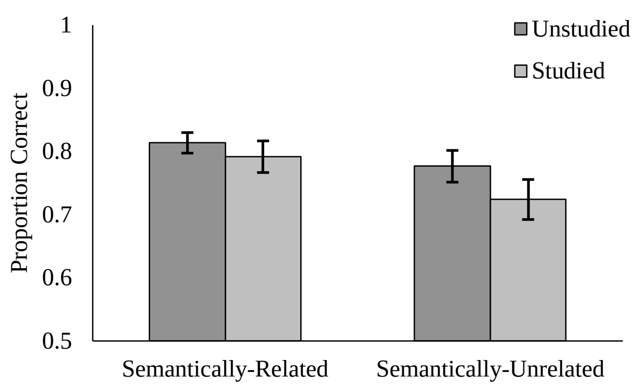

Figure 8. Figure (a) represents average change detection accuracy, displaying no main effects of LTM availability or semantic-relatedness and no interactions. Error bars represent standard error.

Change Detection Response Time

RT data are displayed in Figure 9. Like in Experiment 1, separate 2 x 2 repeated-measures ANOVAs were conducted on no-change and change trials with availability of LTM representation (studied, unstudied) as a within-subjects factor and semantic-relatedness (unrelated, related) as a between-subjects factor. For no-change trials, the repeated measures ANOVA revealed no main effects for either availability of LTM representation, $F(1,67) = .158$, $p = .692$, $n_{p2} = .002$, nor semantic-relatedness, $F(1,67) = .496$, $p = .522$, $n_{p2} = .006$. Furthermore, no interaction between availability of LTM representation and semantic-relatedness was observed, $F(1,67) = 1.24$, $p = .270$, $n_{p2} = .018$. Like in Experiment 1, the same pattern of results was observed for change trials in that no main effects for either availability of LTM representation, $F(1,67) = 2.05$, $p = .157$, $n_{p2} = .03$, nor semantic-relatedness were observed, $F(1,67) = .496$, $p = .484$, $n_{p2} = .007$. Once again, no interaction between availability of LTM representation and semantic-relatedness was observed, $F(1,67) = .6$, $p = .441$, $n_{p2} = .009$.

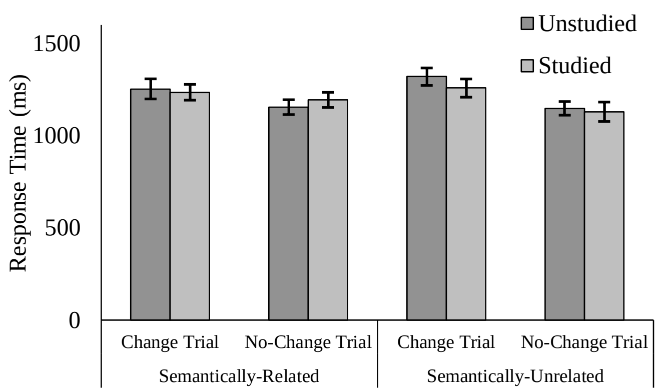

Figure 9. Figure 9 represents change detection RT data, displaying no main effects of LTM availability or semantic-relatedness and no interactions. Error bars represent standard error.

Eye Movement Analysis

Eye movement data for three participants (2 unrelated, 1 related) were not recorded and therefore not included in the current analysis. Figure 10 displays eye movement data. A 2 x 2 repeated-measures ANOVA was conducted on total time spent dwelling on studied and unstudied objects with availability of LTM representation (studied, unstudied) as a within-subjects factor and semantic-relatedness (unrelated, related) as a between-subjects factor. Like in Experiment 1, I summed the total time spent dwelling on studied and unstudied objects separately for each trial. The repeated-measures ANOVA revealed no main effect of semantic-relatedness, $F(1,64) = .001$, $p = .973$, $n_{p2} = 0$. However, there was a main effect of availability of LTM representation with unstudied objects yielding significantly longer dwell times (M = 200.55ms) than studied objects (M = 192.41ms), $F(1,64) = 12.37$, $p = .001$, $n_{p2} = .162$. Finally, no interaction between availability of LTM representation and semantic-relatedness was found, $F(1,64) = 2.12$, $p = .15$, $n_{p2} = .032$.

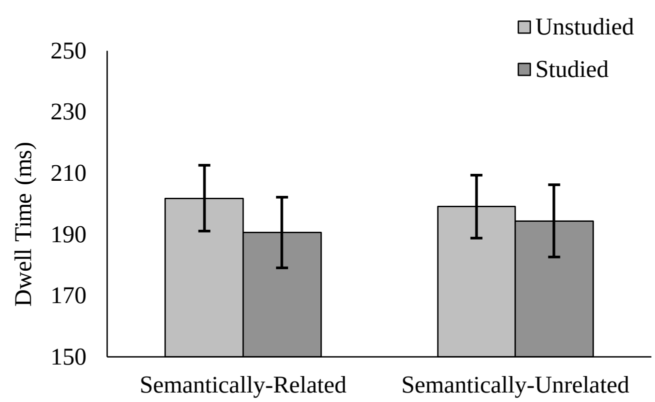

Figure 10. Figure 10 represents average dwell time on objects on the pre-change display during the change detection task. A main effect of LTM availability was found, but no main effect of semantic-relatedness and no interactions were found. Error bars represent standard error.

LTM Test Accuracy

Two participants' data in the semantically-unrelated condition was excluded due to the inability to complete the experiment. Figure 11 displays average accuracy from the 2AFC LTM test. A 2 x 2 repeated-measures ANOVA was conducted on LTM accuracy with type of lure (exemplar, novel category) as a within-subjects factor and semantic-relatedness (unrelated, related) as a between-subjects factor. The repeated-measures ANOVA revealed a main effect of lure type with novel category lures leading to significantly higher accuracy (M = .92) compared to exemplar lures (M = .83), $F(1,67) = 57.77$, $p < .001$, n_{p2} = .463. However, no main effect of semantic-relatedness was observed, $F(1,67) = .806$, $p = .373$, n_{p2} = .012. An interaction between lure type and semantic-relatedness was observed, $F(1,67) = 20.33$, $p < .001$, n_{p2} = .233. In order to explore this interaction, difference scores were computed for the difference between exemplar and novel accuracy for the related and unrelated conditions separately. Similar to Experiment 1, a paired-samples t-test revealed that this interaction was driven by a larger difference between exemplar and novel accuracy for the related condition (M = .129) compared to the unrelated condition (M = .033), $t(32) = 2.96$, p = .001.

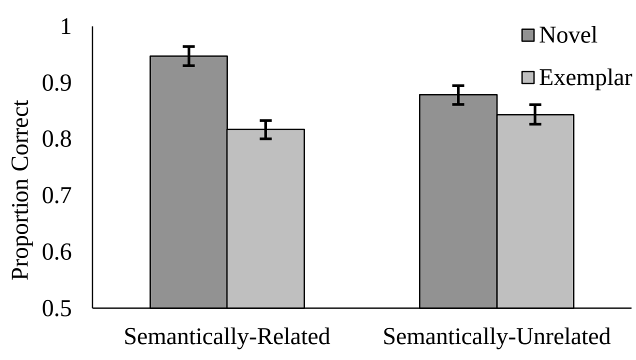

Figure 11. Figure 11 represents accuracy on the LTM 2AFC test, displaying a main effect of lure type and an interaction between semantic-relatedness and lure type. Error bars represent standard error.

Experiment 2. Discussion

Results from Experiment 2 replicated results from Experiment 1. Thus, I can conclude that the current study did not find evidence for facilitation from LTM on WM performance. However, like in Experiment 1, I cannot conclude that LTM representations were not accessible. I can only conclude that LTM representations were not used to improve performance during the change detection task. Increasing the interference and difficulty within the WM task did not result in an increased reliance on LTM representations. Like in Experiment 1, it is possible that LTM representations were accessed and used, but that this did not improve WM performance. It is also possible that WM representations remained sufficient to complete the task in Experiment 2. Furthermore, also like in Experiment 1, I also did not find any evidence for an effect of PI in LTM on WM facilitation, displayed by similar change detection accuracy between the semantically-related and unrelated conditions. Again, it is possible that the lack of a significant effect is due to the strength of our manipulation of PI in LTM. Like in Experiment 1, there was no main effect of semantic-relatedness on 2AFC LTM performance but there was a larger difference between novel and exemplar lures for the semantically-related condition compared to the unrelated condition. Therefore, it remains inconclusive whether or not our manipulation of PI in LTM was strong enough to elicit an impact on LTM facilitation.

General Discussion

Although most researchers agree that LTM and WM interact with each other to some degree (Atkinson & Shiffrin, 1968; Brady et al., 2016; Maxcey et al., 2015; Oberauer et al., 2017), little research has been conducted to directly measure the effect of LTM representations on WM task performance. Across two experiments, there was no evidence of facilitation from LTM on WM performance, as displayed by similar change detection accuracy between studied and unstudied objects. This lack of a facilitatory effect was true when the change detection task was less difficult and required encoding less detailed representations (novel category changes in Experiment 1) and when the task was more difficult and required encoding more detailed representations (exemplar changes in Experiment 2). Furthermore, there was no evidence that introducing PI in LTM had an impact on the effects of LTM representations on WM performance. Although there was no evidence of LTM representations facilitating performance on the WM task, there was evidence in both studies of more efficient processing of when encoding objects for the WM task that had previously been encoded into LTM (shorter dwell times on studied objects). Therefore, I cannot conclude that LTM representations were not accessible, but instead they were not used to improve performance on the WM task.

The current study suggests that LTM for real-world objects is not used to improve performance on a WM task. A flexible gate between LTM and WM has been proposed so that useful and relevant information in LTM may be used during a WM task (Oberauer, 2009; Oberauer et al., 2017). When unique object-color combinations are encoded into LTM, these LTM representations can facilitate performance on a WM task if the WM objects are identical to the information in LTM (Oberauer et al., 2017). However, when information in the WM task is not identical with information in LTM, the contribution from LTM is inhibited (Oberauer et al.,

2017). Whereas facilitation from LTM on WM accuracy has been shown with unique color-shape combinations (Oberauer et al., 2017), studies that have examined LTM facilitation on WM performance using real-world objects have not found evidence for LTM facilitation, even though information in LTM and WM were identical (Schurgin et al., 2018; Wood & Simons, 2017). However, in Experiment 1 of Schurgin and colleagues' (2018) study, less active maintenance in WM was observed for objects that had been previously studied. Although no improvement in performance was observed, this suggests that previously stored LTM representations facilitated the encoding and maintenance processes. In both experiments of the current study, we find evidence for more efficient processing during encoding for previously studied objects, as displayed by shorter dwell times on studied compared to unstudied objects, but no improvement in performance.

LTM facilitation may not have been necessary in the current experiment because overall change detection accuracy was fairly high (Experiment 1 – 88%; Experiment 2 – 78%), suggesting that WM representations may have been sufficient to complete the task. In fact, recall that pilot data revealed that with an initial proposed encoding time of 3s, change detection accuracy was near ceiling level performance. Under these circumstances, it seems that WM has the ability to be as accurate as LTM, and is only impaired when encoding time is strictly limited. Additionally, recall that retrieval from LTM is sometimes determined to be more effortful that using representations in WM (Kunar, Flusberg, & Wolfe, 2008). Therefore, I cannot conclude from these results that LTM representations could *not* be used, just that they were not used to improve WM performance. We know that the LTM representations were retrievable because results from the LTM 2AFC test revealed that participants had detailed available LTM representations stored (Experiment 1 – 89%; Experiment 2 – 87%). Therefore, I can conclude

that LTM representations are not necessarily used to improve WM performance, but may have been used to improve efficiency.

Another possible explanation for the lack of evidence for facilitation from LTM on WM performance is that LTM retrieval during a WM task might require some WM capacity. However, more WM capacity may be used when people are required to remember specific details about presented objects, resulting in less WM capacity available for LTM retrieval. In Experiment 2 of their study, Schurgin et al. (2018) investigated whether or not increasing the interference within the WM task affected the amount of active maintenance in WM (i.e., CDA amplitude) as well as WM performance. Behavioral results from this study did not show an increase in performance for objects that had been previously studied. Similar behavioral results have also been found by Wood and Simons (2017). Additionally, there was no difference between CDA amplitude for studied compared to unstudied objects, suggesting a similar amount of active maintenance in WM. The authors concluded that these results imply that WM is engaged (instead of LTM) when interference within the WM task is high. However, when interference is low, LTM is used (Schurgin et al., 2018). If WM capacity is occupied when interference in the WM task is high, facilitation from LTM may be limited if retrieval from LTM is effortful and requires WM capacity. Therefore, interference or limited available capacity in the WM task may ultimately inhibit the accessibility of useful LTM representations.

The secondary goal of the current study was to determine whether or not interference within LTM and the WM task (separately) impacted the accessibility of LTM representations and, ultimately, the facilitatory contribution from LTM on WM performance. Requiring people to remember multiple semantically-related objects can create interference in both LTM and WM that leads to an overall decrease in performance (Baddeley, 1966; Mueller & Watkins, 1977;

Konkle et al., 2010a; 2010b; Brady & Alvarez, 2011; Cohen et al., 2014; Yang et al., 2018). Our results from both Experiment 1 and Experiment 2 did not reveal any effect of semantic-relatedness on objects encoded into LTM. Although participants in the semantically-related condition studied 10 exemplars per category, it is possible that this manipulation was not strong enough to create interference in LTM. The lack of significant differences in 2AFC LTM performance between the semantically-related and unrelated conditions suggests that PI was not present in LTM. In fact, Konkle et al. (2010a; 2010b) only found a slight impairment (~2%) in LTM performance as the number of exemplars per studied category increased (up to 64 exemplars). In order to confidently investigate the effect of PI in LTM via semantic-relatedness, a stronger manipulation, such as having all studied objects from the same category, may be needed. For example, if all 360 encoded objects were different images of a teddy bear, this may create stronger PI in LTM, therefore possibly leading to an effect of semantic-relatedness on LTM facilitation. The results from Experiment 1 and 2 suggest that neither semantically-related nor unrelated objects encoded in LTM facilitated WM performance. To my knowledge, no research has directly examined the effect of interference within LTM and WM task (separately) on the facilitatory contribution on LTM on WM performance.

The current study aimed to expand on theories about the interaction between LTM and WM. Those that support the idea of unified memory system consider WM representations to be temporarily activated subset of LTM representations (Cowan, 1995; Farrell, 2012; Oberauer, 2009). In this view, these WM representations are vulnerable to decay and interference and efficient WM relies on utilizing LTM. On the other hand, theories that support the idea of two separate systems suggest that WM is sheltered from PI in order to be efficient. Recently, Norris (2017) has suggested that LTM functions are involved in WM, but WM does not necessarily rely

on LTM. WM requires an additional mechanism outside of LTM that has the ability to store novel and sequential information. The results from the current study suggest that WM and LTM remain distinct from one another because WM performance was sheltered from PI in LTM (e.g., semantically-related condition). Additionally, if WM is to be considered activated LTM, I may have expected to find evidence for facilitation from LTM on WM performance. I found no such facilitation on WM performance in the current study. However, facilitation from LTM on efficient WM encoding was observed through shorter dwell times on studied objects. Therefore, it remains inconclusive whether or not WM can be considered activated LTM.

Although research examining the direct impact of stored LTM representations on WM performance is scarce, Oberauer et al. (2017) proposed that a flexible gate between WM and LTM allows relevant information to be used. Participants determine if LTM representations are useful in two different ways (Oberauer et al., 2017). The first way is that people first evaluate whether or not the WM representations is relevant and useful. If information in WM is not sufficient to complete the task, participants then attempt to retrieve relevant information in LTM. This suggests that the gate between WM and LTM remains closed until information in LTM is needed. The second way is that people automatically retrieve both WM and LTM representations during a given trial and use the strongest representation to make their response. In this sense, the gate between WM and LTM remains open. If the gate between LTM and WM remained open at all times, then I may expect previously stored LTM representations that are identical to WM representations to always facilitate performance. However, in the current study, we did not find evidence for facilitation on WM performance, but rather facilitation from LTM on encoding efficiency. The results from the current study cannot confirm whether or not the gate between LTM and WM remains open or closed, only that LTM representations did not aid WM

performance. The lack of an improvement in WM performance, but an improvement in encoding efficiency, could be due to a closed gate or an open gate.

The methodological differences between the current study and Oberauer et al. (2017) may have contributed to the different pattern of results. First, participants in Oberauer et al. (2017) completed a color-estimation task and received performance feedback to measure their memory for objects during the LTM learning phase. In the current study, participants were only required to view objects while completing the repetition detection task. Therefore, participants in Oberauer et al.'s (2017) study may have received a deeper initial encoding and processing of objects into LTM than participants in the current study. Second, a color-estimation task was also used as the WM task in Oberauer et al.'s (2017) study, whereas a same/different change detection task was used in the current study. A color-estimation task may provide a more sensitive measure of participants' memory for objects compared to the yes/no response used in the same/different change detection task in the current study. However, with the addition of eye-tracking with our change detection task, the current study included a sensitive measure of differences in encoding. While we did not find differences in WM performance like Oberauer et al. (2017), we did find differences in encoding through the use of eye-tracking measures. Third, the differences in type of WM task between the current study and Oberauer et al.'s (2017) study may have allowed for explorations of different WM processes. With the change detection task in the current study, I was able to measure differences in WM processing on encoding (dwell times on objects in the pre-change array) as well as differences in WM processing during the comparison and decision-making processes (RTs on post-change array). Future studies investigating the influence of previously stored LTM representations on WM performance

should attempt to replicate Oberauer et al. (2017) more directly to better understand how these methodological differences influenced the pattern of results.

One possible explanation as to why participants in the current study may have not used LTM representations to facilitate WM performance is that, assuming a close gate, retrieval from LTM was considered more effortful than using available information in WM. Using repeating visual search displays, Kunar, Flusberg, and Wolfe (2009) found that participants did not engage LTM to guide search because visual search was considered more efficient than retrieval from LTM. Visual search is typically given priority over LTM retrieval during visual search tasks with repeating search arrays (Oliva, Wolfe, & Arsenio, 2004; Wolfe, 2000). That is, it is easier to just look for something then to recall from LTM where it was last seen. Therefore, LTM is not used if perception and WM can do the task easily. Therefore, it can be argued that WM processes were given priority over LTM processes in the current study because retrieval from LTM was considered less efficient.

Although the current study used visual stimuli, it is important to make it clear that the results concluded from this study may generalize to other types of sensory information (i.e., written verbal information, phonological information, acoustic information, etc.). However, it is also possible that the results from the current study may differ from previous studies because visual representations of real-world stimuli in LTM may rely more on perceptual features compared to other types of sensory information. Written or verbal information in LTM is more likely to rely on conceptual features of stimuli. Perceptual features are considered to be related to the identity information of stimuli whereas conceptual features are considered to be related to the semantic knowledge and meaning of stimuli. For example, bicycles can have different perceptual features (i.e., longer handlebars, different color paint, etc.), but the conceptual meaning of a

bicycle always remains the same (i.e., a bicycle transports an individual from point A to point B). According to Konkle et al. (2010b), encoding perceptual features about real-world visual stimuli (i.e., shape, color, orientation, etc.) may aid recognition performance. On the other hand, memory performance for written or spoken verbal stimuli may not be improved by encoding perceptual features (i.e., size of font text, speaker's pitch/tone, etc.).

The results from the current study did not show evidence of facilitation from previously stored LTM representations on WM performance, but did show facilitation on the encoding processes . It is important to point out that using real-world objects in the current study may allow people to draw on pre-existing LTM representations. Therefore, although I did not find evidence that participants used LTM representations that were encoded during the first phase of the study to improve WM performance, I cannot conclude that people did not access or use pre-existing knowledge of the real-world objects to aid WM performance. Encoded and retrievable LTM representations did not improve WM task performance, as displayed by similar change detection performance for studied versus unstudied objects, but did improve encoding efficiency, as displayed by shorter dwell times on studied compared to unstudied objects.

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Vita

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