

ORIGINAL ARTICLE

Object Details Persist in Visual Working Memory Regardless of Category Sufficiency for Search

 Ryan S. Williams¹  | Joseph M. Saito²  | Keisuke Fukuda³  | Susanne Ferber^{1,4} 

¹Department of Psychology, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA | ²Department of Psychology, University of California San Diego, San Diego, California, USA | ³Department of Psychology, University of Toronto Mississauga, Mississauga, Ontario, Canada | ⁴Department of Psychology, University of Toronto, Toronto, Ontario, Canada

Correspondence: Joseph M. Saito (josaito@ucsd.edu)

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ABSTRACT

When searching for objects in complex environments, performance often improves with more specific target representations. Yet, sometimes a more general representation may be preferable. For example, when repeatedly searching for unique exemplars from the same object category, a shared category-based representation could help alleviate the cognitive burden of constantly encoding and maintaining new exemplar representations. We therefore examined whether the format of target representations used for search is sensitive to the sustained preservation of object-category membership. Across two experiments, observers searched consecutively for images of real-world objects from the same basic-level category. We recorded contralateral delay activity (CDA), an electrophysiological marker of visual working memory (VWM) maintenance, to assess whether the encoding of object-specific details diminished across category repetitions in favor of more generalized representations. In Experiment 1, we manipulated whether object-category membership alone sufficiently differentiated each unique target from nontargets in the search array. In Experiment 2, we preserved category sufficiency but allowed the targets to additionally repeat at the level of the exemplar to examine how repeatedly searching for the same object differs from repeatedly searching for the same *kind* of object. We found that while fewer object-specific details were maintained in VWM when category membership was sufficient, the amount of detail only diminished across repetitions of the exact same object. Moreover, observers exhibited sensitivity to the sustained preservation of the target category in the form of perceptual and semantic expectancy violations following category switches, as indexed by N2pc and N400 ERP components. Together, we show that, even though the sustained preservation of a target object category does not continuously reduce the encoding of object-specific details, categorical information is nonetheless represented in parallel. We speculate that object-specific representations principally serve attentional guidance, while categorical representations benefit target-match decisions.

1 | Introduction

We are constantly faced with complex visual scenes composed of different visual inputs, and yet, we navigate and interact with our environments in a seemingly effortless fashion. In large part, this is due to the highly regular nature of the

objects that we encounter, which can be rapidly categorized based on their co-occurring properties. Such categorizations are typically made at a basic level (e.g., bird), but can also be defined more specifically at a subordinate level (e.g., goose) at the cost of between-category differentiation, or more broadly at a superordinate level (e.g., animal) at the cost of

Ryan S. Williams and Joseph M. Saito contributed equally to this article.

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within-category homogeneity (Rosch 1988; Rosch et al. 1976; Rosch and Mervis 1975). In real-world settings, knowledge about object categories is particularly useful in the context of visual search. In this regard, we often leverage known spatial associations to determine where objects are likely to be found (e.g., Castelano and Heaven 2011; Henderson et al. 2009; Vö et al. 2019), but can also use object-category knowledge to efficiently locate category-matching objects in settings where no such associations are present (e.g., Addelman et al. 2024; Alexander and Zelinsky 2011; Bravo and Farid 2012; Hout et al. 2017; Maxfield and Zelinsky 2012; Nako et al. 2014; Robbins and Hout 2015; Schmidt and Zelinsky 2009; Wu et al. 2013; Yang and Zelinsky 2009; Yu et al. 2016; see also, Lim et al. 2021; Wyble et al. 2013). This involves some degree of semantic processing, as conceptually related items are prioritized during search for category-defined targets in a manner not wholly explained by visual properties alone (e.g., Baier and Ansorge 2019; Belke et al. 2008; Jonides and Gleitman 1972; Moores et al. 2003; Yeh and Peelen 2022). This is not to say, however, that category-based search templates are void of featural information. Indeed, the very nature of object categorization allows one to derive some number of expected features about typical category members, such as their size, form, color, and texture, based on a single representative prototype (Rosch and Mervis 1975) or from one's experience with multiple category exemplars (Medin et al. 1978).

While category knowledge can be used to locate targets based on an expected set of visual properties, the efficiency of search still largely depends on the taxonomic level of the target cue, with attentional guidance being strongest for objects labeled at the subordinate level (Maxfield and Zelinsky 2012; Yu et al. 2016). This is because subordinate level cues confer a greater availability and certainty of target features relative to basic and superordinate level cues which, in turn, permits more specific attentional control settings related to the prioritization and filtering of object features. This is evidenced, for example, by observations of improved attentional guidance with the addition of feature descriptions to category labels (Maxfield and Zelinsky 2012; Schmidt and Zelinsky 2009), and superior guidance for object categories with minimal feature variation relative to those with greater heterogeneity (e.g., school buses versus sedans; Hout et al. 2017; see also Ajith et al. 2026). Consequently, when individuals have perfect knowledge of the perceptual details that define an upcoming target, such as when targets are cued pictorially, it would seem unlikely for individuals to form or rely on a category-based representation to find the target, since the item-specific representation should facilitate localization of the target better than a more abstract, categorical representation (Cunningham and Wolfe 2014; Maxfield and Zelinsky 2012; Schmidt and Zelinsky 2009; Vickery et al. 2005).

Based on the above logic, it should reasonably follow that individuals prioritize target-specific details in anticipation of search when an object-based representation is available, regardless of whether a target object can be individuated based on its category membership. Yet, this prediction is directly contradicted by the findings of Schmidt and Zelinsky (2017), who examined a neural marker of object-specific maintenance in a visual search task that could be performed using either an object-specific representation or a more general categorical representation. In their

study, participants were tasked with finding exemplars from a common object category (i.e., teddy bears), which were pre-viewed in advance of each search using pictorial cues. Critically, unlike classic search tasks that manipulate the perceptual similarity between targets and distractors through parametric manipulations to individual features (e.g., color, D'Zmura 1991; Bauer et al. 1996; Wolfe and Horowitz 2004), here the authors manipulated perceptual similarity at the semantic category level by presenting targets alongside distractors from a different object category (e.g., flowers) in easy search blocks or alongside distractors from the same category as the target (e.g., all items were teddy bears) in difficult search blocks. Perceptual features conferred by knowledge of the target category alone were therefore sufficient to discriminate the target from the dissimilar distractors in the easy search condition, but not in the difficult search condition. In the latter case, observers would need to rely on a stimulus-specific representation that included other perceptual features that were diagnostic of the target exemplar, but peripheral to its category membership.

To quantify differences in the object-specific representation of the target between conditions, Schmidt and Zelinsky (2017) recorded contralateral delay activity (CDA) using electroencephalography (EEG) as a load-dependent measure of visual working memory (VWM) maintenance. This EEG component is defined by a sustained negative difference over parieto-occipital channels contralateral to an encoded set of stimuli (Luria et al. 2016; McCollough et al. 2007; Vogel and Machizawa 2004). In visual search tasks, CDA is elicited over an anticipatory period prior to search onset where target features are actively held in VWM following the presentation of a lateralized target cue (Carlisle et al. 2011; Gunseli et al. 2014; Woodman and Arita 2011). On this basis, Schmidt and Zelinsky (2017) predicted and found that CDA amplitude would be higher in the difficult search condition relative to the easy search condition, as more object details would need to be maintained in the former. Strikingly, however, the authors failed to find a statistically reliable CDA in the easy search condition, implying that search was either being performed without the use of object-specific details or that the representation of these details was so weak that it was undetectable. In other words, perceptual details were available to observers that perfectly predicted the properties of the target, and yet, there was no positive evidence that such information was used to guide selection or to identify the target.

If these findings can be taken to reflect the absence of object-specific encoding under conditions of category-sufficient search, it raises the question of why individuals would favor a categorical representation if doing so is suboptimal for search. One possibility is that individuals act as cognitive misers (e.g., Dunn and Risko 2019; Kool et al. 2010; Westbrook et al. 2013). That is, while the maintenance of a single item in VWM may present little effortful demand on its own (Vogel et al. 2020; Xie and Zhang 2023), individuals may still seek to minimize any fatiguing effects caused by the sustained effort to constantly encode and maintain new target representations (Lorist 2008; Westbrook and Braver 2015). Indeed, such a proposition is consistent with a recent model of visual search which argues that observers do not necessarily aim to guide attention as efficiently as possible during search, but rather to meet some acceptable threshold that is deemed “good-enough”

given the task context and one's motivations (Yu et al. 2023). However, simply assuming that object-specific details are not maintained when unnecessary for search fails to explain why others have found performance enhancements for pictorially cued targets over categorically defined targets (e.g., Maxfield and Zelinsky 2012; Schmidt and Zelinsky 2009). In this regard, we hypothesized that the discrepancy primarily lies in whether target-category membership remains constant across consecutive searches or varies from search to search. That is, when one repeatedly searches for different object exemplars (e.g., robin, eagle, sparrow) from the same category (e.g., bird), there are bound to be redundancies in the target's perceptual and semantic properties that can be carried over across searches, even if the exact target never repeats. Categories containing perceptually-similar object exemplars, such as the teddy bears used by Schmidt and Zelinsky (2017), should be especially amenable to this carry over across trials given the considerable visual redundancy between exemplars that could help to preserve object-specific detail in the category representation. In contrast, when category membership changes from search to search, such redundancies are unlikely to be present across consecutive searches, which would necessitate a complete updating of the target in memory.

The notion that observers are sensitive to inter-trial dependencies between target items is supported by the attenuation of pre-search CDA when individuals are repeatedly cued to find the same target exemplar. For example, Carlisle et al. (2011) showed that pre-search CDA declines monotonically across consecutive searches for the same orientation-defined target. This effect was later extended by Gunseli et al. (2014), who found that declines in CDA with exemplar repetition occur regardless of the degree of feature-specificity that is required for search (see also Reinhart et al. 2016; Reinhart and Woodman 2014; Schneider et al. 2018). More recently, this reduction in CDA across consecutive target repetitions was shown to generalize beyond simplistic experimental stimuli to real-world objects (Drew et al. 2018; Özdemir et al. 2024; Şentürk et al. 2024). As such, if the use of categorical representations over object-specific representations during visual search depends on the preservation of target-category membership across searches, then one would expect to observe a continuous monotonic decline in CDA amplitude whenever the target category repeats, including in cases where the specific target exemplar changes.

Among those studies that have examined target-repetition effects on CDA, it has also been common to measure the N2pc—a lateralized event-related potential (ERP) over parieto-occipital sites that reliably indexes spatially selective processing of objects (Eimer 1996; Kiss et al. 2008; Luck et al. 1993; Luck and Hillyard 1994; Woodman et al. 2009; Zivony et al. 2018) – as a marker of attentional engagement. Interestingly, for studies that used real-world stimuli, the N2pc was noticeably reduced on trials where a new target exemplar was cued relative to those where the target repeated, while no such effect was observed in those previous studies using simple target stimuli. In this regard, it is important to highlight that, in addition to using experimental stimuli that were richer in perceptual detail and semantic meaning, Özdemir et al. (2024) and Şentürk et al. (2024) cued target images using spatial pre-cues, instead of relying on a secondary object property (e.g., color) that had to be localized.

As such, the observed effect of repetition on N2pc amplitudes may have been explained by the perceptual match between the stimulus at the attended location and an anticipated item rather than by spatial orienting per se. Indeed, it has long been established that attentional selection is modulated by a joint combination of spatial and featural expectations (e.g., Egnér et al. 2008; Kingstone 1992), with more recent studies providing evidence of a reduced N2pc when targets are defined by a feature that is unexpected compared to one that is expected (Berggren and Eimer 2019; Grubert and Eimer 2023; but see also Marzecová et al. 2018). From this perspective, the value of the N2pc for understanding attentional and mnemonic effects related to target repetition may extend beyond serving as a simple marker of task engagement to additionally indicate a perceptual matching process by which individuals identify whether the target stimulus has changed, and by extension, whether a new target representation is needed. If this is the case, then such an effect should be further complemented by other neural signatures that are commonly associated with the mismatch between incoming stimuli and expectations.

One such component that may be particularly relevant in search tasks defined by category membership is the N400, a midline ERP component that typically peaks over centroparietal sites during word processing and tends to be more frontally distributed when processing images (e.g., Ganis et al. 1996; Ganis and Kutas 2003). The N400 is commonly associated with a semantic congruity effect where its amplitude is larger when a word or image is semantically incongruous with the preceding context (Friedrich and Friederici 2004; Ganis et al. 1996; Kutas and Iragui 1998; McPherson and Holcomb 1999; Nigam et al. 1992), or when a semantic violation is present within a scene (Balconi and Caldiroli 2011; Draschkow et al. 2018; Ganis and Kutas 2003; Proverbio and Riva 2009; Vö and Wolfe 2013), compared to when semantic expectations are met. To our knowledge, only Drew et al. (2018) have previously measured this component in relation to target-repeating search. In their study, N400 amplitudes were larger following changes to target object identity than following target repetitions. Critically, this effect was only observed when target stimuli were defined by real-world objects and was absent for simplistic stimuli. Relatedly, Lindborg et al. (2023) recently provided evidence that the N400 tracks changes in category identity. In their study, participants were required to make simple judgments about sequentially presented words. These words were presented in runs where up to eight words in a row were sampled from the same semantic category (e.g., mammals) before switching to a new category (e.g., vehicles). Category switches were marked by spikes in N400 amplitude despite category identity being irrelevant to the ongoing task. This finding was interpreted to reflect a mismatch between the semantic category of the current word and that of an internal representation that was generated by the preceding words. When the stimulus category repeated across consecutive trials, observers were assumed to form an anticipatory representation of the category of the next stimulus. When the category switched and the stimulus was ultimately drawn from a different category than what was expected, a semantic-level violation occurred, and a stronger N400 deflection was observed. The N400 could therefore serve a role in tracking the violation of semantic expectations in much the same way that the N2pc may track the violation of perceptual expectations. Together, these signatures may

provide useful signals to the observer that a repeating search target has changed at the perceptual or semantic level, which could then prompt the encoding of a new target representation.

Overall, the primary aim of the current study was to test whether the prioritization of object-specific representations over categorical representations depends upon the long-term utility of the category beyond a single search. More precisely, we sought to test whether we could use pre-search CDA amplitude to track a gradual transition of the target representation away from object-specific features actively stored in VWM toward a more stable, abstract representation when targets could be sufficiently localized by a shared category across consecutive searches. In Experiment 1, we had individuals repeatedly search for target objects from the same basic-level category under conditions where knowledge of the category was either sufficient or insufficient to localize and identify the targets among distractors, similar to Schmidt and Zelinsky (2017). However, instead of using the same target category for the entire task, we incorporated a trial run structure similar to Carlisle et al. (2011) where the target category was fixed across several consecutive searches before changing. This allowed us to more continuously quantify the effect of category-repetition on CDA as a function of category utility. In Experiment 2, we rendered category knowledge to be sufficient for all searches and used CDA to directly compare the storage of item-specific details in VWM between conditions where observers repeatedly searched for different objects from the same basic-level category or repeatedly searched for the same exemplar from one of the object categories. In both experiments, we measured N2pc and N400 responses generated by the target cue, which we believed could provide insight into an underlying matching process where observers compute the perceptual and semantic congruity between the cued stimulus and an internal expectation, which might then inform whether a new or updated representation is needed to perform the task.

2 | Experiment 1

2.1 | Method

2.1.1 | Participants

All participants in the experiment were undergraduate students from the University of Toronto or similarly aged adults from the surrounding community (defined by an eligibility criterion of 18–35 years of age) that reported normal or corrected-to-normal visual acuity. Each participant provided informed consent in accordance with the procedures approved by the Research Ethics Board at the University of Toronto. Participants completed the experiment in exchange for monetary compensation or a combination of monetary compensation and course credit.

To determine the appropriate sample size, we conducted an a priori power analysis using the Superpower package (Lakens and Caldwell 2021) in R (R Core Team 2025). As part of this analysis, we predicted that CDA amplitude would decline across five consecutive presentations of the same target category when it was sufficient for search (i.e., category search) and that CDA would not change across category repetitions when the category was insufficient for search (i.e., exemplar search). Based on these

predictions, we simulated a 5 (repetition number, [0–4]) $\times$ 2 (search type [category search, exemplar search]) ANOVA using the declining CDA amplitudes from Experiment 1 of Gunseli et al. (2014). For exemplar search, we fixed the amplitude across repetitions to the amplitude observed by Gunseli et al. (2014) at repetition 0. From this simulation, we determined that a sample size of 13 participants would be required to reliably detect the interaction of interest at an 80% power level (estimated effect size: $\eta_p^2 = 0.25$). However, because we anticipated that the effect of category repetition might not be as strong as that observed in the case where an exact target stimulus is repeated, we increased our target sample size to 30 participants to be able to reliably detect the same interaction at a smaller effect size (i.e., $\eta_p^2 = 0.12$). In total, 37 participants were recruited. Two participants were excluded for poor behavioral performance ($> 20\%$ trials contained an incorrect response, no response, or a response that occurred within 200 ms of search onset, indicating a guess) and five were excluded for an excessive number of EEG artifacts ($> 20\%$ trials were marked for rejection, see *EEG Analysis* section). Data collected from the remaining 30 participants (4 male, 26 female, mean age = 19.6 years old) were submitted to analysis.

2.1.2 | Stimuli

Experimental stimuli consisted of 128 images of real-world objects sampled evenly across four natural categories (i.e., small birds, butterflies, flowerheads, and potted plants) and four manmade categories (i.e., hats, dresses, backpacks, and binoculars). To maximize the likelihood of observing a CDA reduction across category repetitions, the objects in each category were selected to be perceptually similar and typical of their semantic category (see Figure 1 for an example). These images were collected from an existing database (Konkle et al. 2010) and from free online image repositories and were defined by a 500×500 pixel area that contained an object superimposed on a white background. To ensure that the objects were easily recognized during the task, the aspect ratio of the objects was left intact so that their actual size varied slightly within the constraints of a maximum surface area ($3.5^\circ \times 3.5^\circ$) and was approximately the same within a given category. We also converted the images to greyscale and matched them for luminance. While the color of an object can sometimes communicate meaningful information about its category membership, we wanted to ensure that observers could not rely on a strategy where they performed the search using only the color of the target object (e.g., searching for anything blue in the search array when cued with a bluejay) as this could contaminate our interpretation of the CDA measure that was used to index object-specific encoding. Luminance correction was performed in MATLAB using the `lumMatch` function of the SHINE toolbox (Willenbockel et al. 2010) after separating the objects from their backgrounds. This function worked to rescale the luminance values of the individual pixels within each object through a normalization formula that incorporated the luminance mean and SD from all objects (for more detail, see Willenbockel et al. 2010). All of the images were presented against a white background. For each participant, eight exemplars from each object category were randomly assigned as possible target items, while the remaining eight items from each category were designated as nontarget items. All participants were seated 57 cm away from a 24-in. LCD monitor with

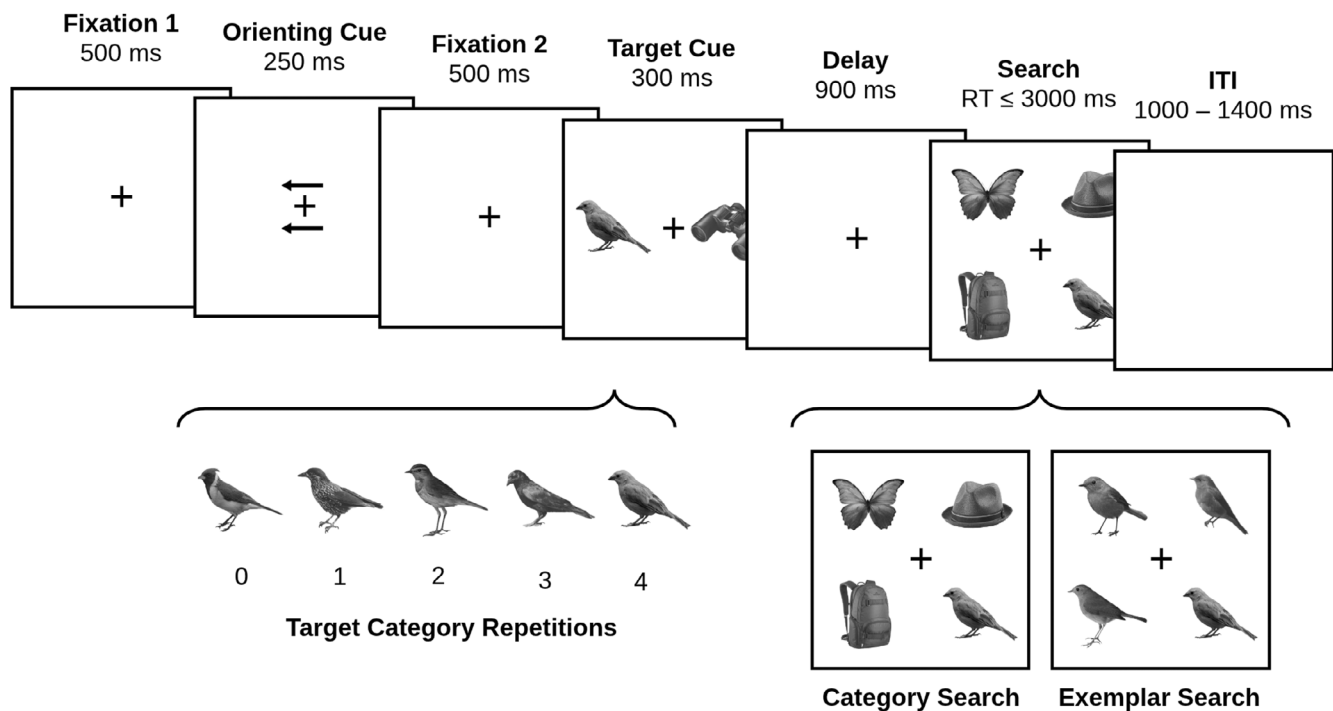


FIGURE 1 | Schematic of experimental task in Experiment 1. Shown is an illustration of a target-present trial (top), the target-category repetition sequence (bottom left), and examples of a category-search array and exemplar-search array (bottom right).

a refresh rate of 144 Hz, with their head position stabilized by a desk-mounted chinrest.

2.1.3 | Procedure

A schematic of the trial procedure is shown in Figure 1. Each trial began with the presentation of a black fixation cross ($0.4^\circ \times 0.4^\circ$) for 500 ms before two left- or right-pointing, black arrows ($1.25^\circ \times 0.4^\circ$; linewidth = 0.13°) appeared above and below the fixation cross, respectively, with a center-to-center distance of 0.5° in visual angle. These arrows served as orienting cues to the location of an upcoming target stimulus and remained onscreen for 250 ms before leaving only the fixation cross for an additional 500 ms. Two images of objects ($3.5^\circ \times 3.5^\circ$) were then presented bilaterally for 300 ms, with each object having a center-to-center distance of 3° from the central fixation cross. Participants were instructed to memorize the object at the location cued by the previous two arrows, as this item would serve as the target for the upcoming search task, and ignore the object at the un-cued location, as it was task irrelevant. Importantly, the object cued as the search target was sampled without replacement from the same stimulus category for at least five consecutive trials (e.g., search for a unique bird five trials in a row). The un-cued objects were always sampled from a different category than the target.

Following target encoding, there was a 900 ms delay period in which only the central fixation cross was present before the visual search array appeared. The search array contained four objects presented in a 2×2 grid (3.5° center-to-center distance from central fixation) that remained onscreen until the participant responded with a button press or a maximum duration of 3000 ms elapsed. During presentation of the search array, participants were instructed to indicate whether the target object was

present or absent by pressing one of two buttons on the keyboard using their right and left index fingers, respectively. Participants were instructed to make this response as quickly as possible without sacrificing accuracy. If the correct response was made, a 600 Hz auditory tone was played for 200 ms. If an incorrect or no response was made, a 200 Hz auditory tone was played instead. This auditory tone marked the onset of a blank inter-trial interval that varied randomly between 1000 ms to 1400 ms.

Participants completed 16 blocks of 54 trials (864 total). In *category-search* blocks, all candidate items were sampled from unique object categories, with the target being the only candidate from its respective category that could appear in the search array. In *exemplar-search* blocks, all candidates were unique items sampled from the same category as the target without replacement. This meant that knowledge about the target category alone was sufficient to determine the presence or absence of the target during category search, but not during exemplar search. These search conditions were completed in alternating blocks in a counterbalanced order across participants. Prior to the start of each block, participants were explicitly informed whether the upcoming block would be an “easy search block” corresponding to the category-search condition or a “difficult search block” corresponding to the exemplar-search condition. This language was used to avoid directly influencing the strategies used by participants in each condition. Each block consisted of 10 target repetition runs, eight of which included five consecutive target-category repetitions and two of which included seven consecutive target-category repetitions. The seven repetition runs were implemented solely to prevent the transition to a new target object category from being perfectly predictable, and the data collected on repetitions 5 and 6 were excluded from analyses. These runs were randomly intermixed within blocks. Practice trials consisting of 27 category-search trials and 27

exemplar-search trials were performed, in order, at the beginning of the experiment.

2.1.4 | EEG Acquisition and Pre-Processing

EEG and electrooculogram (EOG) activity were acquired at a sampling rate of 1024 Hz using an Active Two Biosemi system (Biosemi, Amsterdam, Netherlands) with 70 Ag/AgCl electrodes. Sixty-four electrodes were mounted on an elastic cap, positioned in accordance with the International 10/20 System. The remaining 6 electrodes were positioned over the left and right mastoids, 1 cm lateral to the outer left and right canthi, and 2 cm below the left and right eyes. Two additional electrodes served as reference (Common Mode Sense, CMS) and ground (Driven Right Leg passive electrode, DRL). Electrode offsets were held within $\pm 20 \mu\text{V}$ but were typically well below this threshold.

Offline processing of the recorded signals was performed using EEGLAB (Delorme and Makeig 2004) and ERPLAB (Lopez-Calderon and Luck 2014) functions in MATLAB (The MathWorks Inc 2024). As part of this processing, the activity of all electrodes was first referenced to the mastoid electrodes before down-sampling the signal to 256 Hz. A 4th order IIR Butterworth filter with a band-pass of 0.1 Hz to 40.0 Hz was then applied to the data to remove slow drift artifacts and high-frequency noise from the signal. Next, the *clean_artifacts* function in EEGLAB was used to detect and remove noisy/deviant electrodes, followed by the implementation of independent component analysis, which was used to identify and remove eyeblinks from the EEG signal. Spherical interpolation was then used to re-add any channels that had been previously removed. On average, 1.5 electrodes were interpolated ($\text{SD} = 2.7$). Interpolated electrodes were typically positioned frontally near the forehead with artifacts attributable to muscle activity and/or skin potentials. For two participants, an interpolated electrode coincided with an electrode of interest for our analysis, though the inclusion of these individuals had no meaningful impact on the results. Following interpolation, we segmented the data into epochs defined from 200 ms before the onset of the target cue (baseline period) to 1600 ms post-cue onset. Note that time-locking our analyses to the onset of the target cue also incidentally time-locked them to the onset of the orienting cue that occurred 750 ms prior. However, because the data were baseline-corrected and the orienting cue was identical between conditions, this incidental alignment with the orienting cue cannot explain any of the observed differences between conditions.

After creating these epochs, trials were automatically flagged for rejection if a step-like artifact was present in the horizontal EOG (measured as the voltage difference between electrodes positioned at the outer canthi) as determined by a 50-ms sliding window with a voltage threshold of ± 30 microvolts, or if any electrode had an absolute voltage exceeding a threshold of 100 microvolts. Lastly, an experimenter visually inspected the data and manually flagged any additional artifacts for rejection. Independent of behavioral trial exclusions, if more than 20% of trials were marked for rejection—based on the combined total number of eye movement trials, high voltage trials, and manually flagged trials—a participant was excluded from all analyses due to poor data quality. After removing these artifactual trials

from the data, ERPs were created by averaging across epochs as a function of search type and target repetition number, using only trials in which a participant responded correctly within a response window of 200 ms to 3000 ms post search-onset. This exclusion of errors, misses, and fast responses from ERP averaging was done to avoid the inclusion of trials where the target stimulus was not encoded. After excluding artifactual trials and those with poor behavioral responses, there was an average of 68.69 trials ($\text{SD} = 5.02$ across participants) per repetition number in the category search condition and 58.30 trials ($\text{SD} = 6.74$) in the exemplar search condition. This available number of trials per repetition number in each condition is well above the estimate required to detect the presence of CDA, but is somewhat low for detecting differences between conditions (Ngiam et al. 2021). However, this limitation in trial counts was partially offset by our sample size, which was considerably larger than other studies that employed similar experimental designs (e.g., Carlisle et al. 2011 [$N = 18$]; Gunseli et al. 2014 [N 's = 12, 18]; Schneider et al. 2018 [$N = 16$]).

2.1.5 | Analyses

2.1.5.1 | Behavioral Measures. For our behavioral analyses, we examined response times (RT) for correct trials and error rate (Pe), with the exclusion of exceptionally fast responses (i.e., $\text{RT} < 200$ ms) or missed responses. If more than 20% of trials were associated with an error, missed response, or fast response for a given participant, the participant was excluded from all analyses. Additionally, we used an RT trimming procedure in which responses that were > 2.5 SD above a participant's mean for a given condition (i.e., category-repeating or exemplar-repeating) were excluded from analysis. On average, 0.04% of trials were below 200 ms, 0.02% of trials had no response, and 2.72% of RTs were trimmed. In keeping with Gunseli et al. (2014), we limited behavioral analyses to those trials in which the cued target was present in the search array. Target-present trials are specifically designed to capture the attentional guidance and matching processes that are induced by the target stimulus, which was of central interest in the present study. By contrast, guidance toward a target stimulus is not possible in target-absent search, and performance instead indexes an exhaustive search process that only terminates after all of the exemplars are searched individually. For the sake of completeness, we include a behavioral analysis of the target-absent trials in the Appendix.

2.1.5.2 | ERP Measures. All ERP measures of interest were defined relative to the target-cue display and included correct responses from both target-present and -absent trials, except for those where a response was made in under 200 ms after the onset of the search display.

2.1.5.2.1 | CDA Amplitude. Our primary measure was CDA amplitude, as this component is known to track a load-dependent signal of VWM (Luria et al. 2016; McCollough et al. 2007; Vogel and Machizawa 2004) and was thus well-suited to inform whether individuals continued to encode and maintain exemplar-specific details across target category repetitions. For this measure, we planned to use a time window beginning 300 ms from the onset of the target cue until the onset

of the search array (1200 ms), in line with previous studies (e.g., Carlisle et al. 2011; Vogel et al. 2005; Vogel and Machizawa 2004). However, because visual inspection revealed that this window partially overlapped with the end of the N2pc deflection that was observed, we shifted the start of the CDA time window to 350 ms from the onset of the target cue but note that the same results are obtained when the originally planned window is used. This component was measured as the grand-averaged contralateral-ipsilateral difference at electrode pairs of P7/8, PO7/8, and PO3/4, where CDA effects tend to be largest (Roy and Faubert 2023).

2.1.5.2.2 | N2pc Amplitude. Our second ERP measure of interest was N2pc amplitude, which indexes the spatial processing of objects and is widely considered to be a marker of selective attention (Eimer 1996; Kiss et al. 2008; Woodman et al. 2009; Zivony et al. 2018). One reason why this component was measured was to track attentional engagement across target-category repetitions, given that it would be important to establish that, if a monotonic decline was present on CDA amplitude, such an effect was not simply owed to a failure to attend to the target stimuli. Additionally, because N2pc is sensitive to feature-based expectations (Berggren and Eimer 2019; Grubert and Eimer 2023), we were also interested in assessing whether N2pc amplitude would be attenuated following target-category switches, which might signal the presence of a perceptual-expectancy violation. Since this component was also defined by a contralateral-ipsilateral difference, we relied on the same electrodes of interest as those used to measure CDA. Further, we used the same time window as that used by Günseli et al. (2014), which ranged from 225 ms to 300 ms.

2.1.5.2.3 | N400 Amplitude. Our last ERP measure of interest was N400 amplitude, which is commonly modulated by the presence or absence of semantic violations (e.g., Balconi and Caldiroli 2011; Draschkow et al. 2018; Friedrich and Friederici 2004; Ganis et al. 1996; Kutas and Iragui 1998; McPherson and Holcomb 1999; Nigam et al. 1992; Vö and Wolfe 2013). We measured this component at both a frontal electrode (i.e., Fz) and a more posterior site (i.e., CPz), given evidence that the topography of this component is sensitive to task demands and stimulus materials (e.g., Ganis et al. 1996; Ganis and Kutas 2003). For this component, we used a time window that spanned from 300 ms to 500 ms, which was consistent with previous studies (e.g., Guillaume et al. 2017; Lindborg et al. 2023; Voss et al. 2010; Voss and Federmeier 2011). The purpose of measuring this component was similar to that of the N2pc, in that this component could potentially track semantic expectation violations following changes of target-category membership.

Note that our conventional use of electrode Fz and a 300–500 ms time window make it difficult to precisely distinguish the N400 from FN400 (e.g., Rugg and Curran 2007) and N300 (McPherson and Holcomb 1999) ERP signatures that have been identified previously using very similar time windows and electrode as-says. However, given that all three of these signatures exhibit comparable responses to semantic incongruities (e.g., FN400, Voss and Federmeier 2011; N300, Draschkow et al. 2018), their differences were assumed to be nominal for the purpose of the

present study, and we chose to maintain the term N400 for simplicity. It should also be recognized that, while N400 amplitude can also be modulated by perceptual factors, including stimulus familiarity (see Kutas and Federmeier 2011 for a review), we believed that this component would better serve as an index of semantic violations in the current study. N400 amplitude is insensitive to perceptual violations that occur in the absence of a semantic discrepancy (e.g., Vö and Wolfe 2013), and does not respond to perceptual priming, despite being sensitive to conceptual priming (e.g., Voss et al. 2010). As such, while it is possible that perceptual factors could affect N400 amplitude at a global level, we thought that it would be unlikely that such modulation would be present locally within category-repeating runs.

2.1.5.3 | Linear Mixed Effect Modeling Analyzes. Because the effect of target repetition number was based on temporally-ordered data, we opted to treat this variable as a continuous predictor with an unstructured covariance structure using linear mixed effects analyzes. This was done using the *lmerTest* Package in R (Kuznetsova et al. 2017). We included a fixed-effects term for target repetition number, corresponding to the number of consecutive trials in which the preceding target category matched the respective target category on the current trial, ranging from 0 to 4 (mean-centered). We also included a fixed-effects term for search type (contrast-coded), which indicated whether a category-based representation was sufficient for search, or instead whether an exemplar-based representation was necessary, and an interaction term for target repetition number by search type. The distribution of the participant means obtained for the measures of RT and Pe were both positively skewed (RT skewness = 1.09; Pe skewness = 1.21), and thus violated the assumption of normality, so we applied square-root transformations to the data to bring skewness into an acceptable range. Additionally, for the model used to analyze N400 amplitude, we included a fixed-effects term of electrode site (contrast-coded) to determine whether the amplitude of this component was larger more frontally (i.e., Fz) or more posteriorly (i.e., CPz). We did not include any interaction terms involving this effect as we did not have an a priori reason to believe that the other effects would vary by electrode location and wanted to avoid adding unnecessary complexity to the model.

Further, because the targets repeated for multiple consecutive trials, we reasoned that repetitions that occur later in the run of trials might elicit diminishing returns in the dependent measures and would not be well-characterized by a linear function. That is, we might expect that repetitions 2–4 confer a weaker additive effect on existing expectations than repetitions 0–1 where the category switches and a new repetition cycle begins. In these circumstances, we might expect a large change in the dependent measure between repetition 0 and 1 that is followed by more subtle changes afterwards that are not necessarily monotonic in nature. Therefore, in addition to constructing models with the fixed-effects terms described above, we also constructed the same models with the addition of a quadratic fixed-effects term for target repetition number, along with an interaction of this quadratic term by target repetition-type. This quadratic function is typical in growth curve models that are fit to dependent measures whose change accelerates or decelerates across time (e.g., Duncan and Duncan 2009). With respect to the random-effects, for

each model we began with a maximal structure which included a random intercept that varied by participant, and random slopes for each fixed-effect term which were allowed to vary randomly by participant (Barr et al. 2013). However, in each instance this led to a singular fit of the data. So, to avoid overfitting the data, we assessed the contribution of the random slopes included in the models and removed those that provided little to no explanatory power to the model (see Bates et al. 2015). The random intercepts were always retained.

After determining the most appropriate random-effects structure for each model, we then used Akaike Information Criterion (AIC) to compare the model that included only a monotonic effect of target repetition number to the quadratic model for each dependent measure. To allow for such comparisons, all models were initially fit using maximum likelihood estimation. In instances where an AIC difference of at least 4 was present in favor of the quadratic model, this model was chosen as the final model; otherwise, the monotonic model was chosen as the preferred model. Finally, to ensure that our results were not biased by the specific random slopes that we elected to include or exclude from our final models, we additionally compared the AICs of our selected models to the maximally random models. In doing so, we found no instance where the maximally random model offered a better fit than our selected models. Moreover, when comparing the outputs of the maximally random models to our selected models, the observed pattern of results, with respect to what was deemed significant, was identical across all dependent measures. Below, we report only the output of the selected models. For these models, restricted maximum likelihood estimation was used to fit the data and significance was assessed by estimating the degrees of freedom and corresponding p -values for each fixed-effect term using Satterthwaite approximation (Satterthwaite 1946). To provide a measure of effect size, we calculated a partial R^2 statistic (R^2_β) for each fixed effect (Edwards et al. 2008).

2.2 | Results

2.2.1 | Behavior

For the RT and Pe (i.e., error rate) means without the data transformation, see Table 1. We began by assessing the effect of category sufficiency on observers' search performance. For RT, we selected a model that included no quadratic terms and no random slopes (Figure 2A). In doing so, we found that search performance was substantially slower for exemplar-search than category-search ($b = 1.49 \sqrt{\text{ms}}$, $\text{SE} = 0.06$, $t(267) = 24.61$, $p < 0.001$, $R^2_\beta = 0.694$). We also found that search did not speed up as a function of repetition ($b = -0.01 \sqrt{\text{ms}}$, $\text{SE} = 0.04$, $t(267) = -0.299$, $p = 0.770$, $R^2_\beta < 0.00$), even when considering category-search and exemplar-search conditions separately ($b = 0.04 \sqrt{\text{ms}}$, $\text{SE} = 0.04$, $t(267) = 0.87$, $p = 0.384$, $R^2_\beta = 0.003$). The model chosen to analyze Pe was identical to that used for RT, as was the overall pattern of results. That is, errors were found to be more frequent during exemplar-search than category search (Figure 2B, $b = 0.089$, $\text{SE} = 0.006$, $t(270) = 15.63$, $p < 0.001$, $R^2_\beta = 0.475$), they remained constant across target repetitions ($b = -0.005$, $\text{SE} = 0.004$, $t(270) = -1.33$, $p = 0.184$,

TABLE 1 | Behavioral means for Experiment 1.

Rep. #	RT (ms)	Pe (%)
	<i>M</i> (SD)	<i>M</i> (SD)
Category-Search		
0	573 (106)	6.2 (5.8)
1	566 (116)	4.9 (4.8)
2	551 (103)	5.2 (5.3)
3	561 (108)	5.5 (4.6)
4	564 (116)	4.4 (4.1)
Exemplar-Search		
0	726 (170)	16.3 (8.8)
1	704 (175)	14.1 (9.2)
2	710 (154)	14.0 (8.1)
3	712 (162)	14.5 (8.2)
4	729 (179)	14.1 (6.8)

$R^2_\beta = 0.007$), and there was no interaction of search type by repetition number ($b = 0.002$, $\text{SE} = 0.004$, $t(270) = 0.57$, $p = 0.570$, $R^2_\beta = 0.001$).

2.2.2 | ERPs

ERP waveforms and scalp maps corresponding to the lateralized (i.e., CDA and N2pc) and nonlateralized (i.e., N400) ERP components are depicted in Figures 3 and 4, respectively.

2.2.2.1 | Exemplar-Specific Feature Maintenance Indexed by CDA. We analyzed CDA amplitude using a model that treated the effect of repetition number as a monotonic function with no random slopes. From this analysis, we found that CDA amplitude was significantly larger (i.e., more negative) for exemplar-search blocks than category-search blocks (Figure 5A, $b = -0.20 \mu\text{V}$, $\text{SE} = 0.04$, $t(270) = -4.92$, $p < 0.001$, $R^2_\beta = 0.082$), suggesting that sensitivity to category sufficiency was exhibited by CDA in the form of an overall decrease in its amplitude. However, there was no overall effect of repetition number (Figure 5B, $b = 0.05 \mu\text{V}$, $\text{SE} = 0.03$, $t(270) = 1.64$, $p = 0.102$, $R^2_\beta = 0.009$), nor an interaction between repetition number and search type ($b = 0.01 \mu\text{V}$, $\text{SE} = 0.03$, $t(270) = 0.43$, p , $R^2_\beta < 0.001$), meaning that observers continued to encode and maintain object-specific target details in VWM regardless of whether the target object's category was sufficient to perform the search task.

2.2.2.2 | Spatially Selective Processing of Target Cues Indexed by N2pc. Having addressed the primary research question of Experiment 1, we moved to test whether changes of target-category membership were marked by differences in N2pc and N400 amplitudes, which could signal the need to update the perceptual or semantic content of an internal target representation. Starting with the N2pc, the preferred

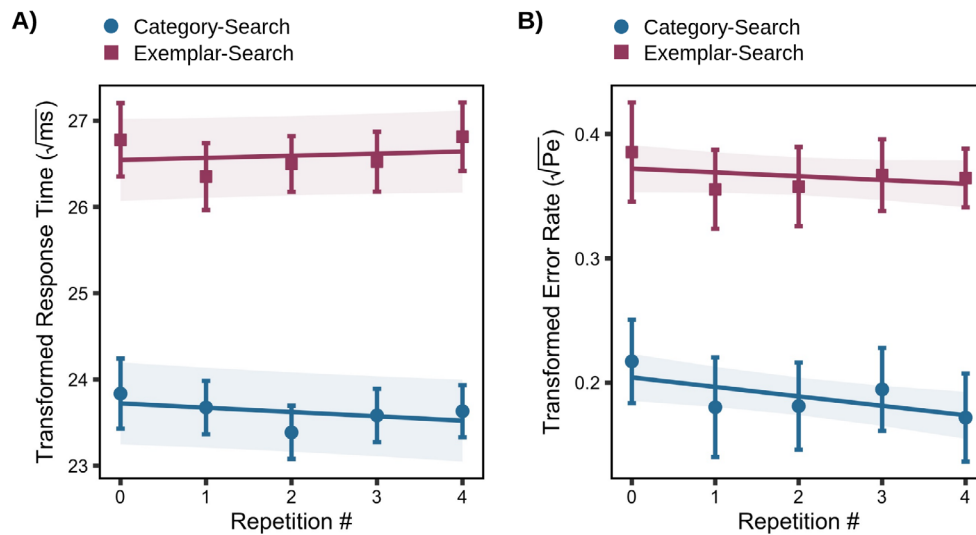


FIGURE 2 | Behavioral results for Experiment 1. Plotted are the participant aggregated means for square-root transformed (A) response time and (B) error rate as a function of target repetition number (i.e., 0–4) and search type (i.e., category-search and exemplar-search). For all panels, error bars for each data point represent 95% within-subject confidence intervals (Cousineau 2005), line fits depict the modeled response, and error ribbons illustrate the modeled response ± 1 standard error of the mean, estimated using the *emmeans* package in R (Lenth 2024).

model was defined by quadratic terms for the effect of target repetition number along with a random slope for the linear effect of target repetition number (Figure 6A). We found an overall difference in N2pc amplitude between category- and exemplar-search conditions ($b = -0.28 \mu\text{V}$, $\text{SE} = 0.07$, $t(240) = -3.82$, $p < 0.001$, $R^2_\beta = 0.057$), with exemplar search eliciting larger N2pc amplitudes than category search. Further, N2pc amplitude was found to increase across target repetitions, as indicated by a significant linear effect of target repetition number ($b = -0.13 \mu\text{V}$, $\text{SE} = 0.04$, $t(30) = -3.17$, $p = 0.003$, $R^2_\beta = 0.251$) that was coupled with a significant quadratic effect ($b = 0.14 \mu\text{V}$, $\text{SE} = 0.03$, $t(240) = 4.97$, $p < 0.001$, $R^2_\beta = 0.093$) marked by amplitudes that peaked around the first or second repetition before stabilizing thereafter. Neither the linear ($b = -0.04 \mu\text{V}$, $\text{SE} = 0.03$, $t(240) = -1.22$, $p = 0.225$, $R^2_\beta = 0.006$) nor quadratic effect of target repetition number interacted with search type ($b = -0.01 \mu\text{V}$, $\text{SE} = 0.03$, $t(240) = -0.29$, $p = 0.772$, $R^2_\beta < 0.001$).

2.2.2.3 | Semantic Processing of Target Cues Indexed by N400. With regard to the N400, amplitudes were best fit by a model that included quadratic terms for the effect of repetition number with no random slopes. The model showed an effect of electrode site with N400 amplitudes being more negative at Fz than CPz (Figure 6B, $b = 1.76 \mu\text{V}$, $\text{SE} = 0.10$, $t(564) = 18.15$, $p < 0.001$, $R^2_\beta = 0.369$), suggesting a frontal topographic distribution. There was no effect of search type ($b = 0.30 \mu\text{V}$, $\text{SE} = 0.15$, $t(564) = 1.96$, $p = 0.051$, $R^2_\beta = 0.007$), but there was a linear decline in N400 amplitude across repetitions ($b = 0.34 \mu\text{V}$, $\text{SE} = 0.07$, $t(564) = 5.02$, $p < 0.001$, $R^2_\beta = 0.043$) that was coupled with a quadratic effect ($b = -0.20 \mu\text{V}$, $\text{SE} = 0.06$, $t(564) = -3.44$, $p = 0.001$, $R^2_\beta = 0.020$). Interestingly, while the linear effect of category repetition was unaffected by search type ($b = 0.01 \mu\text{V}$, $\text{SE} = 0.07$, $t(564) = 0.15$, $p = 0.879$, $R^2_\beta < 0.001$), the quadratic effect was found to vary respectively ($b = -0.12 \mu\text{V}$, $\text{SE} = 0.06$, $t(564) = -2.02$, $p = 0.044$, $R^2_\beta = 0.007$). In this regard, a quadratic effect of repetition number was present for exemplar search ($b = -0.32 \mu\text{V}$, $\text{SE} = 0.09$, $t(267) = -3.67$,

$p < 0.001$, $R^2_\beta = 0.048$), as defined by a larger amplitude change from the first to second item in the repetition run with little change thereafter, while this pattern was not present for category search ($b = -0.08 \mu\text{V}$, $\text{SE} = 0.08$, $t(267) = -1.07$, $p = 0.287$, $R^2_\beta = 0.004$).

2.3 | Discussion

In Experiment 1, we assessed whether the maintenance of exemplar-specific details in VWM depends on the sustained preservation of a target category across consecutive searches. To this end, we relied on pre-search CDA amplitude, as this load-sensitive marker of VWM activity is known to decline monotonically when searches are consistently defined by the same target stimulus (e.g., Carlisle et al. 2011; Gunseli et al. 2014; Özdemir et al. 2024; Reinhart et al. 2016; Reinhart and Woodman 2014; Schneider et al. 2018; Şentürk et al. 2024) and was previously shown to be indistinguishable from baseline when individuals searched for targets defined by a common object category that sufficiently differentiated targets from nontargets (Schmidt and Zelinsky 2017). In examining this component, we found an overall effect of category-sufficiency, with the contralateral-ipsilateral difference being smaller during category-sufficient search than during exemplar-specific search. Critically, though, we did not observe the typical CDA reduction that is seen when an exact target stimulus is repeated across consecutive searches. Instead, CDA amplitude was stable across category repetitions regardless of category-sufficiency for search. This pattern was further mirrored by behavior, as search times and errors were similarly found to be consistent across target category repetitions, despite performance being better overall during category-sufficient search. These results suggest that when a target is adequately defined by its basic-level category, fewer object-specific details are encoded and maintained in VWM than when veridical representations are needed to locate and identify target objects.

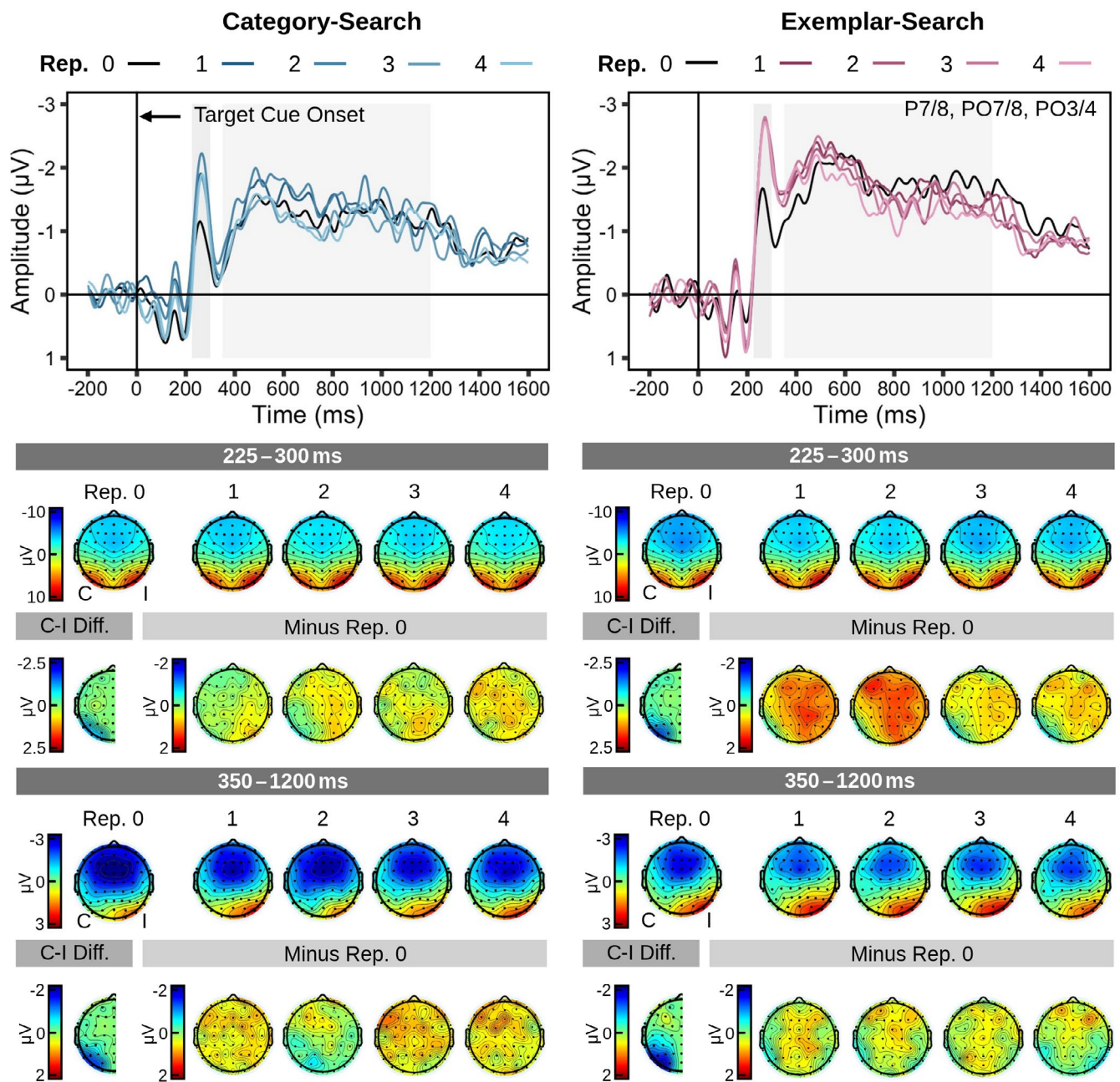


FIGURE 3 | Lateralized ERP waveforms and associated scalp maps in Experiment 1. The ERP waveforms correspond to the contralateral minus ipsilateral hemispheric differences (relative to the position of the target cue at encoding) averaged across P7/8, PO7/8, and PO3/4 electrode sites. Dark gray, shaded regions depict the time window used to measure the N2pc (i.e., 225 ms–300 ms) and the light gray, shaded regions depict the time window used to measure the CDA (i.e., 350 ms–1200 ms). The category-search condition is presented on the left, the exemplar-search condition is shown on the right, and target repetition number (Rep.) is represented by the lightness of the waveform line, with repetition 0 depicted in black. The shown ERPs were lowpass filtered at 15 Hz for plotting purposes only. The scalp plots depict mean amplitudes over the N2pc (middle rows) and CDA (bottom rows) time windows as a function of repetition number and search type (left = category search, right = exemplar search). For both the N2pc and CDA time windows, the top row of scalp maps depicts the overall topography of the EEG activity as a function of repetition number, with the side contralateral to the target cue (C) mapped to the left and the ipsilateral side (I) mapped to the right. The second row of scalp maps shows a split scalp map, depicting the contralateral minus ipsilateral difference at repetition zero, along with whole scalp maps showing the EEG topography for repetitions one through four after removing the activity present at repetition zero.

Speculatively, the encoded subset of features may correspond to the most salient or distinct aspects of the object, with the remaining details being sufficiently defined by one's categorical knowledge. However, contrary to our prediction, this compression of target objects to some base number of features

seems to be unaffected by the sustained preservation of the target object category, even though there would inevitably be some featural overlap between the exemplars. Put another way, when participants were tasked with finding a bird, for example, they actively held the same number of details in

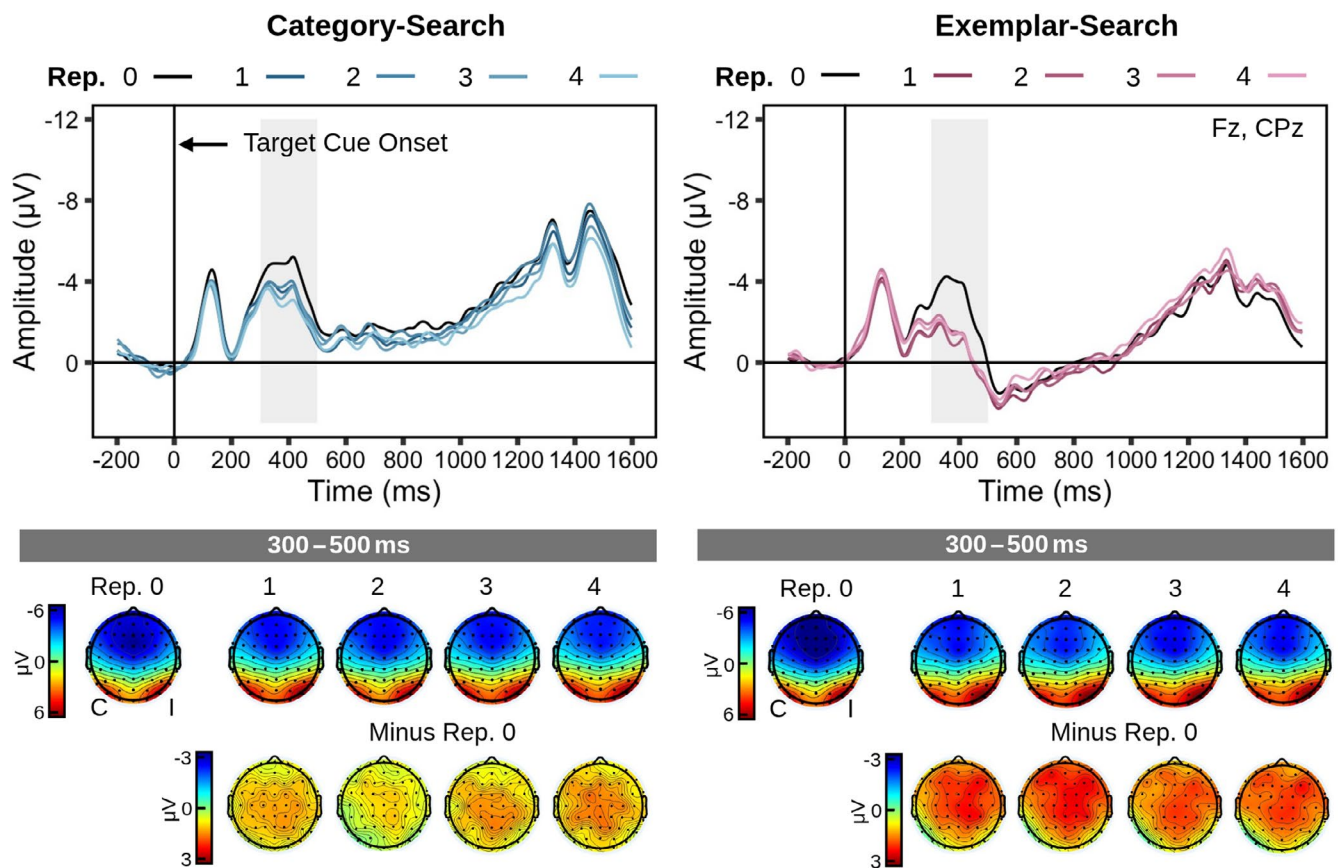


FIGURE 4 | Midline ERP waveforms and associated scalp maps in Experiment 1. ERP waveforms at midline sites (Fz, CPz) used to measure the N400 (shaded region: 300 ms–500 ms) along with scalp maps illustrating mean amplitudes over this window. The category-search condition is presented on the left and the exemplar-search condition is shown on the right. For the waveforms, target repetition number (Rep.) is represented by the lightness of the line, with repetition 0 depicted in black. The shown ERPs were lowpass filtered at 15 Hz for plotting purposes only. For the scalp maps, left-side electrodes correspond to those that were contralateral to the target cue (C) and right-side electrodes correspond to those that were ipsilateral to the target cue (I). The top row of scalp maps depicts the overall topography of the EEG activity over the N400 time window, while the second row shows the EEG topography for repetitions one through four after removing the activity present at repetition zero.

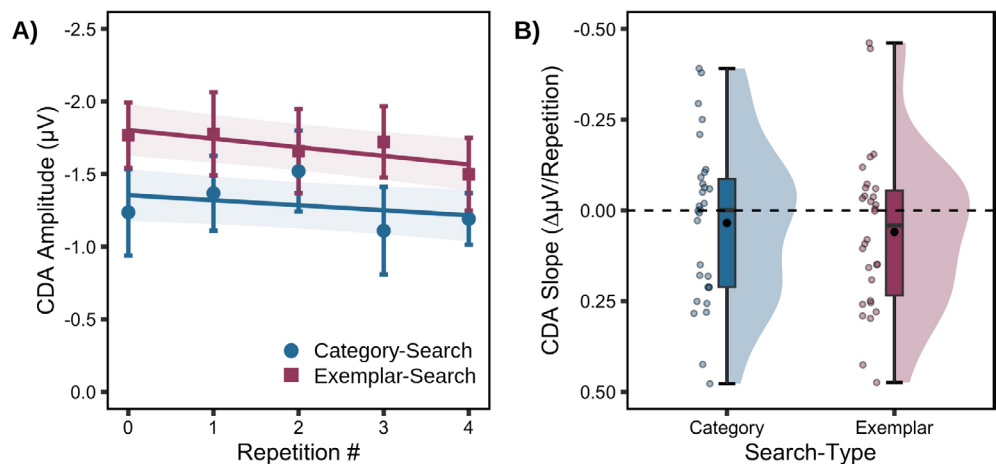


FIGURE 5 | CDA results for Experiment 1. (A) Participant aggregated means corresponding to CDA amplitude as a function of target repetition number (i.e., 0–4) and search type (i.e., category-search and exemplar-search), and (B) raincloud plots illustrating the slope of CDA amplitude across target repetitions (both category-based and exemplar-based) at the individual subject level. For panel A, error bars for each data point represent 95% within-subject confidence intervals (Cousineau 2005), line fits depict the modeled response, and error ribbons illustrate the modeled response $\pm$ 1 standard error of the mean, estimated using the *emmeans* package in R (Lenth 2024).

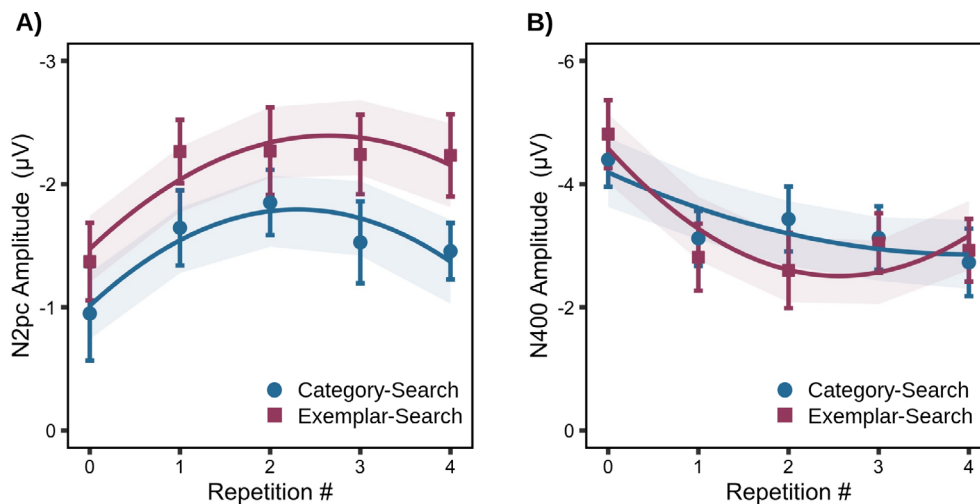


FIGURE 6 | N2pc and N400 results for Experiment 1. Participant aggregated means corresponding to (A) N2pc amplitude and (B) N400 amplitude as a function of target repetition number and repetition type. Error bars for each data point represent 95% within-subject confidence intervals (Cousineau 2005), line fits depict the modeled response, and error ribbons illustrate the modeled response ± 1 standard error of the mean, estimated using the *emmeans* package in R (Lenth 2024).

VWM regardless of whether they had just searched for several other similar-looking birds or if they had just repeatedly searched for something entirely different, such as various pairs of binoculars.

In addition to examining CDA, we also measured N2pc and N400 ERP components, which provided evidence of attentional and semantic-based processing of the target stimuli that was sensitive to the repeating category structure, despite no observable change in the number of target-specific details maintained in VWM. With respect to N2pc, we found an overall effect of search type, likely reflecting greater attentional engagement at the time of encoding when a precise target representation was required. Importantly, though, N2pc amplitude was also found to be weakest at the beginning of category-repeating runs when the target object category could not be anticipated. This was true regardless of whether search could be performed using a categorical representation. At first pass, increasing N2pc amplitudes with target repetition may be surprising, as one might have intuitively expected repetitions to dampen attentional engagement with the cue and produce the opposite trajectory. However, many studies of visual search that use targets composed of even simpler stimuli (e.g., Landolt Cs) suggest that attentional engagement is actually quite stable within this repetition paradigm (Carlisle et al. 2011; Gunseli et al. 2014). Furthermore, when considered alongside existing evidence showing that the N2pc is also sensitive to feature-based expectations (Berggren and Eimer 2019; Grubert and Eimer 2023), increases in N2pc with repetition found here and in previous work (Özdemir et al. 2024; Şentürk et al. 2024) may indicate a perceptual match signal that is generated by comparing target cues with category-based representations that are implicitly primed by the preceding stimuli or explicitly activated in long-term memory (Cowan 1999).

This idea was further supported by the N400 results. Specifically, N400 amplitude, which typically tracks semantic-congruency violations (e.g., Balconi and Caldiroli 2011; Draschkow et al. 2018; Friedrich and Friederici 2004; Ganis et al. 1996; Kutas and Iragui 1998; McPherson and Holcomb 1999; Nigam et al. 1992;

Võ and Wolfe 2013), showed an inverse pattern to that observed for N2pc with respect to target category repetition. Consistent with both Drew et al. (2018) and Lindborg et al. (2023), N400 amplitude was largest for the first category exemplar presented in a run, then declined linearly (category-sufficient search) or quadratically (exemplar-specific search) thereafter, suggesting that semantic violations were present when target object categories changed between searches, which would necessitate the presence of a categorical template at some level of representation.

When taken together, these findings appear to demonstrate the coexistence of exemplar-specific target representations and category-general representations during visual search, with the former being sensitive to category sufficiency, but not the sustainment of the category itself, and the latter being sensitive to the persistence of the target category but not sufficiency of it. Still, it is important to acknowledge that the pattern of results we observed for CDA differed considerably from the pattern we expected to find. Further, while it is not necessarily the case that category repetitions should have produced behavioral improvements, it is possible that the category-sufficient search condition was simply too easy and produced a ceiling effect that masked the true effect of category repetition on search performance. To address these concerns, we found it necessary to conduct a follow-up experiment.

3 | Experiment 2

Following from Experiment 1, we sought to replicate the observation that pre-search CDA amplitude is insensitive to target-category repetitions under conditions of category-sufficient search. To do so, we removed the exemplar-specific search condition, allowing for the task to always be completed using only categorical representations and appended an additional exemplar-repeating trial structure where a single category exemplar was repeated across consecutive searches. From a theoretical perspective, this design allowed us to directly compare the representations that are held actively in mind when repeatedly

searching for the same object versus repeatedly searching for the same *kind* of object. From an experimental perspective, the presence of a repetition effect on CDA for exemplar-repeating targets, but not category-repeating targets, would allow for greater confidence in our results from Experiment 1 by establishing that our task design and stimuli are indeed sensitive to gradual changes in stimulus representation that occur with repetition. We also increased the set size of the search arrays from four to six items in hopes of making the task more difficult and, by extension, alleviating behavioral ceiling effects that may have been present in Experiment 1.

3.1 | Method

3.1.1 | Participants

All participants in the experiment were undergraduate students from the University of Toronto or similarly aged adults from the surrounding community that reported normal or corrected-to-normal visual acuity. Each participant provided informed consent in accordance with the procedures approved by the Research Ethics Board at the University of Toronto. Participants completed the experiment in exchange for monetary compensation or a combination of monetary compensation and course credit.

We recruited 34 participants. Using the same exclusion criteria as Experiment 1 (see *Participants* section), one participant was excluded for poor behavioral performance ($> 20\%$ trials containing either an incorrect response, no response, or a response that occurred within 200ms of search onset, indicating a guess) and three were excluded for an excessive number of EEG artifacts ($> 20\%$ trials marked for rejection, see *EEG Analysis* section). Data collected from the remaining 30 participants (4 male, 25 female, 1 non-binary, mean age = 21.3 years old) were submitted to analysis. This sample size was determined using the same power analysis used in Experiment 1, as the interaction of interest followed the same logic (i.e., selective reduction of CDA across repetitions of a target stimulus, but not a common target-object category).

3.1.2 | Stimuli

Same as Experiment 1.

3.1.3 | Procedure

The procedure was the same as Experiment 1, with the following 3 exceptions. First, we removed the exemplar-search condition so that a categorical target representation was now sufficient to perform search across all trials. Second, we increased the number of items present within each search array from 4 to 6 to minimize ceiling effects that may have been present in Experiment 1. These items were evenly spaced along an imaginary circle (radius = 4°). Third, and most critically, we introduced exemplar-repeating runs where the exact same stimulus from the selected target category was repeated for at least 5 consecutive presentations (e.g., searching for the same bird 5 or 7 times in a row) before switching to a new target stimulus from a different object category.

One of the two repetition conditions (i.e., exemplar-repeating or category-repeating) was performed for the first eight blocks, while the other respective condition was performed for the last eight blocks (counterbalanced), with each condition following a single practice block of 54 trials that followed the same repetition structure. Participants were not told that the second practice block was separate from the main experimental task, and no additional instructions were provided. This block structure was implemented to allow participants to form clear expectations regarding the target repetition structure without explicitly drawing attention to the manipulation. A schematic of the trial procedure is shown in Figure 7.

3.1.4 | EEG Acquisition and Pre-Processing

Same as Experiment 1. On average, 2.1 electrodes were interpolated during pre-processing ($SD = 3.9$). Again, these electrodes were typically positioned frontally with artifacts associated with muscle activity and/or skin potentials. For one participant, Fz was interpolated and included in the N400 analysis, though the inclusion of this individual did not affect the results. No other interpolated electrodes were used for analysis.

3.1.5 | Analyzes

All behavioral and EEG analyzes were the same as Experiment 1, with the following two exceptions. For behavioral analysis of target-absent trials, see the [Appendix](#). First, the factor of search type was replaced with the factor of target repetition type (i.e., exemplar-repeating or category-repeating). Second, because RT and P_e were not found to be skewed, no data transformations were applied to these measures. For our behavioral analysis, 0.02% of trials were excluded because of RTs below 200ms, 0.04% of trials were excluded because no response was registered, and 2.60% of RTs were trimmed. For the ERP data, there was an average of 64.89 trials ($SD = 7.09$) per repetition number in the category-repeating condition and 67.20 trials ($SD = 6.10$) in the exemplar-repeating condition, after removing both artifactual trials and those associated with an error, missed response or exceptionally fast response.

3.2 | Results

3.2.1 | Behavior

We began by assessing the effects of exemplar and category repetitions on observers' search performance. A monotonic model with a random slope for the effect of repetition type was selected first to analyze RT (Figure 8A). When using this model, RTs were found to be comparable overall between category-repeating and exemplar-repeating search conditions ($b = -2.49$ ms, $SE = 8.52$, $t(29) = -0.29$, $p = 0.772$, $R^2_\beta = 0.003$). Contrasting Experiment 1, here there was a significant effect of repetition number ($b = -4.10$ ms, $SE = 1.16$, $t(238) = -3.531$, $p < 0.001$, $R^2_\beta = 0.050$), indicating that RTs became progressively faster when the target repeated. Most notably, this effect of repetition number did not interact with repetition type ($b = -1.22$ ms, $SE = 1.16$, $t(238) = -1.05$, $p = 0.294$, $R^2_\beta = 0.005$),

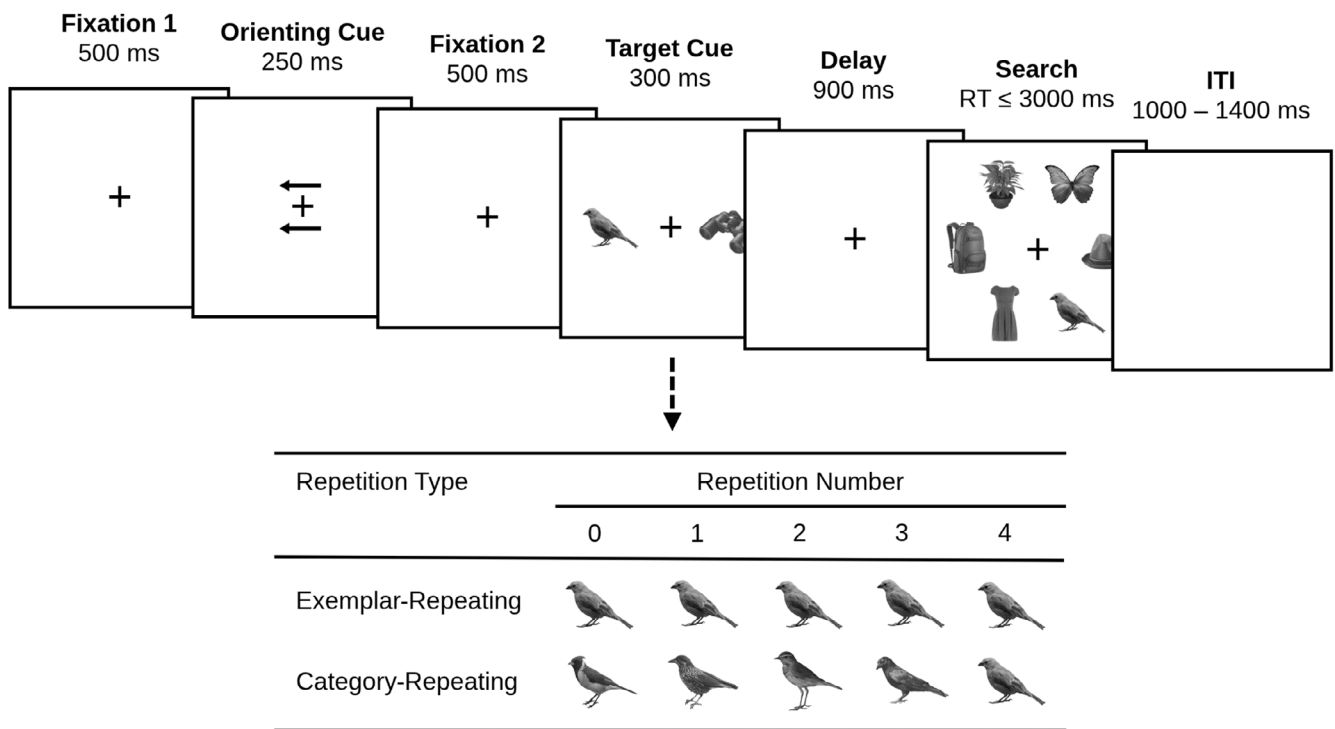


FIGURE 7 | Schematic of experimental task in Experiment 2. Shown is an example of a target-present trial (top-panel), along with an example of the target repetition sequence for the exemplar-repeating and category-repeating conditions (bottom-panel).

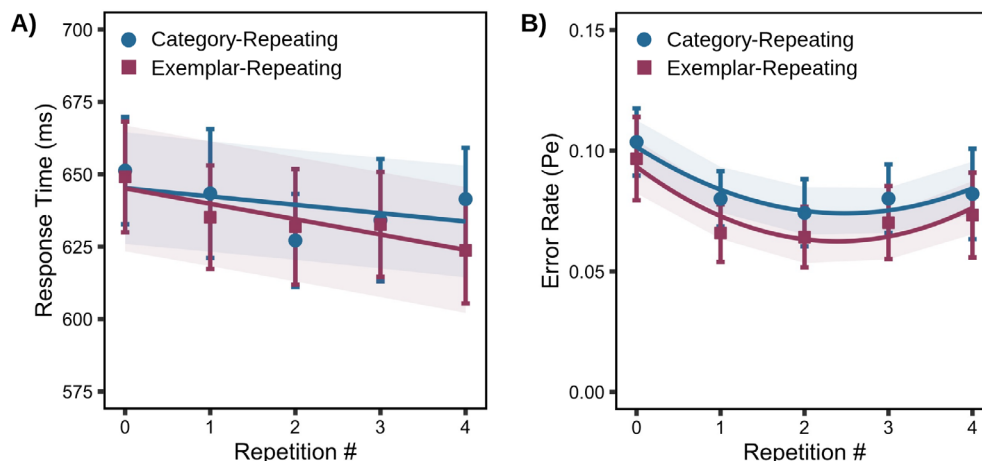


FIGURE 8 | Behavioral results for Experiment 2. Plotted are the participant aggregated means for (A) response time and (B) error rate as a function of target repetition number (i.e., 0–4) and repetition type (i.e., category-repeating and exemplar-repeating). For all panels, error bars for each data point represent 95% within-subject confidence intervals (Cousineau 2005), line fits depict the modeled response, and error ribbons illustrate the modeled response ± 1 standard error of the mean, estimated using the *emmeans* package in R (Lenth 2024).

which meant that the speed benefit afforded by target repetition was comparable between category and exemplar repetitions.

From here, we analyzed participants' Pe during search using a model that included quadratic terms for the effect of repetition number and no random slopes (Figure 8B). Consistent with the pattern observed in RT, we did not observe any overall effect of repetition type on Pe ($b = -5.91 \times 10^{-3}$, $SE = 3.93 \times 10^{-3}$,

$t(265) = -1.51$, $p = 0.133$, $R^2_\beta = 0.008$). Likewise, we also found that Pe decreased linearly across repetitions (-4.27×10^{-3} , $SE = 1.78 \times 10^{-3}$, $t(265) = -2.40$, $p = 0.017$, $R^2_\beta = 0.021$), combined with a significant quadratic function ($b = 4.94 \times 10^{-3}$, $SE = 1.51 \times 10^{-3}$, $t(265) = 3.28$, $p = 0.001$, $R^2_\beta = 0.039$) which suggested that decreases in Pe were most pronounced between repetitions 0 and 1, and then leveled off afterwards. Here again, neither the linear ($b < 0.01 \times 10^{-3}$, $SE = 1.78 \times 10^{-3}$,

$t(265)=0.01$, $p=0.989$, $R^2<0.001$) nor quadratic ($b=0.04\times 10^{-3}$, $SE=1.51\times 10^{-3}$, $t(265)=0.31$, $p=0.761$, $R^2<0.001$) effect of repetition number interacted with repetition type, which suggested that category and exemplar repetitions elicited comparable benefits on Pe .

3.2.2 | ERPs

ERP waveforms and scalp maps corresponding to the lateralized (i.e., CDA and N2pc) and nonlateralized (i.e., N400) ERP components are depicted in Figures 9 and 10, respectively.

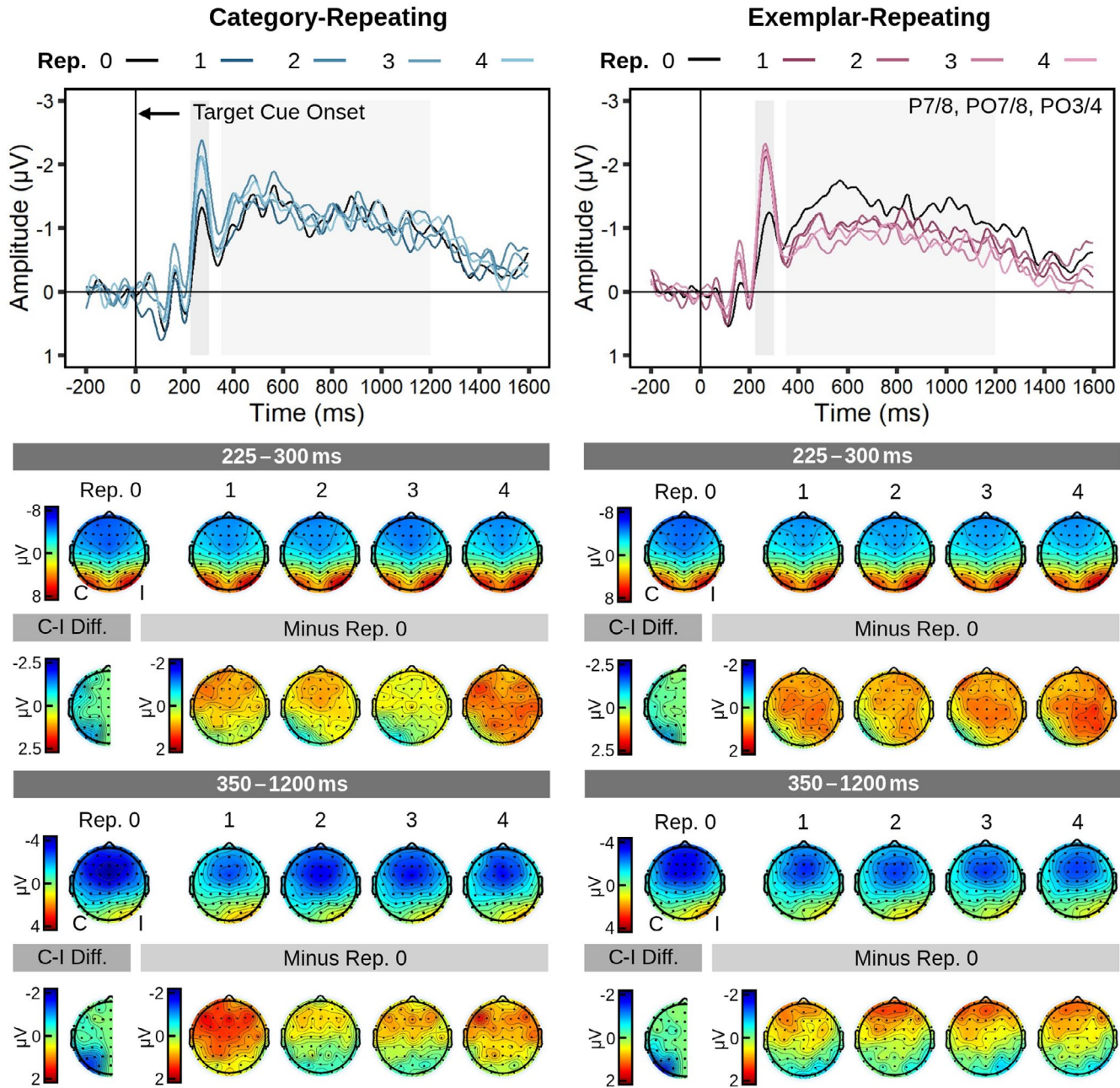


FIGURE 9 | Lateralized ERP waveforms and associated scalp maps in Experiment 2. The ERP waveforms correspond to the contralateral minus ipsilateral hemispheric differences (relative to the position of the target cue at encoding) averaged across P7/8, PO7/8, and PO3/4 electrode sites. Dark gray, shaded regions depict the time window used to measure the N2pc (i.e., 225 ms–300 ms) and the light gray, shaded regions depict the time window used to measure the CDA (i.e., 350 ms–1200 ms). The category-repeating condition is presented on the left, the exemplar-repeating condition is shown on the right, and target repetition number (Rep.) is represented by the lightness of the waveform line, with repetition 0 depicted in black. The shown ERPs were lowpass filtered at 15 Hz for plotting purposes only. The scalp plots depict mean amplitudes over the N2pc (middle rows) and CDA (bottom rows) time windows as a function of repetition number and search type (left = category search, right = exemplar search). For both the N2pc and CDA time windows, the top row of scalp maps depicts the overall topography of the EEG activity as a function of repetition number, with the side contralateral to the target cue mapped to the left (C) and the ipsilateral side mapped to the right (I). The second row of scalp maps shows a split scalp map, depicting the contralateral minus ipsilateral difference at repetition zero, along with whole scalp maps showing the EEG topography for repetitions one through four after removing the activity present at repetition zero.

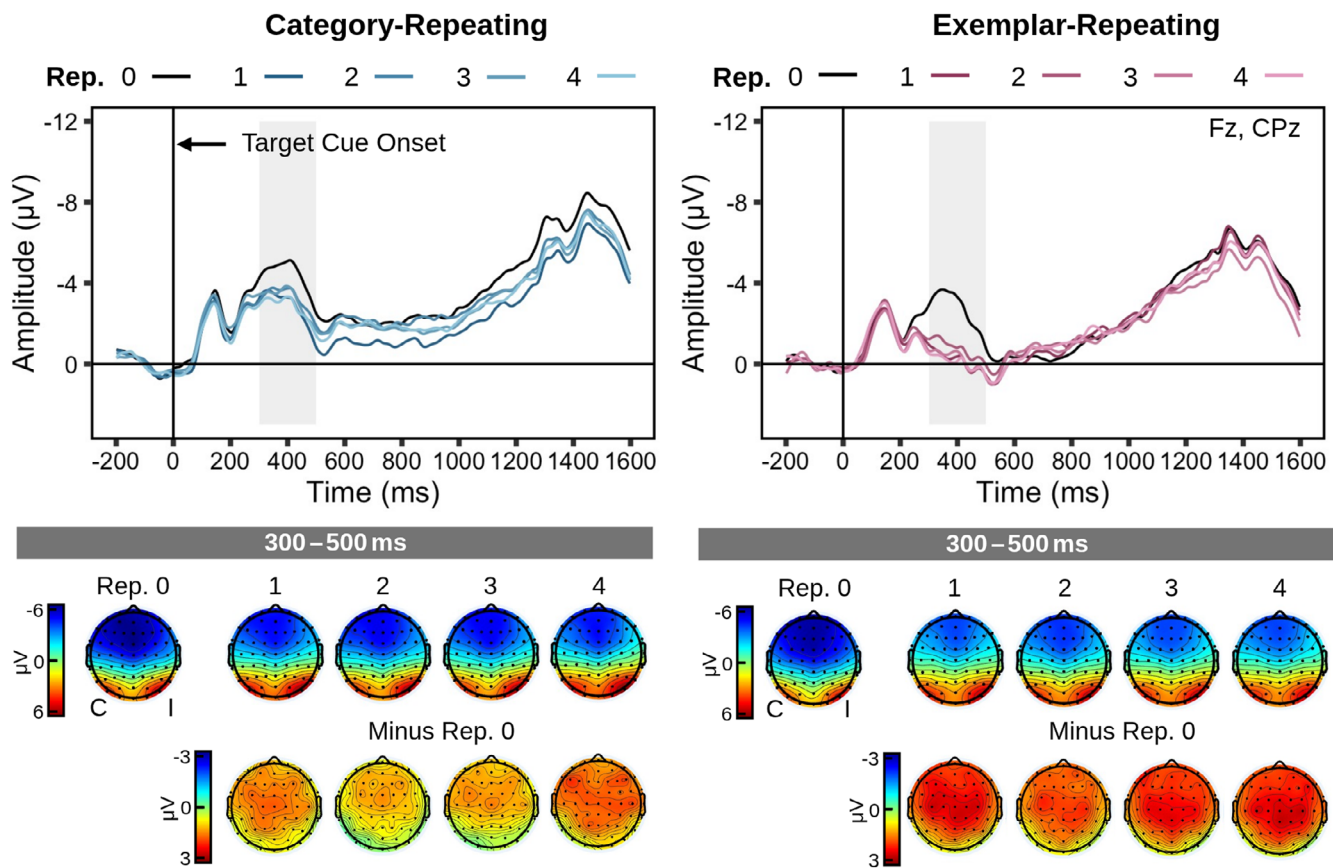


FIGURE 10 | Midline ERP waveforms and associated scalp maps in Experiment 2. ERP waveforms at midline sites (Fz, CPz) used to measure the N400 (shaded region: 300 ms–500 ms) along with scalp maps illustrating mean amplitudes over this window. The category-repeating condition is presented on the left, and the exemplar-repeating condition is shown on the right. For the waveforms, target repetition number (Rep.) is represented by the lightness of the line, with repetition 0 depicted in black. The shown ERPs were lowpass filtered at 15 Hz for plotting purposes only. For the scalp maps, left-side electrodes correspond to those that were contralateral to the target cue (C) and right-side electrodes correspond to those that were ipsilateral to the target cue (I). The top row of scalp maps depicts the overall topography of the EEG activity over the N400 time window, while the second row shows the EEG topography for repetitions one through four after removing the activity present at repetition zero.

3.2.2.1 | Exemplar-Specific Feature Maintenance Indexed by CDA

Having established equivalent behavioral patterns between category and exemplar repetitions, we next moved to determine whether the observed effects on performance were mirrored by comparable modulation of CDA across the two conditions. We analyzed the CDA data using a model that treated the effect of repetition number as a monotonic function with no random slopes. As shown in Figure 11A,B, CDA amplitude was reduced overall for the exemplar-repeating condition compared to the category-repeating condition ($b = 0.11 \mu\text{V}$, $\text{SE} = 0.04$, $t(267) = 2.83$, $p = 0.005$, $R^2 = 0.029$) with no overall effect of repetition number ($b = 0.07 \mu\text{V}$, $\text{SE} = 0.03$, $t(267) = 1.95$, $p = 0.052$, $R^2 = 0.014$). However, there was a significant interaction between repetition type and repetition number ($b = 0.07 \mu\text{V}$, $\text{SE} = 0.03$, $t(267) = 2.46$, $p = 0.015$, $R^2 = 0.022$) driven by CDA amplitudes that declined linearly across repetitions in the exemplar-repeating condition ($b = 0.13 \mu\text{V}$, $\text{SE} = 0.04$, $t(119) = 3.20$, $p = 0.002$, $R^2 = 0.079$), but remained constant for the category-repeating condition ($b = -0.01 \mu\text{V}$, $\text{SE} = 0.04$, $t(119) = -0.37$, $p = 0.709$, $R^2 = 0.001$). This finding clearly shows that repeatedly searching for an identical exemplar reduced reliance on VWM, while searching for perceptually-similar exemplars from the same repeating category did not.

3.2.2.2 | Spatially Selective Processing of Target Cues Indexed by N2pc

Having addressed the primary research question of Experiment 2, we moved to test whether the corresponding effects of category repetition on N2pc and N400 were replicated. Starting with N2pc amplitude, the best-fitting model was defined by quadratic terms for the effect of repetition number along with a random slope for the effect of repetition type. Using this model, we found no overall differences in N2pc between category- and exemplar-repeating conditions (Figure 12A, $b = -0.08 \mu\text{V}$, $\text{SE} = 0.09$, $t(60) = -0.87$, $p = 0.386$, $R^2 = 0.013$) but did find significant linear ($b = -0.20 \mu\text{V}$, $\text{SE} = 0.03$, $t(240) = -6.92$, $p < 0.001$, $R^2 = 0.167$) and quadratic effects ($b = 0.12 \mu\text{V}$, $\text{SE} = 0.02$, $t(240) = 5.10$, $p < 0.001$, $R^2 = 0.098$) of repetition number, suggesting that N2pc amplitudes increased across target repetitions, especially during the first and second repetitions in the run before leveling off. Neither the linear ($b > -0.01 \mu\text{V}$, $\text{SE} = 0.03$, $t(240) = -0.08$, $p = 0.935$, $R^2 < 0.001$) nor quadratic effects ($b > -0.01 \mu\text{V}$, $\text{SE} = 0.02$, $t(240) = -0.16$, $p = 0.875$, $R^2 < 0.001$) of repetition number interacted with repetition type. As in Experiment 1, these repetition effects on N2pc amplitude suggest that spatial processing of the lateralized target cue became stronger with category and exemplar repetition.

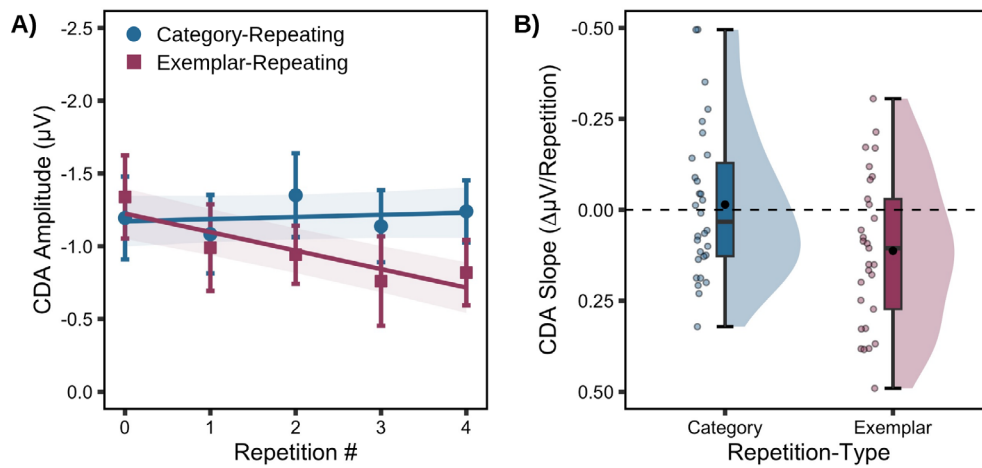


FIGURE 11 | CDA results for Experiment 2. (A) Participant aggregated means corresponding to CDA amplitude as a function of target repetition number (i.e., 0–4) and repetition-type (i.e., category-repeating and exemplar-repeating), and (B) raincloud plots illustrating the slope of CDA amplitude across target repetitions (both category-based and exemplar-based) at the individual subject level. For panel A, error bars for each data point represent 95% within-subject confidence intervals (Cousineau 2005), line fits depict the modeled response, and error ribbons illustrate the modeled response ± 1 standard error of the mean, estimated using the *emmeans* package in R (Lenth 2024).

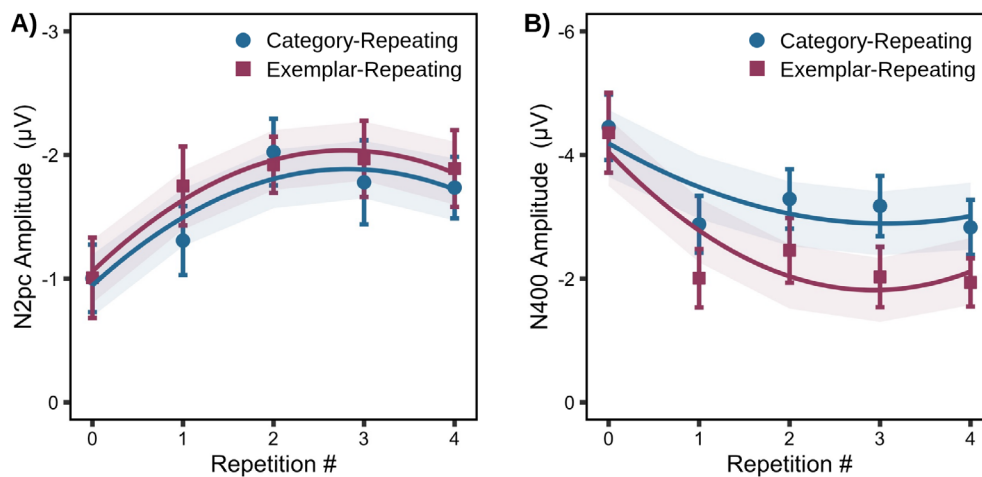


FIGURE 12 | N2pc and N400 results for Experiment 2. Participant aggregated means corresponding to (A) N2pc amplitude and (B) N400 amplitude as a function of target repetition number and repetition type. Error bars for each data point represent 95% within-subject confidence intervals (Cousineau 2005), line fits depict the modeled response, and error ribbons illustrate the modeled response ± 1 standard error of the mean, estimated using the *emmeans* package in R (Lenth 2024).

3.2.2.3 | Semantic Processing of Target Cues Indexed by N400. With regard to N400 amplitude, the best-fitting model was defined by quadratic terms for the effect of repetition number with no random slopes. As was the case in Experiment 1, N400 amplitudes were more pronounced frontally at Fz than posteriorly at CPz ($b = 1.75 \mu\text{V}$, $\text{SE} = 0.07$, $t(564) = 23.75$, $p < 0.001$, $R^2_\beta = 0.500$). Additionally, we found that N400 varied as a function of repetition type, with greater positivity overall for exemplar repetitions than category repetitions (Figure 12B, $b = 0.51 \mu\text{V}$, $\text{SE} = 0.11$, $t(564) = 4.41$, $p < 0.001$, $R^2_\beta = 0.033$). Importantly, similar to what was observed in Experiment 1, N400 showed a linear decline across repetitions ($b = 0.39 \mu\text{V}$, $\text{SE} = 0.05$, $t(564) = 7.45$, $p < 0.001$, $R^2_\beta = 0.090$), which was coupled with a quadratic function ($b = -0.20 \mu\text{V}$, $\text{SE} = 0.04$, $t(564) = -4.52$, $p < 0.001$, $R^2_\beta = 0.035$), showing that increased positivity was most pronounced for the first repetition of the target or category,

and then plateaued afterward. These repetition effects were unaffected by repetition type, as neither the linear effect ($b = 0.09 \mu\text{V}$, $\text{SE} = 0.05$, $t(564) = 1.80$, $p = 0.073$, $R^2_\beta = 0.006$) nor the quadratic effect ($-0.06 \mu\text{V}$, $\text{SE} = 0.04$, $t(564) = -1.40$, $p = 0.162$, $R^2_\beta = 0.003$) interacted with repetition type.

3.3 | Discussion

In Experiment 2, we had individuals search consecutively for targets that were defined by either a common object category or identical stimulus features under conditions where knowledge of the category was sufficient to perform the task. Replicating our results from Experiment 1, we again found that CDA amplitude remained constant across searches when targets repeated at the categorical level, indicating that individuals encoded and

maintained the same number of details in VWM, regardless of whether preceding targets shared perceptual and semantic features. In contrast, when the exact target stimulus was repeated, we observed the typical monotonic decline in CDA amplitude across target repetitions (e.g., Carlisle et al. 2011; Gunseli et al. 2014; Özdemir et al. 2024; Reinhart et al. 2016; Reinhart and Woodman 2014; Schneider et al. 2018; Şentürk et al. 2024), suggesting that individuals increasingly relied on long-term memory to perform the task when target stimuli were unchanged. Importantly, the presence of such an effect rules out the possibility that the lack of CDA modulation in the category-repeating condition can be explained by some inability of the task or stimuli to produce such effects. Instead, these findings suggest that the active maintenance of target features in VWM is not necessary for visual search, especially when a well-established trace is available, but that category-level repetitions of perceptually-similar exemplars fail to reduce one's reliance on this system, either because the detection of stimulus changes triggers encoding automatically or because there is a strategic reason to hold exemplar-specific details in VWM during category repetitions, but not exemplar repetitions.

Interestingly, unlike Experiment 1, where sustained CDA amplitudes during category repetitions were mirrored by stable behavioral performance, here we found that sustained CDA amplitudes in the category-repeating condition were accompanied by behavioral improvements. Again, these behavioral discrepancies can be explained in part by the fact that we increased the number of items in the search array from 4 to 6 items, which could have counteracted a potential ceiling effect that was present in Experiment 1. However, this change in search difficulty alone cannot explain why category- and exemplar-repeating searches elicited comparable behavioral improvements despite observers' differential reliance on VWM to store the attentional template. According to longstanding theories of learning and automaticity, gradual improvements in behavioral performance under stable task demands are caused by a shift in the representations that control processing from VWM to long-term memory (Anderson 2000, 2010; Bundesen and Habekost 2008; Logan 1988, 2002; Poldrack and Gabrieli 2001). In the case of visual search, this shift in reliance is thought to be marked by reductions in CDA that occur across stimulus repetitions (Carlisle et al. 2011; Woodman et al. 2007). This account would therefore make the prediction that search performance does not improve when CDA remains elevated because attentional guidance is still reliant on VWM.

At first pass, our findings appear to contradict these theories of automaticity. However, it may be the case that long-term memory exerted its influence on search performance outside of attentional guidance. Evidence from eye movement patterns and dwell times during search suggest that the behavioral benefits traditionally induced by exemplar repetitions are explained by faster target recognition decisions that occur after attentional selection, rather than by changes in the initial guidance process (Goldstein and Beck 2018). Critically, if guidance is unaffected by target repetition, this means that guidance by templates represented in VWM and long-term memory may be equally efficient and that changes in CDA amplitude with repetition are not causally related to the behavioral improvements that are typically observed. Instead, performance would be primarily

determined by the information that is accessed to recognize the target after a candidate item is selected by attention. In this regard, it has long been established that object recognition decisions are most efficient when identity judgments are made at the basic category level (e.g., Rosch et al. 1976). Therefore, behavioral improvements may be explained by the accumulation of a basic-level category representation in long-term memory across repetitions that facilitates target recognition independently of preceding attentional guidance.

Of course, for it to be the case that target recognition decisions were made more efficiently using category representations, there would need to be some evidence to suggest that individuals represented, or were at least sensitive to, the target category during the task. In both experiments, such evidence was present in the form of N2pc and N400 amplitude modulations which were most apparent following target category switches. In both the category- and exemplar-repeating conditions, the N2pc response to target cues was weakest when a new object category was presented, while the N400 response was at its strongest. We take these results to reflect the presence of perceptual and semantic expectation violations, respectively, following the presentation of a new object category. In this way, while the pattern of results observed for CDA might suggest that individuals did not utilize categorical information during the task, the N2pc and N400 results tell a different story, pointing to target recognition processes as the key beneficiary of category repetition. Future work should seek to test this account more directly by using a design that is capable of independently measuring attentional guidance and decision-making processes.

4 | General Discussion

We are constantly required to find objects in our environment that are defined only by category labels, whether it be finding sneakers at a department store, a waste bin at a park, or a stapler in an unfamiliar office. While plenty of studies have established that the knowledge associated with such labels can be used to localize objects effectively (e.g., Addleman et al. 2024; Alexander and Zelinsky 2011; Bravo and Farid 2012; Jonides and Gleitman 1972; Lim et al. 2021; Nako et al. 2014; Robbins and Hout 2015; Schmidt and Zelinsky 2009; Wu et al. 2013; Wyble et al. 2013; Yang and Zelinsky 2009; Yeh and Peelen 2022), there is also broad agreement that searching for categorically defined targets is less efficient than searching for targets that are more precisely defined or previewed in advance (e.g., Cunningham and Wolfe 2014; Hout et al. 2017; Maxfield and Zelinsky 2012; Schmidt and Zelinsky 2009; Vickery et al. 2005; Yu et al. 2016). It is puzzling then that pre-search CDA—a neural indicator of object-specific attentional templates in VWM—is not always distinguishable from baseline when object-specific and category-general representations are both available and sufficient to perform a given search (e.g., Schmidt and Zelinsky 2017).

Here, we hypothesized that this discrepancy may depend upon the target repetition structure that is used in the task. Specifically, when the category of the target object is fixed across multiple consecutive searches, individuals may forgo the process of encoding a unique object-specific representation before each search to instead maintain a single categorical representation that capitalizes on the perceptual and

semantic redundancies between successive target objects. While this strategy would be expected to reduce search efficiency, it would also help to minimize cognitive effort without jeopardizing one's ability to perform the task (Yu et al. 2023). To test this, we modified a well-established experimental procedure where target stimuli are repeated consecutively for some number of trials before switching to a new item (e.g., Alfandari et al. 2019; Carlisle et al. 2011; Drew et al. 2018; Gunseli et al. 2014; Özdemir et al. 2024; Reinhart et al. 2016; Reinhart and Woodman 2014; Schneider et al. 2018; Şentürk et al. 2024). Across two experiments, observers were asked to search for the same object or perceptually-similar objects from the same basic-level category across consecutive searches where the category alone was either sufficient or insufficient to find the target. Prior to each search, we measured the amplitude of CDA that was elicited by the target cue to quantify the encoding and maintenance of object-specific details. We predicted that when the category alone was sufficient to find the target, pre-search CDA would decline across target-category repetitions in a manner similar to that of object-specific repetitions.

Contrary to this hypothesis, we did not find any evidence for a change in CDA amplitude across consecutive searches when the target category was held constant, but the exemplar changed. In Experiment 1, we found that fixing the target category had no appreciable impact on CDA amplitude across consecutive searches, regardless of whether the category was sufficient or not. Notably, this finding could not be attributed to an inability of the participants to recognize when the category was sufficient to perform the task, as there was a clear, global scaling of CDA amplitude with category sufficiency. In Experiment 2, we then further demonstrated that the absence of a category-repetition effect on CDA was partly owed to the exemplar variation that was present in category-repeating runs, as we showed CDA amplitude to diminish monotonically when a single category exemplar was repeated and all else was held equal. Thus, we can confidently conclude that maintaining the relevance of a target object category for search does not necessarily lead individuals to immediately reduce their encoding of object-specific details, even when the objects themselves are perceptually similar.

Why would individuals consistently encode new target representations if doing so is unnecessary to achieve their goals? We speculate that there are at least two possibilities. First, it may be the case that stimulus novelty triggers the encoding of object-specific details automatically or obligatorily (see Hasher and Zacks 1979). Novelty is known to serve as a salient environmental cue that is fundamental to survival in biological organisms (James 1890; Kohonen 1989; Sokolov 1975) and can be processed pre-attentively (Tiitinen et al. 1994). Furthermore, studies of memory control have shown that it is exceptionally challenging for observers to flexibly suppress their encoding of novel stimuli, even when doing so is highly desirable or explicitly demanded (Gao et al. 2016; Sundby et al. 2019; Tozios and Fukuda 2020; Zwissler et al. 2015). However, some have suggested that encoding suppression is possible when observers are granted a sufficiently long amount of time (Cheng et al. 2012; Fawcett et al. 2016; Fawcett and Taylor 2008) or many consecutive opportunities

(Cunningham and Egeth 2016; Moher and Egeth 2012; Noonan et al. 2016, 2018).

Indeed, a distinction in the number of consecutive opportunities might explain why our CDA results differed from those of Schmidt and Zelinsky (2017). In the present study, we constrained the number of consecutive category repetitions to five to seven trials to try and capture the evolution of the target representation across repetitions and found that CDA was always present and scaled with the amount of detail about the target that was required to perform the search but did not visibly decline with each successive repetition (see also Schmidt et al. 2014). By contrast, in Schmidt and Zelinsky (2017), the target category repeated for entire blocks of trials and led to the presence and absence of CDA in exemplar and category search, respectively. One straightforward possibility is that perceptual variability in the category exemplars induced a strong tendency toward object-specific encoding in both studies, but the much longer repetition sequence used by Schmidt and Zelinsky (2017) provided the amount of exposure that was necessary for observers to disengage object-specific encoding and shift reliance to a category representation—an amount of exposure that may be similar to what is typically required for observers to calibrate their criterion to target prevalence in visual search (e.g., Wolfe et al. 2007, 2013).

However, this possibility is partly undermined by the fact that Schmidt and Zelinsky's paradigm (2017) did not evoke a reliable N2pc component in the typical time window following the onset of the target cue. Instead, they reported evidence of a slightly delayed deflection that was only present when object-specific details were necessary for search. Therefore, it could either be the case that performing many consecutive repetitions of category-sufficient search with variable exemplars allows for CDA to slowly decline or simply incentivizes observers to stop attending to the target cues, which necessarily limits the formation of an object-specific representation in VWM. In either case, the present findings still clearly establish that observers are able to scale the amount of detail in their object-specific representations with category sufficiency during search, a conclusion that was otherwise impossible to determine based on extant evidence where CDA varied discretely between being present and absent.

Another possibility is that individuals may have continued to volitionally encode exemplars from the repeating category. Notably, the same theory of visual search which argues that search performance is determined by an optimal balance between search efficiency and effort minimization also posits that individuals principally rely on the most diagnostic target features to guide their attention (Yu et al. 2023, see also Wolfe 2021). Therefore, it is important to consider what features might have best served attentional guidance in the object categories that were used in the present study. To provide a concrete example, when searching for a monarch butterfly, the most diagnostic feature may be the stained-glass pattern that blankets the insect's wings. In contrast, when searching for an owl butterfly, attentional guidance might be optimized by prioritizing the creature's distinctive eyespots. Because the pictorial cues used in the present study were perceptually identical to the search targets, observers may have continuously

encoded a small number of object-specific features that were diagnostic of each exemplar rather than relied on a larger set of categorically-defined features that were shared between exemplars. Therefore, it will be essential to test whether pre-search CDA declines across category repetitions when the pictorial cues inform individuals of the relevant target category without actually previewing the target stimulus (e.g., using a different bird for the cue and the target). If pre-search CDA reflects the maintenance of exemplar-specific features for guidance, then there should be no reason to encode the diagnostic features of each exemplar in this case, and CDA should either be at baseline or decline across category repetitions. In contrast, if CDA remains elevated, this could indicate that exemplar-specific encoding is either automatic or marks something different from what we argue here.

Importantly, while the maintenance of object-specific details may be beneficial to attentional guidance, such features may not carry the same utility for recognizing targets, particularly when category membership is sufficient. To continue with the example of butterflies, it can be understood that one would be able to quickly determine whether a selected item is a butterfly based on its form, given the distinctive shape of the insect's wings. In contrast, determining whether the same insect is a monarch butterfly as opposed to an owl butterfly would require further inspection of additional features. This highlights two important points for consideration. First, the same features that might be well-suited for attentional guidance may make target recognition decisions less efficient by unnecessarily increasing the number of details for consideration (see Rosch 1988; Rosch et al. 1976). Second, the features that best serve target recognition decisions are likely those which are most common among category members. That is, while the features that best serve attentional guidance may be those that make an item unique, the features that best serve object recognition are likely those that are most strongly shared among category members. Indeed, attentional guidance and target recognition decisions are believed to rely on separate information (e.g., Hamblin-Frohman and Becker 2021; Wolfe 2021; Yu et al. 2022, 2023), which means that even if object-specific details were consistently encoded for attentional guidance, individuals may have still used category-based representations at the decisional stage.

Within the current study, evidence for parallel target representations was provided by the observed dissociation of CDA amplitude from N2pc amplitude, N400 amplitude and behavioral performance during category-sufficient search. While CDA amplitude was sustained across category repetitions when exemplar variability was present, we found that N2pc amplitude increased, N400 amplitude decreased, and behavioral performance improved. Notably, these N2pc and N400 results, which replicate previous findings involving repeating, naturalistic targets (Drew et al. 2018; Özdemir et al. 2024; Şentürk et al. 2024), may reflect perceptual and semantic expectancies, respectively, that were established by preceding targets. As noted previously, our interpretation of the N2pc results is based on existing evidence showing that the amplitude of this component is reduced when target information mismatches expected featural information (Berggren and Eimer 2019; Grubert and Eimer 2023). Likewise, our interpretation of the N400 results is based on the well-established

role of this component in the detection of semantic incongruencies (e.g., Balconi and Caldiroli 2011; Draschkow et al. 2018; Friedrich and Friederici 2004; Ganis et al. 1996; Kutas and Iragui 1998; McPherson and Holcomb 1999; Nigam et al. 1992; Võ and Wolfe 2013), with such featural and semantic violations being most likely to occur in the present study following category switches. With respect to the behavioral improvements that were observed across category repetitions in Experiment 2, such behavioral facilitation has already been attributed to the target verification stage (Goldstein and Beck 2018). As such, even if categorical repetitions failed to improve attentional guidance, it is very possible that such repetitions nonetheless benefited performance by improving the speed and accuracy of target recognition.

While the present findings provide key insights for understanding how object-specific and category-specific representations act in concert during visual search, there remain some open questions for future works that lie beyond the scope of the present study. A primary limitation in this work, and in others like it, is the lack of an electrophysiological correlate that can directly track reliance on categorical representations during search. Here, in the category-repeating search condition, we used N400 and N2pc measures of expectancy to show that a categorical representation was likely present across repetitions while behavior improved and CDA was stable, which implies reliance on that representation to perform the search. However, these measures cannot directly track the increasing reliance on that categorical representation across repetitions in the same way that CDA can be used to track reliance on an object-specific representation. While early research efforts initially identified P170 as a plausible correlate to fill this gap, studies have since failed to replicate its sensitivity to the repetition of real-world objects (e.g., Drew et al. 2018). When we conducted a post hoc exploratory analysis of P170 in our own data, we replicated this null effect of repeating real-world objects (see Appendix). As such, the ability to track the relative weighting of category-specific representations during search remains wanting.

Another aim worth pursuing is better dissociating the contribution of semantic and perceptual factors to our findings. In our category-repeating runs, target stimuli varied both perceptually and semantically at the subordinate level. In order to know whether the lack of CDA modulation with category repetition was driven exclusively by perceptual variability, one would need to test whether a similar effect is observed when semantic information is held constant. This could be achieved, for example, by holding the identity of a target constant, but varying the viewpoint or pose it is presented in (e.g., flying vs. perched). Beyond the contributions of perceptual and semantic factors, it would also be valuable to use eye-tracking to definitively differentiate the effects of category repetition on attentional guidance and decisional processes. As we have described, previous works have shown that the behavioral benefits conferred by exemplar repetitions are attributable to the target verification stage of search (Goldstein and Beck 2018). Here, we posit that improvements in target verification can also explain the behavioral effect that we observed with category repetitions in Experiment 2. A conclusive eye-tracking test of our account should examine whether category repetitions reduce dwell time on target stimuli (reflecting faster decisional processing) without affecting target saccade probabilities (reflecting stable attentional guidance).

5 | Conclusion

When searching for objects in everyday life, there are at least two forms of mnemonic representation that may be engaged to locate and identify one's target: (1) object-specific representations, which carry some number of perceptual details that define the singular identity of a target object and (2) category-general representations, which do not perfectly define the properties of any single item but capture several key features of many items of a similar kind. While object-specific representations should maximize search efficiency by minimizing target uncertainty or ambiguity, we predicted that there may nonetheless be instances where individuals favor category-based representations. Specifically, we hypothesized that individuals would rely more strongly on such representations if they could be leveraged across multiple searches and reduce effortful demand. Contrary to this prediction, we found that individuals maintained the same number of exemplar-specific details in VWM regardless of the number of category repetitions leading up to a given search, indicating that observers' reliance on object-specific representations was unaffected by the sustained preservation of the object category. Still, general category representations appeared to be held in parallel with these object-specific representations, as evidenced by the presence of behavioral enhancements across target category repetitions in Experiment 2 and modulations in N2pc and N400 amplitudes following category switches in Experiments 1 and 2. Speculatively, we argue that when both object-specific and category-general representations are available and sufficient for search, individuals may prioritize a small number of unique features to quickly localize candidate items, then use categorical representations to identify targets, bypassing the need to verify all unique elements of a target.

Author Contributions

Ryan S. Williams: conceptualization, investigation, writing – original draft, methodology, visualization, writing – review and editing, formal analysis, data curation, project administration. **Joseph M. Saito:** conceptualization, investigation, writing – original draft, methodology, writing – review and editing. **Keisuke Fukuda:** writing – review and editing, supervision. **Susanne Ferber:** funding acquisition, writing – review and editing, supervision, resources, software.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available at the Open Science Foundation at <https://osf.io/xghc2/>.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix A:** Behavioral analysis of target absent trials in Experiment 1. **Table S1:** Error rate means as percentages for target absent trials in Experiment 1. **Figure S1:** Behavioral results for target absent trials in Experiment 1. **Appendix B:** Behavioral analysis of target absent trials in Experiment 2. **Table S2:** Error rate means as percentages for target absent trials in Experiment 2. **Figure S2:** Behavioral results for target absent trials in Experiment 2. **Appendix C:** P170 amplitude analysis for Experiment 1. **Figure S3:** P170 results in Experiment 1. **Appendix D:** P170 amplitude analysis for Experiment 2. **Figure S4:** P170 results in Experiment 1.