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# Prior knowledge of category size impacts visual search

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**Abstract**

Prior research has shown that category search can be similar to one-item search (as measured by the N2pc ERP marker of attentional selection) for highly familiar, smaller categories (e.g., letters and numbers) because the finite set of items in a category can be grouped into one unit to guide search. Other studies have shown that larger, more broadly defined categories (e.g., healthy food) also can elicit N2pc components during category search, but the amplitude of these components is typically attenuated. Two experiments investigated whether the perceived size of a familiar category impacts category and exemplar search. We presented participants with 16 familiar company logos: 8 from a smaller category (social media companies) and 8 from a larger category (entertainment/recreation manufacturing companies). The ERP results from Experiment 1 revealed that, in a two-item search array, search was more efficient for the smaller category of logos compared to the larger category. In a four-item search array (Experiment 2), where two of the four items were placeholders, search was largely similar between the category types, but there was more attentional capture by nontarget members from the same category as the target for smaller rather than larger categories. These results support a growing literature on how prior knowledge of categories affects attentional selection and capture during visual search. We discuss the implications of these findings in relation to assessing cognitive abilities across the lifespan, given that prior knowledge typically increases with age.

**KEYWORDS**

categorization, N2pc, prior knowledge, visual search

## 1 | INTRODUCTION

There is a growing literature demonstrating that prior knowledge, in terms of long-term memory, impacts visual search (i.e., attentional selection) in interesting and meaningful ways (for a review, see Wu & Zhao, 2017). There are largely two types of effects that prior knowledge has on visual search—facilitation and interference. Research on category knowledge has been particularly consistent in demonstrating the duality of facilitation and interference: As items become more unitized, they also become more difficult to isolate.

In terms of facilitation, a number of studies have shown that searching for many related objects in a category can be similar to searching for a specific item, because all of the items in a category can be grouped into one unit (e.g., Nako, Wu, & Eimer, 2014; Nako, Wu, Smith, & Eimer, 2014; Wu et al., 2015; Wu, Pruitt, Runkle, Scerif, & Aislin, 2016). This "unit" can help guide visual search as an attentional template, a prioritized working memory representation (Olivers, Peters, Houtkamp, & Roelfsema, 2011; see also Robbins & Hout, 2015). Nako, Wu, and Eimer (2014) showed that the N2pc (an ERP marker of attentional selection) has a similar amplitude when searching for a specific target (e.g., a specific letter target) and a category of multiple targets (e.g., searching for any letter target) among distractors from another category (e.g., numbers). Nako and colleagues also showed that the N2pc amplitude decreased when category knowledge could not be applied to search for many items (e.g., searching for one of three letter targets among other letter distractors). In other words, neural search efficiency (N2pc amplitude and latency) is highest when searching for one target or a category of targets among distractors in another category, but becomes attenuated when category knowledge cannot be applied to discriminate between targets and distractors. These facilitation effects also are reflected in behavioral studies that have shown in general that search is faster and more accurate for items within the same category compared to items from different categories, especially when search becomes more difficult as the number of targets increases (Cunningham & Wolfe, 2014; Egeth, Jonides, & Wall, 1972; Karlin & Bower, 1976; Yang & Zelinksy, 2009).

In terms of interference, Nako, Wu, and Eimer (2014) also found that items related to the target (i.e., foils, which are items in the same category as the target object) induce attentional capture when searching for the target. For example, when searching for the letter *A*, there was obligatory attentional capture to the letter *G* when it appeared, because *A* and *G* are both letters. A recent N2pc study (Wu, Pruitt, Zinszer, & Cheung, 2017) found that increased real-world experience (dieting) with the search categories (healthy vs. unhealthy foods) predicted larger N2pc amplitudes on foil trials. The findings from that ERP study are in line with those from behavioral studies showing that objects of expertise, such as faces and cars, can capture attention, and that this effect scales with level of experience (McGugin, McKeeff, Tong, & Gauthier, 2011). Other behavioral studies have shown that objects that are semantically related to the target (e.g., a banana is semantically related to a monkey; De Groot, Huettig, & Olivers, 2016; see also Telling, Kumar, Meyer, & Humphreys, 2010, for N2pc evidence) or that share a similar known feature to the target (e.g., two street signs typically of the same color in the natural environment, even when the experimental stimuli are grayscale; Olivers, 2011) can capture attention in an obligatory manner.

Many of these visual search studies have employed categories that are familiar, easily learnable, easily distinguishable, and/or narrowly defined. Therefore, although a variety of categories have been shown to elicit an N2pc during category search (e.g., letters, numbers, faces, clothing, kitchen items, novel alien characters), it is unclear how the underlying category characteristics impact neural search efficiency (i.e., the N2pc amplitude and latency). A recent study (Wu, Pruitt et al., 2017) investigated the effect of searching for broad, subjective categories (healthy food vs. unhealthy food) on the N2pc amplitude and found that, although an N2pc could be elicited during category search, the component was heavily attenuated compared to N2pc amplitudes from prior category search studies with smaller, well-defined categories (e.g., letters and numbers; Nako, Wu, & Eimer, 2014). In other words, extrapolating from results between studies, it seems that smaller categories lead to higher neural search efficiency (i.e., higher N2pc amplitude and shorter latency), whereas larger categories lead to lower neural search efficiency. A recent study that used novel alien stimuli also suggests that smaller categories may elicit larger N2pc components compared to larger categories (Wu et al., 2016), although this idea was not explicitly tested in the study. One category contained 8 aliens as search targets, and only these 8 aliens were possible given the search rule. By contrast, the other category contained 8 other aliens as search targets, but 256 aliens were possible (but never made explicit) under a different search rule. The idea that smaller categories may lead to stronger N2pc components also is in line with the general finding that neural search efficiency increases with enhanced specificity of the target (for reviews, see Eimer, 2014; Olivers et al., 2011). A behavioral study found that search performance decreases with increasing category scope (and size), from subordinate to basic to superordinate categories (Maxfield & Zelinsky, 2012). However, in this study, the subordinate, basic, and superordinate categories differed not only in their size, but also in their perceptual similarity among items in the category. Differences in the perceptual similarity of items between search categories is an issue in studies comparing search for different categories, because it is easier to create a prototype template to guide search when items are perceptually similar within a category (e.g., using a canonical bear image to guide search for any bears) compared to when items are dissimilar within a category (e.g., difficulty in developing a prototype template to search for all types of mammals). Search is always more efficient when one can use a prototype search template compared to when one cannot, due to issues related to the specificity of the target. Another study using different types of categories (e.g., animals vs. artifacts) found that, when possible, participants rely on the perceptual differences between categories to complete the task (Levin, Takarae, Miner, & Keil, 2001; see also Long, Konkle, Cohen, & Alvarez, 2016). Because search is faster and more accurate when target similarity is high and when targets are distinct from distractors (e.g., Duncan & Humphreys, 1989), a study investigating whether prior knowledge of category size impacts search would require the use of stimuli that do not differ significantly between categories and do not allow for a prototype template.

Although it may seem intuitive that search would be more efficient for smaller categories compared to larger categories, visual search studies using the N2pc component have not yet confirmed this effect in a direct contrast. One N2pc study compared visual searches for a set of six single-digit numerals versus a set of 12 letters and did not find a difference in the amplitude of the N2pc (Wu et al., 2013). However, this study manipulated the number of items selected from each category in the search task, but it did not account for each category's size outside of the experimental paradigm. Both the numerals and letters were drawn from very small categories of 10 and 26 members, respectively, with very little ambiguity about the existence of novel items (such as new unfamiliar letters or numerals). Perhaps the finite nature and the small difference between these two categories masked a potential effect of prior knowledge of category size on visual search.

Confirming a category-size effect (as well as other effects due to prior knowledge) would be an important theoretical and methodological advance for visual search and, more broadly, attention research. First, such findings would indicate that performance on a visual search task does not only reflect knowledge-irrelevant (i.e., "fluid") cognitive abilities, but also the combination of short-term task demands with long-term representations. Even when less meaningful stimuli, such as colored shapes, are included to minimize the impact of knowledge on cognitive tasks, the resulting performance still may be dependent on the prior knowledge that underlies the simplified stimuli and task demands, and therefore may underestimate or overestimate fluid abilities with other objects, including more naturalistic objects (see Brady, Störmer, & Alvarez, 2016; Wu & Zhao, 2017). Methodologically, investigations into the impact of prior knowledge on visual search also would inform how different types of stimuli impact the study results at the group level and individual level, guiding how stimuli are selected and utilized in tasks based on their real-world significance (e.g., Orhan & Jacobs, 2014).

## 1.1 | The present study

In the present study, two experiments investigated whether the perceived size of a familiar category impacts category search, as well as exemplar search (i.e., searching for a specific target). Critically, differences in category size in these experiments were based only on participants' prior knowledge about the categories, rather than the number or properties of the specific experimental stimuli. We presented participants with 16 items: 8 logos from a smaller category (social media companies) and 8 logos from a larger category (manufacturers of popular entertainment and recreational products, hereafter, manufacturing company). Given prior research in separate studies demonstrating more efficient search for smaller categories (e.g., letters and numbers; Nako, Wu, & Eimer, 2014) compared to larger categories (healthy vs. unhealthy food; Wu, Pruitt et al., 2017), we hypothesized that search would be more efficient for the smaller category (social media logos) compared to the larger category (manufacturing company logos). Specifically, we predicted higher N2pc amplitudes, faster reaction times, and higher accuracy when searching for social media logos compared to searching for manufacturing logos. Given prior research in separate studies demonstrating larger task-irrelevant attentional capture for related items in smaller categories (e.g., Nako, Wu, & Eimer, 2014) compared to those in larger categories (e.g., Wu, Pruitt et al., 2017), we predicted that this effect would be pronounced in the foil N2pc components when searching for the smaller category.

# 2 | EXPERIMENT 1

## 2.1 | Method

### 2.1.1 | Participants

Eighteen participants ($M = 23.28$, $SD = 3.88$, 5 male, 13 female) were included in Experiment 1. An additional four participants were excluded: one participant was excluded due to excessive eye movements (> 50% of trials excluded due to horizontal eye movements), one participant was excluded due to low accuracy (< 75%) in the search task, and two participants were excluded due to low familiarity with the logos (naming accuracy < 62% for social media logos). All participants had normal or corrected-to-normal vision. Participants were recruited via campus flyers targeting undergraduate students from all majors, as well as the University of California, Riverside subject pool, which consists of undergraduate psychology students. All participants were compensated either with course credit (whenever possible) or \$10/hour (usually \$20–\$30 total).

### 2.1.2 | Stimuli

The black and white logo images included eight logos from a set of social media companies (smaller category: Facebook, Pinterest, Twitter, Vine, Snapchat, Instagram, Tumblr, YouTube) and eight logos from a set of manufacturers of entertainment and recreation products (hereafter, manufacturing—larger category: PlayStation, Beats, Adidas, Xbox, Disney, Windows, T-Mobile, Nike; Figure 1). These items were chosen due to their familiarity among undergraduate students in general. Eight items were included in each category to ensure that searching for either category involved the same number of task-specific targets and distractors. Throughout the experiment, the same stimulus sets were used across all trials, with only the instructions differing across tasks.

When selecting which stimuli to include, we ensured that each item from the social media logo category was visually similar to another item from the manufacturing logo category, to minimize pop-out effects. Specifically, we chose items that were similar in general size, shape, and/or complexity (e.g., Pinterest vs. Beats). The total number of black pixels between the categories did not differ significantly, $t(7) = .57$, $p = .584$.

All stimuli, subtending 3.58° × 3.58° (3.94° from the central fixation point), were presented on a 24" 60 Hz Dell monitor. The search array presented two black logos simultaneously, one on each side of a small black fixation point, on a white background (Figure 2).

### 2.1.3 | Familiarity and naming tasks

To confirm the participants' familiarity with the logos and to rule out familiarity as a confound for category size, all

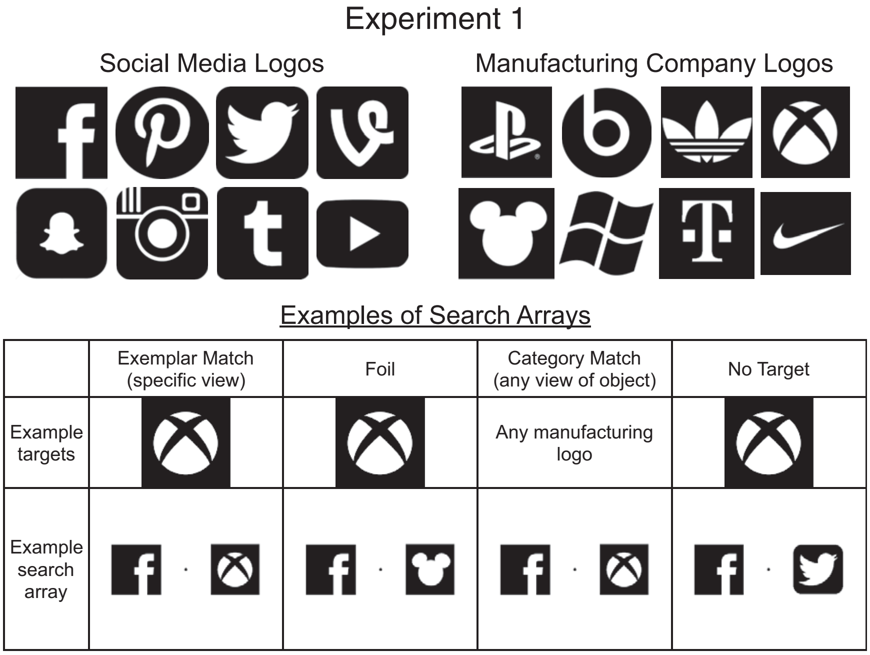


**FIGURE 1** Social media and manufacturing company logos used as search stimuli in Experiment 1 (top), and example search arrays from exemplar match, category match, foil, and no target trials (bottom)

participants completed a logo-naming task and a familiarity-rating task (in that order) prior to beginning the experiment. Both the naming and familiarity tasks were conducted on the experimental computer via E-Prime. In the naming task, participants verbally named each of the 16 logos as they were sequentially presented on the screen in a random order. At the onset of each naming trial (when the logo appeared), participants heard a beep indicating the start of the trial. Participants were instructed to name the logo as quickly and as accurately as possible. After the participants named the logo, the experimenter started the next trial. Naming responses were recorded on an iPhone app (Recorder Plus) for later timing analyses. To determine the naming reaction time, research assistants hand coded the data for beep onset times and the onset of the named logo. In the familiarity task, all 16 logos were again presented to participants sequentially, in

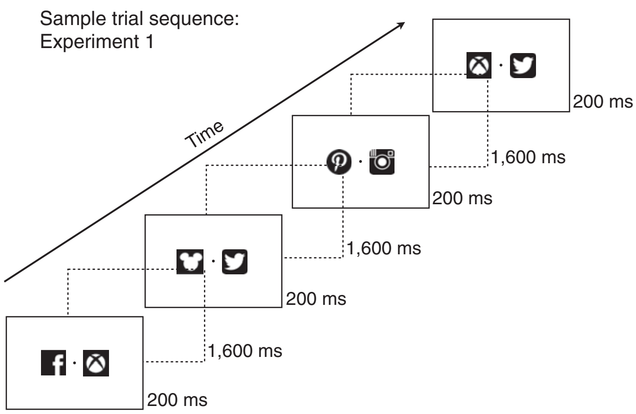


**FIGURE 2** Sample trial sequence from Experiment 1 during both exemplar search and category search tasks

a random order. In this task, participants were instructed to rate their familiarity with each logo on a scale from 1–5 (1 = *not familiar*, 5 = *very familiar*) using the number pad on a standard keyboard.

The results from both of these tasks indicated that the participants were highly familiar with all 16 logos, but slightly more familiar with the 8 manufacturing logos compared to the 8 social media logos. Only participants who accurately named 5 or more of 8 logos in both social media and manufacturing categories (i.e., more than 50% per category) were included in the final analyses. Two participants were excluded based on this criterion. Participants' accuracy when naming manufacturing logos ($M = .90$, $SD = .12$) was significantly higher than their accuracy when naming social media logos ($M = .79$, $SD = .15$; $t(17) = 2.95$, $p = .009$). Reaction times were numerically faster for identifying manufacturing logos ($M = 1.33$ s, $SD = .35$) compared to social media logos ($M = 1.47$ s, $SD = .41$), but this difference was not significant, $t(17) = 1.38$, $p = .184$. Although participants rated manufacturing logos as slightly more familiar ($M = 4.25$, $SD = .56$) than social media logos ($M = 4.02$, $SD = .65$), this difference also was not significant, $t(17) = 1.66$, $p = .116$.

### 2.1.4 | Design and procedure

Experiment 1 consisted of four visual search tasks: two exemplar search tasks (search for a specific social media logo and a specific manufacturing logo) and two category search tasks (search for any item from the social media logo category and from the manufacturing logo category). The task order for category and exemplar search was counterbalanced via a Latin square. For example, one participant may have received the following order: social media exemplar search, manufacturing category search, social media category search, manufacturing exemplar search, whereas another may have received the following order: manufacturing category search, social media exemplar search, social media category search, manufacturing exemplar search. Approximately half of the participants completed an exemplar search task prior to a category search task.

Both exemplar and category search tasks comprised six blocks each. The six blocks in each of the two exemplar search tasks included a total of 168 exemplar match trials (the specific target logo was presented on one side of the fixation point and a logo from the nontarget category was presented on the other side), 168 foil trials (one logo was from the target's category but was not the target and the other logo was from the nontarget category), and 36 no exemplar target trials (both logos presented were from the nontarget category). In each of the six exemplar search blocks, there were 28 exemplar match trials, 28 foil trials, and 6 no exemplar target trials. In the category search tasks, participants were instructed that either any of the eight manufacturing logos or any of the eight social media logos were their targets for the duration of that task. The six blocks in each of the two category search tasks included a total of 168 category match trials (any logo from the target category appeared on one side, while a logo from the nontarget category appeared on the other side) and 168 no category target trials (only logos from the nontarget category appeared). In each of the six category search blocks, there were 28 category match trials and 28 no category target trials. For each of the four search tasks, the target was held constant throughout the six blocks of the task. Participants completed a total of 1,416 trials during the EEG experiment. This design is similar to that from Wu et al. (2016).

The logos were presented on the left and right side of a black fixation dot on a white screen for 200 ms, followed by a 1,600-ms interstimulus interval displaying the white screen with only the fixation dot. Participants were instructed to fixate on the dot for the duration of the experiment, and to search for targets via their peripheral vision. Participants were told to press the left arrow key when a target was present, and the right arrow key when the target was absent. Approximately half of the trials required a "target present" response, and half required a "target absent" response. Participants could respond within the 1,800-ms time window from the onset of the array to the onset of the next array, and were instructed to respond as quickly and as accurately as possible.

### 2.1.5 | EEG recording and data preparation

Following prior studies (Wu et al., 2015, 2016; Wu, Pruitt et al., 2017), the EEG data were DC-recorded from 32 scalp electrodes at standard positions of the extended 10/20 system

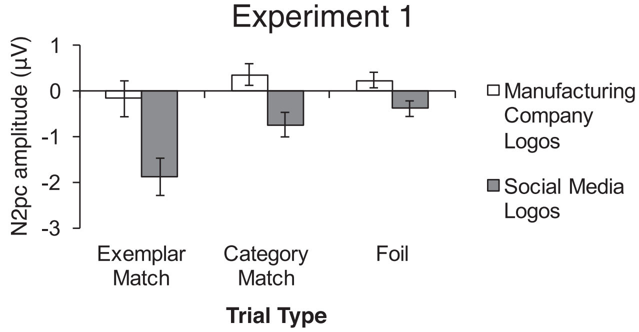


**FIGURE 3** N2pc mean amplitudes from exemplar match, category match, and foil trials in Experiment 1 for social media and manufacturing company logos. Error bars represent ± 1 *SE*

using a 500 Hz sampling rate. Offline, we applied a 40 Hz Butterworth zero phase IIR low-pass filter (48 dB/octave) and a 0.1 Hz high-pass filter (12 dB/octave), in addition to a 60 Hz notch filter, after rereferencing to averaged earlobes. Epochs were created from −100 ms to 500 ms relative to the onset of the search target, and a 100-ms prestimulus baseline was applied to these epochs. Artifact rejection criteria included horizontal electrooculogram (EOG) exceeding ± 25 μV, vertical EOG exceeding ± 60 μV, and all other channels exceeding ± 80 μV. These criteria were applied to the waveforms from −100 ms to 300 ms poststimulus onset. In addition, only correct trials were used in the ERP analyses. After eye-movement artifact rejection, we retained 81.29% of all correct trials on average per participant. The time window used to determine the mean N2pc amplitude was 200–320 ms poststimulus onset at lateral posterior electrodes PO7 and PO8. Neural search efficiency was operationally defined as mean N2pc amplitude in the present study. Latency measures were not conducted in the present study, because they may be difficult to determine and unreliable when N2pc amplitudes are below −1 μV, as is often the case when searching for large categories (e.g., Wu, Pruitt et al., 2017).

### 2.1.6 | Perceived category size

Following the EEG experiment, participants were asked to estimate how many companies existed for each of the categories that they had viewed. We $\log_{10}$-transformed their responses, and the reported statistics were performed on these log values. Every participant ($N = 18$) reported that the manufacturing category ($M = 4.07$, $SD = 1.96$) was much larger than the social media category ($M = 1.90$, $SD = .77$), paired $t(17) = 5.96$, $p < .001$, although the participants varied in their estimate of the magnitude of this difference.

## 2.2 | Results

To investigate whether prior knowledge of category size impacts visual search, we analyzed target present trials (exemplar match

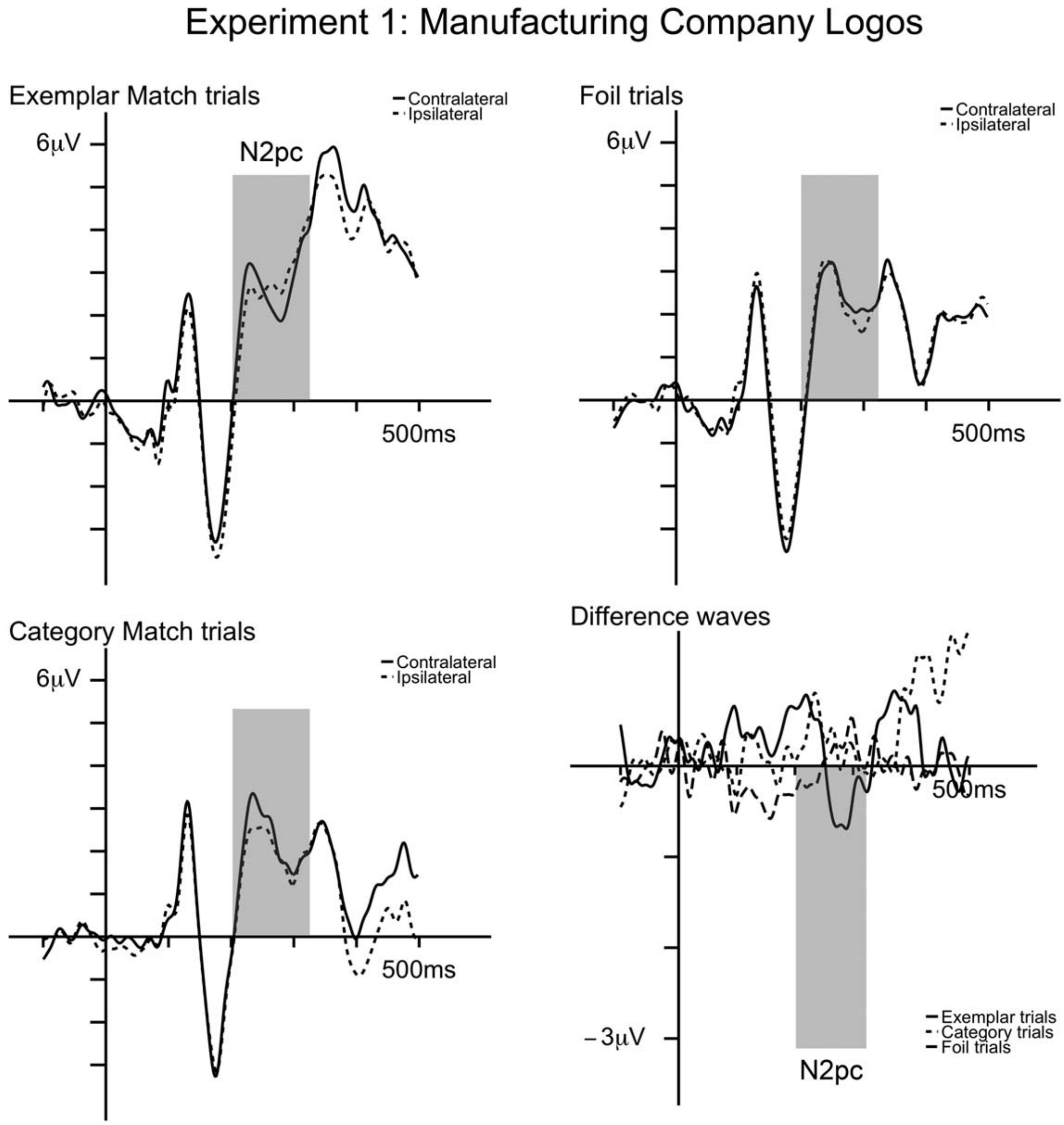


**FIGURE 4** Grand-averaged ERPs from Experiment 1 elicited when searching for manufacturing company logos during exemplar match, category match, and foil trials from electrodes PO7/8 contralateral and ipsilateral to the target. The N2pc difference waveforms result from subtracting ipsilateral from contralateral ERP waveforms at PO7/8 electrodes

and category match trials), as well as target absent trials (foil trials, no exemplar target trials, and no category target trials). The EEG data from the no target trials were not analyzed because N2pc analyses require referencing a target or foil to specify ipsilateral/contralateral electrodes for each trial.

### 2.2.1 | EEG data

A 2 (Company Type: manufacturing vs. social media) × 3 (Trial Type: exemplar match, category match, foil) repeated measures analysis of variance (ANOVA) revealed a main effect of company type, $F(1, 17) = 16.40$, $p = .001$, $\eta^2 = .49$, where mean N2pc amplitudes were larger when searching for social media logos ($M = -1.00$, $SE = .21$) compared to manufacturing logos ($M = .14$, $SE = .12$). There was also a main effect of trial type, $F(2, 34) = 4.50$, $p = .018$, $\eta^2 = .21$, and a marginal interaction between company type and trial type, $F(2, 34) = 3.17$, $p = .055$, $\eta^2 = .16$ (Figure 3–5).

To investigate the marginal interaction, separate Bonferroni-corrected paired comparisons (corrected alpha = .05/3 = .017) were conducted to compare company type for each trial type. Compared to manufacturing logos, social media logos elicited larger N2pc components during exemplar match trials, $t(17) = 3.72$, $p = .002$, and category match trials, $t(17) = 2.80$, $p = .012$. There was a marginal effect for foil trials, $t(17) = 2.40$, $p = .028$.

#### Presence of the N2pc

To determine whether the prior analyses were conducted on valid N2pc components, we conducted Bonferroni-corrected

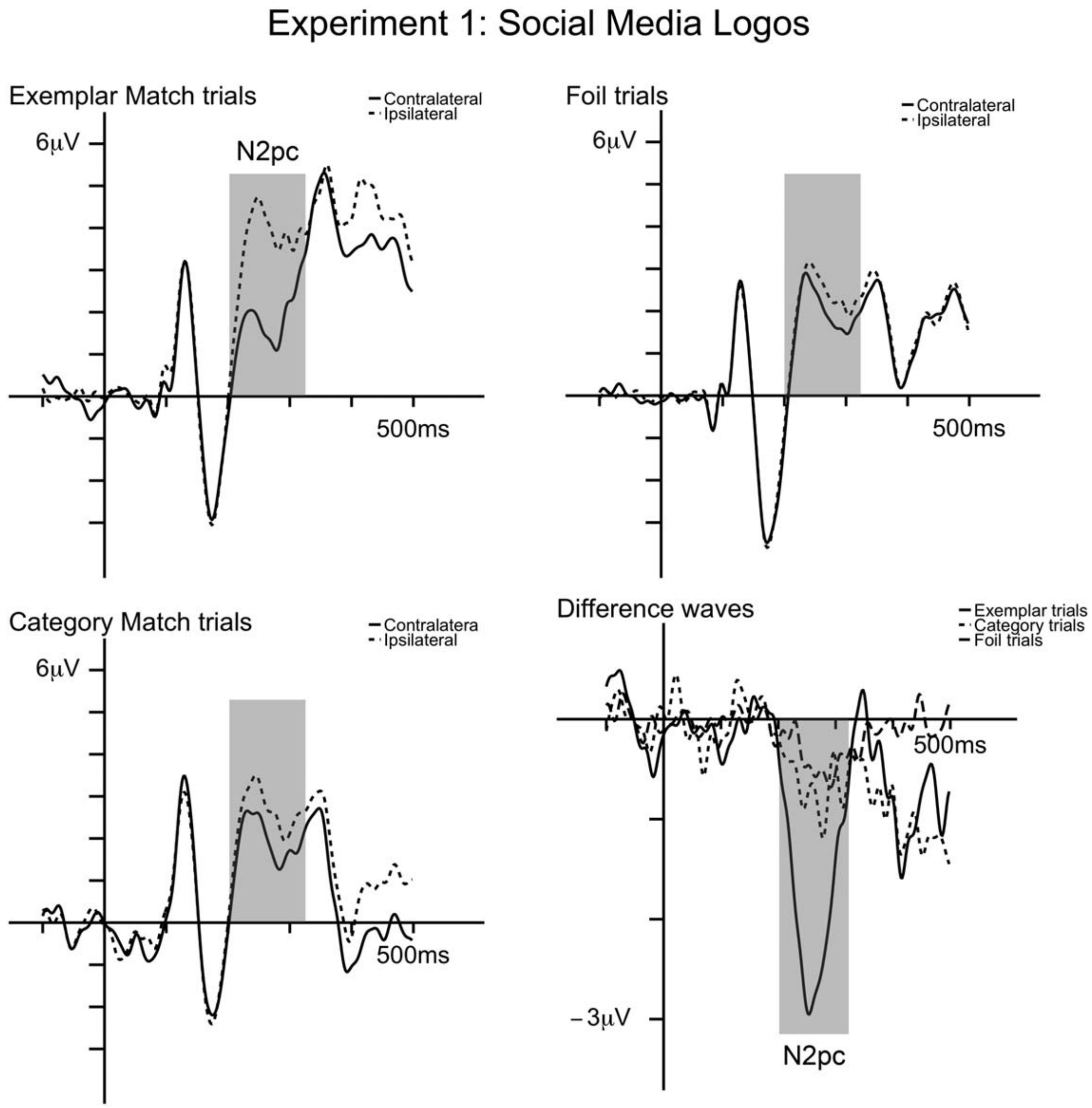


**FIGURE 5** Grand-averaged ERPs from Experiment 1 elicited when searching for social media logos during exemplar match, category match, and foil trials from electrodes PO7/8 contralateral and ipsilateral to the target. The N2pc difference waveforms result from subtracting ipsilateral from contralateral ERP waveforms at PO7/8 electrodes

one-sample *t* tests on each trial type (corrected alpha = .05/3 = .017) to determine the presence of the N2pc. There were significant N2pc components when searching for social media logos during exemplar match trials, $t(17) = 4.49$, $p < .001$, category match trials, $t(17) = 2.85$, $p = .011$, and a marginally significant N2pc component on foil trials, $t(17) = 2.26$, $p = .037$. By contrast, there were no significant N2pc components when searching for manufacturing company logos, $|t| < 1.52$.

### 2.2.2 | Behavioral results

A 2 (Company Type: manufacturing vs. social media) × 5 (Trial Type: exemplar match, category match, foil, no exemplar target, no category target) repeated measures ANOVA on accuracy and reaction time revealed a main effect of trial type for accuracy, $F(4, 68) = 23.67$, $p < .001$, $\eta^2 = .58$, and reaction time, $F(4, 68) = 98.73$, $p < .001$, $\eta^2 = .85$, and no other main effects or interactions, $F < 1.09$ (Figure 6).

To investigate the main effect of trial type for accuracy, following prior studies (Wu et al., 2015, 2016; Wu, Pruitt et al., 2017), we conducted separate analyses on target present trials (exemplar match vs. category match) and target absent trials (foil vs. no exemplar target vs. no category target) collapsed across company type. Similar to previous studies (Wu et al., 2015, 2016; Wu, Pruitt et al., 2017), exemplar match trials had higher accuracy ($M = .95$, $SE = .01$) than category match trials ($M = .88$, $SE = .02$), $t(17) = 5.56$, $p < .001$, which is not surprising given that exemplar search is an easier task than category search. Using Bonferroni-corrected comparisons (corrected alpha = .05/3 = .17), foil

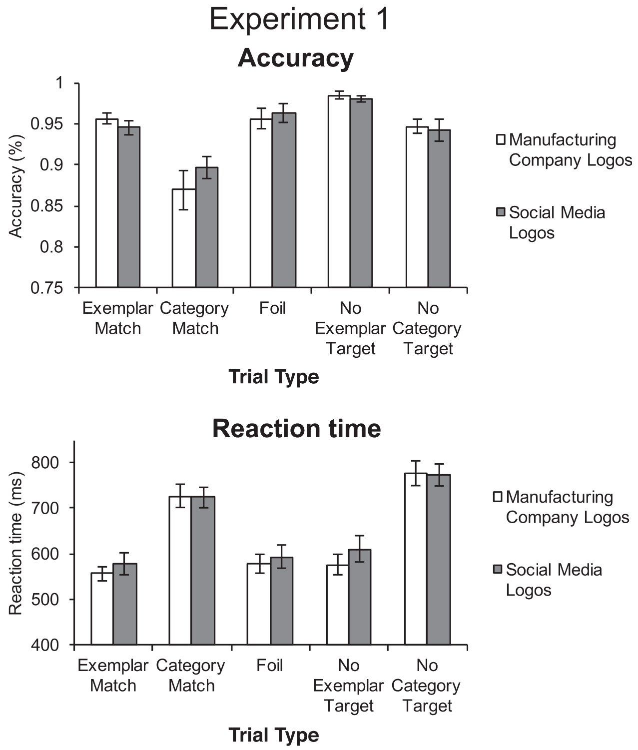


**FIGURE 6** Behavioral results from Experiment 1 for reaction time and accuracy when searching for social media and manufacturing company logos. Error bars represent ± 1 *SE*

trials had lower accuracy ($M = .96$, $SE = .01$) compared to no exemplar target trials ($M = .98$, $SE = .004$), $t(17) = 2.74$, $p = .014$, but not when compared to no category target trials ($M = .94$, $SE = .01$), $t(17) = 1.41$, $p = .176$. No exemplar target trials had higher accuracy compared to no category target trials, $t(17) = 4.40$, $p < .001$.

Probing the main effect of trial type for reaction time, we found that, similar to the accuracy results, exemplar match trials had faster reaction times ($M = 567.27$, $SE = 19.25$) than category match trials ($M = 725.56$, $SE = 21.55$), $t(17) = 11.72$, $p < .001$. Using Bonferroni-corrected comparisons (corrected alpha = .05/3 = .17), foil trials had faster reaction times ($M = 585.60$, $SE = 22.33$) compared to no category target trials ($M = 774.34$, $SE = 23.36$), $t(17) = 10.77$, $p < .001$, but not when compared to no exemplar target trials ($M = 593.31$, $SE = 24.65$), $t(17) = 1.87$, $p = .080$. No exemplar target trials had faster reaction times compared to no category target trials, $t(17) = 9.95$, $p < .001$.

## 2.3 | Discussion

The ERP (N2pc) results support our overall hypothesis that prior knowledge about category size impacts visual search. We found a main effect of company type based on the N2pc data, and Bonferroni-corrected comparisons on these data revealed larger N2pc amplitudes when searching for social media targets rather than manufacturing targets during exemplar match and category match trials. By contrast, the behavioral data revealed no such differences between company type, only differences between trial type, suggesting that searching for logos from either category was similar in difficulty.

We encountered the unexpected finding that there was no N2pc component when searching for manufacturing logos, not even for exemplar match trials, although there were significant N2pc components when searching for social media logos. Because we used a within-subject design, we knew that the participants were capable of generating N2pc components. And because the participants had relatively high accuracy and fast reaction times in general, we knew that the participants completed the task well. However, it was unclear based on the data why the participants on average did not exhibit an N2pc component during exemplar match trials for manufacturing logos, especially given their slightly greater familiarity with the manufacturing logos and their behavioral data demonstrating their ability to complete the manufacturing search task in a similar manner as the social media search task. This finding is unexpected given decades of research demonstrating the existence of the N2pc when searching for one item since the component was discovered by Luck and Hillyard (1994), even in a two-item array (e.g., Eimer, 1996; Wu et al., 2015, 2016; Wu, Pruitt et al., 2017). Further inspection of the ERP data from the manufacturing logo trials revealed that 11 out of 18 participants had a typical N2pc component (negative component) during exemplar match trials, whereas 7 had a positive component (i.e., selection of the distractor) in the same time window. The participants producing a positive component may have attended first to the distractor stimulus, which could be used in a rapid process of elimination strategy to complete the task (i.e., first identifying a social media logo distractor on the opposite side of the target, and then switching attention to the manufacturing logo target). However, this explanation was not supported by our behavioral analyses, which perhaps would have revealed slower behavioral responses on manufacturing compared to social media trials. Moreover, it is difficult to justify why participants would exhibit this strategy during search for manufacturing logos, but not for social media logos.

The results from the familiarity and naming tasks showed a slight difference between the categories in naming accuracy, with the manufacturing company logos being named more accurately than the social media logos, but neither the naming response time nor the familiarity ratings differed between the two categories. Previous N2pc research has generally shown that amplitude is high for familiar stimuli (e.g., Nako, Wu, & Eimer, 2014; Nako, Wu, Smith, & Eimer, 2014; Wu et al., 2013, 2015). Therefore, it is very unlikely that participants' slightly greater recognition of the manufacturing logos would be the cause for a decrease in the

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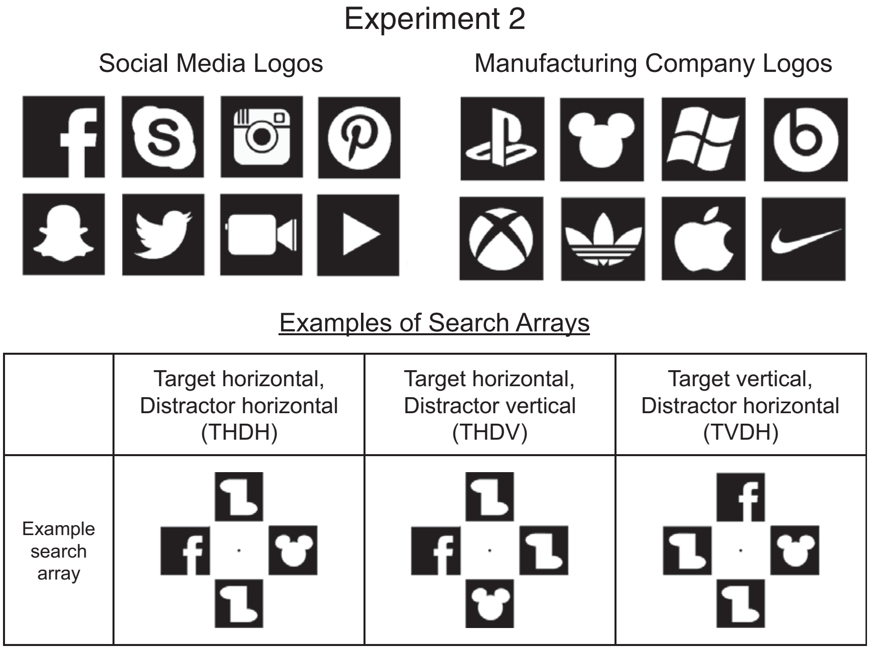


**FIGURE 7** Social media and manufacturing company logos used as search stimuli in Experiment 2 (top), and example search arrays from exemplar match, category match, foil, and no target trials (bottom)

amplitude of the corresponding N2pc in this study. Alternatively, our measure of familiarity may not have been adequate to detect subtle differences in familiarity between the social media and manufacturing categories. In addition, some of the logos (mostly social media logos) were not well recognized by the participants, possibly weakening the role of prior knowledge on the visual search task. These issues are addressed in Experiment 2.

Finally, although we aimed to minimize differences between the stimuli between categories, the social media logos naturally tended to have rounded corners, while the manufacturing logos tended to have sharper corners. However, we had no a priori reason to expect that either rounded corners or sharper corners would facilitate search for one of the categories over another. To minimize this difference between categories, we placed all of the stimuli on a black square background for Experiment 2.

# 3 | EXPERIMENT 2

## 3.1 | Method

In Experiment 2, we eliminated other possible causes of the decreased N2pc amplitudes that we observed in Experiment 1 to isolate the effects of the impact of prior knowledge of category size on neural search efficiency. In order to control for the target-first versus distractor-first search strategies, the visual search task in this experiment used a four-item array, where two of the items were on the vertical and two were on the horizontal. Given the contralateral nature of the N2pc, this "cross" design with placeholders allowed us to isolate the N2pc to the target logo when the target logo was on the horizontal and the distractor logo was on the vertical, and vice versa (cf. Eimer & Grubert, 2014; Eimer, Kiss, & Nicholas, 2011). To avoid increasing the difficulty in an already very challenging task, we included two logo stimuli and two identical placeholder stimuli (Figure 7) on every trial. We expected that social media logos would still elicit larger N2pc components compared to manufacturing logos, while addressing the previous issues related to distractor selection strategies via the four-item array.

### 3.1.1 | Participants

Twenty participants (age: $M = 19.20$, $SD = 1.01$; 10 male, 10 female) comprised the final sample in Experiment 2. An additional two participants were excluded due to low accuracy on the behavioral naming survey. All participants had normal or corrected-to-normal vision. Participants were recruited in the same manner as Experiment 1 and were either compensated with course credit or $10/hr for their time.

### 3.1.2 | Stimuli

Experiment 2 replaced the least familiar logos from Experiment 1 with more familiar logos. Indeed, Vine was a social media company that was disbanded by Twitter while Experiment 2 was being conducted. From the social media category, Tumblr and Vine were replaced with FaceTime and Skype. From the manufacturing category, T-Mobile was replaced with Apple. In the end, the black and white logo images included eight social media logos (Facebook, Skype, Instagram, Pinterest, Snapchat, Twitter, FaceTime, YouTube) and eight manufacturing logos (PlayStation, Disney, Windows, Beats, Xbox, Adidas, Apple, Nike) on a uniform black square background (Figure 7). As with Experiment 1, we ensured that each item from the social media logo category was visually similar to another item in the manufacturing logo category, to minimize pop-out effects. The total number of black pixels between the categories did not differ significantly, $t(7) = .35$, $p = .736$.

In addition to the company logos, one placeholder image was presented on every trial in two out of four locations. The other two locations contained logos. This placeholder image was a novel white shape displayed on a square black background and was visually similar in general to the black and white logos (to minimize pop-out effects), but it clearly was not a logo that could be a target or distractor. The number of black pixels in the placeholder image (1.66E+5 pixels) was similar to the average number of black pixels in the social media logos ($M$ = 1.77E+5 pixels, $SD$ = 2.13E+4) and manufacturing logos ($M$ = 1.75E+5 pixels, $SD$ = 2.97E+4). The search array, presented on a white background, included two black and white logos and two black and white placeholder images in a cross configuration centered around a small black fixation point. All stimuli, subtending $2.51° \times 2.51°$ (3.04° from the fixation point), were presented on the same monitor as that from Experiment 1.

#### 3.1.3 | Familiarity and naming tasks

As in Experiment 1, all participants completed a familiarity and naming task. The results from both of these tasks indicated that the participants were highly familiar with these logos, and slightly more familiar with the manufacturing logos than the social media logos.

The naming task presented the logos in a random sequence and required the participants to verbally name each of the 16 logos on the screen. Only participants who accurately named five or more out of eight logos (i.e., more than 50%) for both social media and manufacturing categories were included in the final analyses. Two participants were excluded based on this criterion. Similar to Experiment 1, participants' accuracy when naming manufacturing logos ($M = .96$, $SD = .06$) was significantly higher than their accuracy when naming social media logos ($M = .87$, $SD = .09$), $t(19) = 4.77$, $p < .001$. The naming accuracy for both categories numerically increased from Experiment 1, especially for social media companies. Reaction times did not differ significantly between manufacturing logos ($M = .92$ s, $SD = .21$) and social media logos ($M = 1.00$ s, $SD = .25$), $t(19) = 1.15$, $p = .266$.

The familiarity task from Experiment 2 was similar to that from Experiment 1, but it included a larger scale, 1–9 (1 = *not familiar*, 9 = *very familiar*), because the familiarity ratings in Experiment 1 appeared to be limited by a ceiling effect, with ratings clustered between the top two values on the scale. There was no significant difference in familiarity ratings between the manufacturing logos ($M = 7.34$, $SD = 1.55$) and social media logos ($M = 7.08$, $SD = 1.05$), $t(19) = 1.07$, $p = .297$, similar to Experiment 1.

#### 3.1.4 | Design and procedure

Following Experiment 1, Experiment 2 consisted of four visual search tasks (six blocks each): two exemplar search tasks (search for a specific social media logo and a specific manufacturing logo) and two category search tasks (search for any item from the social media logo category and from the manufacturing logo category). The task order for category and exemplar search was counterbalanced via a Latin square, as in Experiment 1.

To maximize the number of trials that could be included in the N2pc analyses, Experiment 2 did not include any no target trials for either the exemplar search or category search tasks. Therefore, there were only three trial types in Experiment 2: exemplar match, category match, and foil. For each of these trial types, the logos and placeholders were presented on the left, right, top, and bottom of a black fixation dot on a white screen. Therefore, each of these trial types had one of three configurations: Configuration 1—target on the horizontal, distractor on the horizontal (THDH); Configuration 2—target on the horizontal, distractor on the vertical (THDV); and Configuration 3—target on the vertical, distractor on the horizontal (TVDH). THDH resembled the format of the trials from Experiment 1, and we predicted that this configuration would similarly attenuate the N2pc amplitude to the target if participants also attended to the distractor. THDV isolated the N2pc component to the target, because N2pc components cannot be elicited by items in the vertical positions, in this case, the distractor. We used this configuration to reduce any effect of a distractor-first strategy that was a possibility in Experiment 1, by eliminating the influence of the distractor on the resulting N2pc. TVDH isolated the N2pc to the distractor to determine if participants were indeed selecting the distractor prior to a target, especially in the manufacturing logo search trials. However, no conclusions can be drawn about the N2pc to the target in this configuration. We predicted that THDV trials would elicit larger N2pc components compared to THDH trials, and that TVDH trials would elicit a smaller or nonexistent N2pc component, given prior studies demonstrating the usefulness of this configuration in isolating the N2pc to the target (e.g., Eimer & Grubert, 2014).

Because the exemplar search tasks included both exemplar match trials (target present) and foil trials (target absent), in these tasks, participants were instructed to press the Shift key on the left side of a standard keyboard if they determined that the target was not present (i.e., in foil trials). If they determined that the target was present, the participants were to indicate its location using the arrow keys on a standard keyboard (left, right, up, down arrows). Because all category search trials included a target, participants were instructed to indicate the target's location in these trials.

Across six blocks, each of the two exemplar search tasks consisted of 72 exemplar match trials for each of the trial configurations (216 THDH, 216 THDV, 216 TVDH) and 72 foil trials (216 for each of the three configurations). In the category search tasks, there were 144 category match trials for each of the trial configurations (432 total category match trials). For each of the four search tasks, the target was held constant throughout the six blocks of the task. Participants completed a total of 1,728 trials during the EEG experiment. All other procedures followed those from Experiment 1.

### 3.1.5 | EEG recording and data preparation

The recording and data preparation procedures followed those from Experiment 1. After eye-movement artifact rejection, we retained 83.21% of all correct trials on average per participant.

### 3.1.6 | Perceived category size

As in Experiment 1, following the EEG experiment, participants were asked to estimate how many companies existed for each of the categories, and their estimates were $\log_{10}$-transformed prior to computing the statistics. Every participant ($N = 20$) reported that the manufacturing category ($M = 5.34$, $SD = 1.58$) contained more companies than the social media category ($M = 4.18$, $SD = 1.58$), paired $t(17) = 4.91$, $p < .001$, although the participants varied in their estimate of the magnitude of this difference. Notably, this difference (1.16) is smaller for Experiment 2 compared to Experiment 1 (difference = 2.17), $F(1, 36) = 5.60$, $p = .023$, $\eta^2 = .14$. Participants in Experiment 2 reported much larger category sizes for social media categories compared to participants in Experiment 1, $t(36) = 5.53$, $p < .001$, and only somewhat larger sizes for manufacturing companies, $t(36) = 2.21$, $p = .034$. The difference in size estimates between experiments may have been due to the inclusion of a wider variety of social media logos (e.g., including Skype and FaceTime logos).

## 3.2 | Results

### 3.2.1 | EEG results

To investigate the effect of the distractor location on the target N2pc, we can only analyze THDH and THDV trials, since no target N2pc can be measured from TVDH trials. A 2 (Company Type: manufacturing vs. social media) × 3 (Trial Type: exemplar match, category match, foil) × 2 (Distractor Location: THDH, THDV) repeated measures ANOVA revealed a main effect of distractor location, $F(1, 19) = 15.59$, $p = .001$, $\eta^2 = .45$, where THDV trials elicited larger N2pc components ($M = -.96$, $SD = .65$) compared to THDH trials ($M = -.38$, $SD = .65$). There was also a main effect of trial type, $F(2, 38) = 12.58$, $p < .001$, $\eta^2 = .40$, and a marginal interaction between company type and trial type, $F(2, 38) = 3.04$, $p = .060$, $\eta^2 = .14$. (Figure 8–10) There were no other main effects or interactions, $F < 2.14$.

To investigate the main effect of trial type, we collapsed company type and distractor location to conduct Bonferroni-corrected comparisons (corrected alpha = .05/3 = .017) on the trial types. Exemplar match trials elicited larger N2pc components ($M = -1.40$, $SD = 1.36$) compared to category match trials ($M = -.40$, $SD = .51$) and foil trials ($M = -.21$, $SD = .37$), $t(19) > 3.35$, $p \leq .003$, and foil and category match trials did not differ from each other, $t(19) = 1.46$, $p = .161$.

To investigate the marginal interaction between company type and trial type, we collapsed across distractor location and conducted Bonferroni-corrected comparisons (corrected alpha = .05/3 = .017) on company type for each trial type. We found that the foil trials were larger when searching for social media logos ($M = -.56$, $SD = .74$) compared to searching for manufacturing logos ($M = .14$, $SD = .63$), $t(19) = 2.69$, $p = .015$. The N2pc components from exemplar match and category match trials did not differ between company type, $|t| < 1.35$.

We conducted Bonferroni-corrected comparisons (corrected alpha = .05/3 = .017) to test our hypothesis that social media logos would elicit larger N2pc components compared to manufacturing logos on THDV trials for all trial types. We found that the social media foil THDV trials had larger N2pc components ($M = -.82$, $SD = .77$) compared to manufacturing foil THDV trials ($M = .01$, $SD = .79$), $t(19) = 2.93$, $p = .009$, but the other trial types did not differ based on company type, $|t| < 1.27$.

#### Presence of the N2pc

We conducted Bonferroni-corrected one-sample $t$ tests on each trial configuration for both social media and manufacturing logos (corrected alpha = .05/6 = .008) separately for each trial type to determine the presence of the N2pc. For exemplar match trials, there were significant N2pc components for THDV and TVDH trials when searching for both social media and manufacturing logos, $t(19) > 3.71$, $p < .002$, and marginal N2pc components for THDH trials for manufacturing logos, $t(19) = 2.44$, $p = .024$, and social media logos, $t(19) = 1.93$, $p = .069$. For category match trials, there were significant N2pc components for THDV and

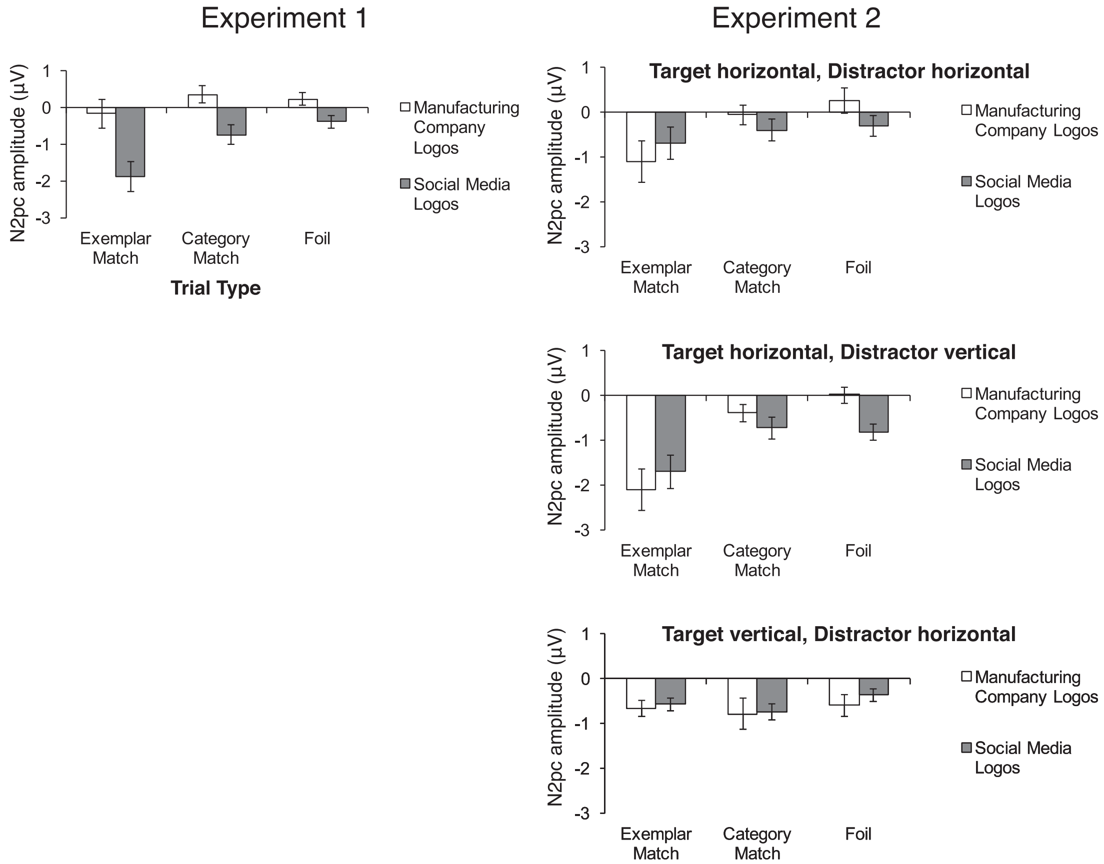


**FIGURE 8** N2pc mean amplitudes from exemplar match, category match, and foil trials (split by trial configuration) in Experiment 2 for social media and manufacturing company logos. Experiment 1 results are included for comparison with Experiment 2 Target horizontal, Distractor horizontal. Error bars represent ± 1 *SE*

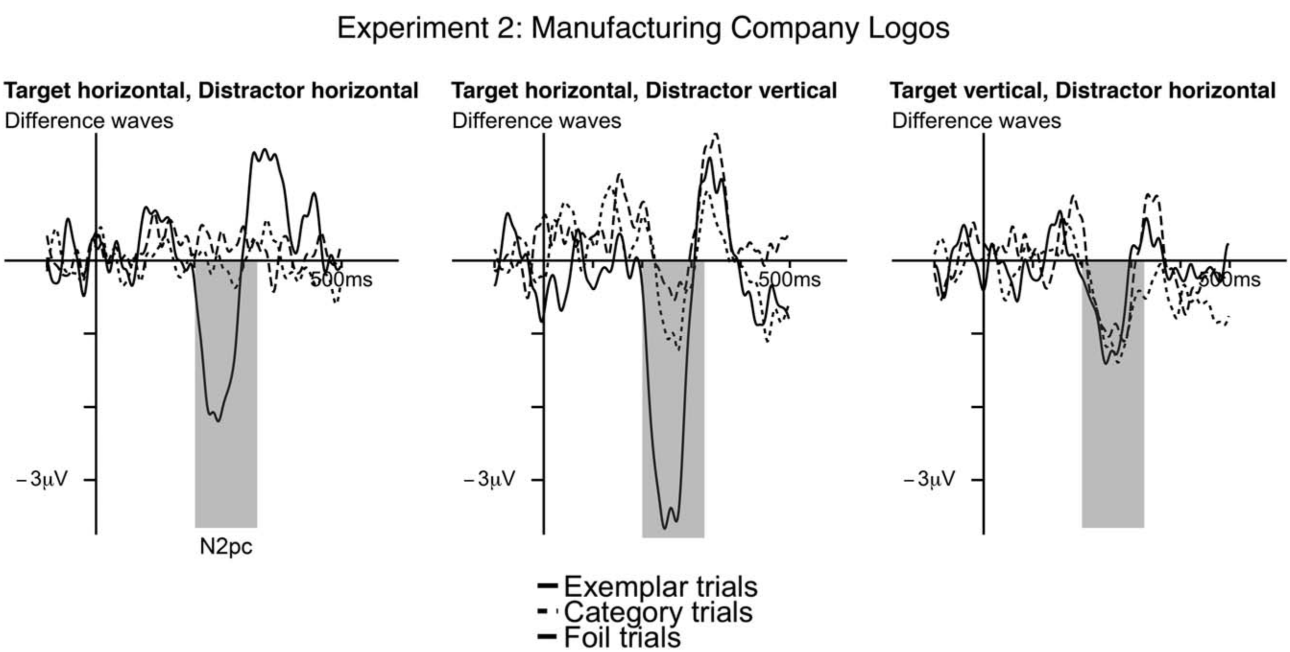


**FIGURE 9** Grand-averaged ERPs from Experiment 2 elicited when searching for manufacturing company logos during exemplar match, category match, and foil trials separated by trial configuration. The N2pc difference waveforms result from subtracting ipsilateral from contralateral ERP waveforms at PO7/8 electrodes

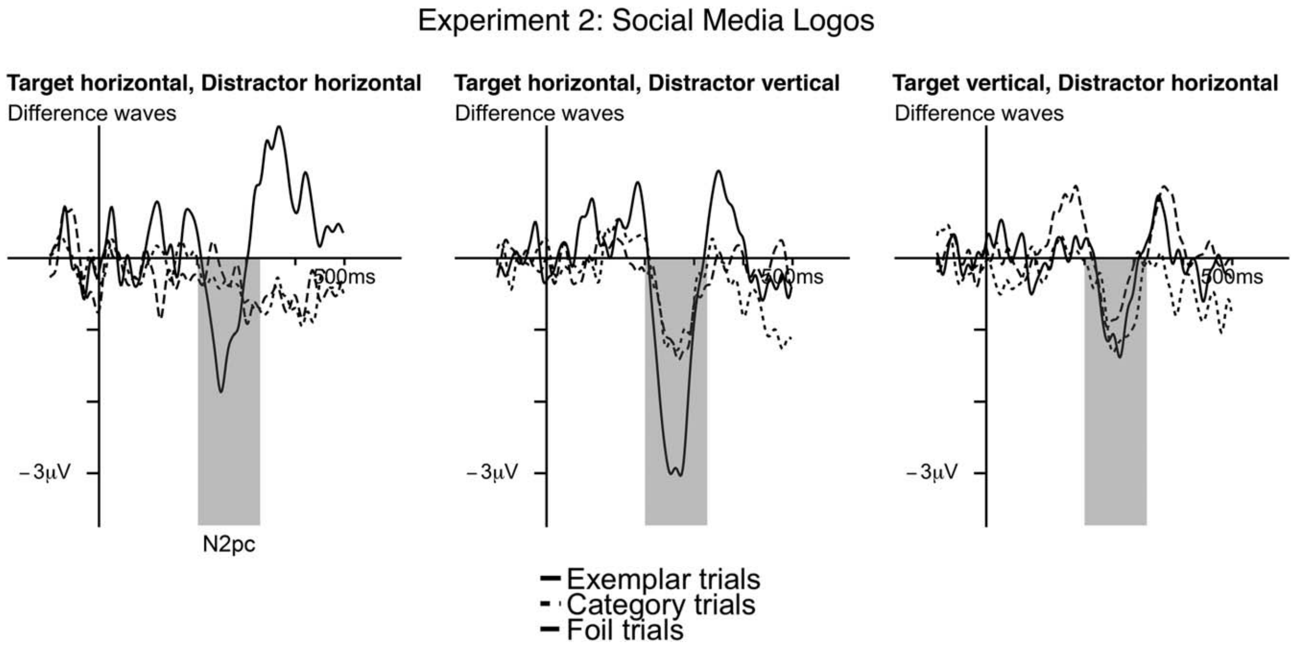


**FIGURE 10** Grand-averaged ERPs from Experiment 2 elicited when searching for social media logos during exemplar match, category match, and foil trials separated by trial configuration. The N2pc difference waveforms result from subtracting ipsilateral from contralateral ERP waveforms at PO7/8 electrodes

TVDH trials when searching for social media logos, $t(19) > 3.04$, $p < .008$, and marginal N2pc components for THDV and TVDH trials when searching for manufacturing logos, $t(19) = 1.99$ and 2.27, $p = .062$ and .035, respectively. For foil trials, there was a significant N2pc component on THDV trials when searching for social media logos, $t(19) = 4.76$, $p < .001$, and marginal N2pc components for TVDH trials for social media and manufacturing logos, $t(19) = 2.41$ and 2.49, $p = .026$ and .022, respectively. There were no other significant N2pc components, $|t| < 1.68$.

### 3.2.2 | Behavioral results

Because the different trial configurations only were relevant for the ERP analyses, we did not include them in the behavioral analyses. Following the behavioral analyses from Experiment 1, a 2 (Company Type: manufacturing vs. social media) × 3 (Trial Type: exemplar match, category match, foil) repeated measures ANOVA revealed a main effect of company type on accuracy, $F(1, 19) = 21.06$, $p < .001$, $\eta^2 = .53$, where manufacturing company logos elicited higher accuracy ($M = .95$, $SD = .004$) compared to social media logos ($M = .93$, $SD = .004$; Figure 11). Reaction time did not differ based on company type, $F(1, 19) = .25$. There was a main effect of trial type on accuracy, $F(1, 19) = 90.69$, $p < .001$, $\eta^2 = .83$, and on reaction time, $F(2, 38) = 149.80$, $p < .001$, $\eta^2 = .89$. Finally, there was an interaction between the two for accuracy, $F(2, 38) = 28.13$, $p < .001$, $\eta^2 = .60$, but not for reaction time, $F < .50$.

To investigate the main effect of trial type for accuracy, we conducted Bonferroni-corrected paired comparisons (corrected alpha = .05/3 = .017) collapsed by company type. Exemplar match trials ($M = .98$, $SE = .003$) and foil trials ($M = .96$, $SE = .006$) had higher accuracy compared to category match trials ($M = .88$, $SE = .007$), $|t|(19) > 8.75$, $p < .001$. Exemplar match trials had marginally higher accuracy compared to foil trials, $t(19) = 2.06$, $p = .054$. To investigate the interaction, we conducted Bonferroni-corrected paired comparisons (corrected alpha = .05/3 = .017) for each trial type. Manufacturing company logos elicited higher accuracy for both exemplar match and category match trials compared to social media logos, $t(19) > 3.31$, $p < .005$, but not for foil trials, $t(19) = 1.59$.

Probing the main effect of trial type for reaction time, we found that exemplar match trials elicited the fastest reaction times ($M = 530.43$, $SE = 6.68$), followed by foil trials ($M = 595.37$, $SE = 9.11$), and finally category match trials ($M = 776.08$, $SE = 15.01$), $t(19) > 10.19$, $p < .001$.

## 3.3 | Discussion

Experiment 2 aimed to investigate whether the differences in the N2pc elicited by the smaller and larger categories of logos in Experiment 1 would be preserved and even heightened when isolating the N2pc to the target. The cross configuration of the search array in Experiment 2 allowed us to distinguish between selecting both targets and distractors versus selecting only the target by manipulating the locations of the target and distractor. We minimized the increase in task difficulty by using placeholder images. We also addressed possible differences in the familiarity and visual properties of the logos by modifying or replacing

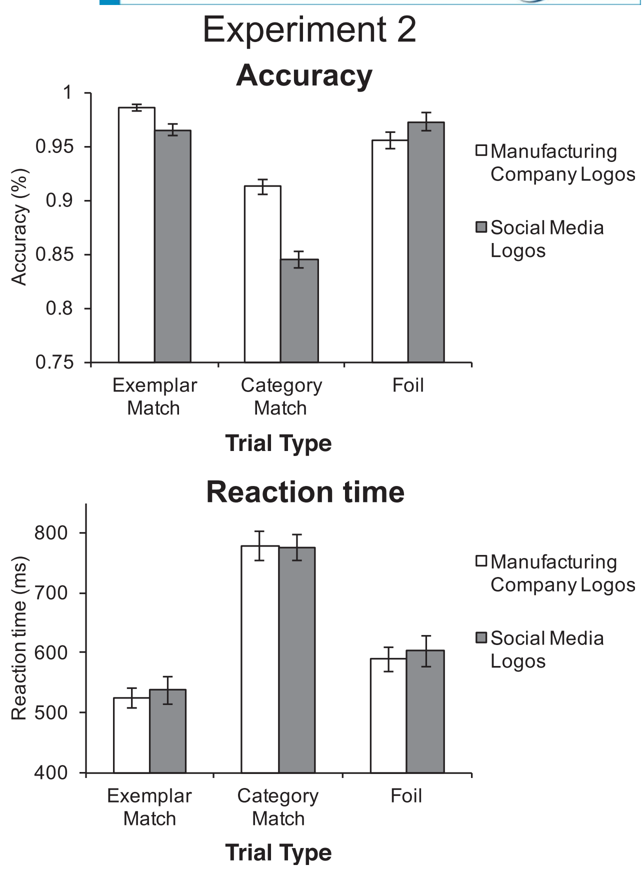


**FIGURE 11** Behavioral results from Experiment 2 for reaction time and accuracy when searching for social media and manufacturing company logos. Error bars represent ± 1 *SE*

stimuli from Experiment 1 and using a larger rating scale for familiarity ratings. These changes allowed us to better examine the differences in the N2pc as a function of category size.

Although we did not replicate Experiment 1's main effect of company type for exemplar match and category match trials, we replicated the finding that foil trials were larger during search for social media logo targets compared to search for manufacturing company logo targets. This finding is in line with other studies demonstrating that increased neural search efficiency (larger N2pc amplitude) during category search may manifest in increased attentional capture to nontarget category items (e.g., Nako, Wu, & Eimer, 2014; Nako, Wu, Smith, & Eimer, 2014; Wu et al., 2015, 2016; Wu, Pruitt et al., 2017).

The significant and marginal N2pc components in the target vertical, distractor horizontal trials suggest that the participants selected distractor logos for both company types. However, it is possible that the placeholder image induced a type of pop-out effect because they were identical images, even though the placeholder had a similar number of black pixels compared to the logos from both company types. Two identical placeholders, as opposed to two distinct placeholders, were chosen for the design to minimize the increase in task difficulty from doubling the number of items in the search array. Finally, like the manufacturing category in Experiment 1, the N2pc component in target horizontal, distractor horizontal trials was relatively small. In fact, in Experiment 2, most of the N2pc components in this configuration did not significantly differ from zero, perhaps due to the pop-out effect induced by the placeholders. Interestingly, search for manufacturing logos elicited higher accuracy compared to social media logos, which differed from the findings of Experiment 1 and could be attributed to the slight differences in naming accuracy and familiarity between the two categories.

## 4 | GENERAL DISCUSSION

The present study, encompassing two experiments, investigated whether perceived category size (i.e., one type of prior knowledge about the stimuli) impacts visual search. We used eight social media logos as the smaller category and eight recreation and entertainment product manufacturing company logos as the larger category. The ERP results from Experiment 1 revealed that, with a two-item search array, search was more efficient with social media logos compared to manufacturing company logos. With a four-item search array (Experiment 2), where two of the four items were placeholders, search was largely similar between the company types, except for foil trials, where attentional capture to nontargets from the social media category was greater than attentional capture to nontargets from the manufacturing category.

Although there were a number of similarities between the results from the two experiments, there also were some inconsistencies. One important difference was that the ERP results from Experiment 1 included larger components (i.e., higher neural search efficiency) when searching for social media logos compared to searching for manufacturing company logos for both target-present and target-absent trials, whereas the results from Experiment 2 revealed this difference only for target-absent trials. One explanation for this difference is that including two identical placeholders on every trial in Experiment 2 may have inadvertently created a pop-out effect based on "same" versus "different" stimuli. Perhaps this initial pop-out effect was included in the N2pc component, along with more subtle category search effects. In addition, the extremely high familiarity of the items in Experiment 2, as indicated by the naming accuracy and familiarity ratings, may have facilitated exemplar and category search tasks for both categories. Either of these effects, the pop-out or increased target familiarity, may have masked the subtle effects of knowledge about the category size that we observed in Experiment 1. Moreover, the difference between the perceived category size dropped a great deal from Experiment 1 to Experiment 2, perhaps further minimizing top-down effects based on category size in Experiment 2.

Overall, the present study provides some evidence that a smaller category may lead to more efficient search compared to a larger category. Taking the findings from Experiment 1 and 2 together, when participants reported a large difference between category size (Experiment 1), we observed a significant difference in neural search efficiency for exemplar and category search; however, when participants reported a smaller difference between category size (Experiment 2), we observed a significant difference only when foils (i.e., non-target items from the same category as the target) captured attention. In general, our ERP findings support the idea that smaller categories allow enhanced unitization of a group of items, thereby increasing neural search efficiency. In other studies, we have indeed found that smaller, finite categories (e.g., letters and numbers; Nako, Wu, & Eimer, 2014) lead to larger N2pc amplitudes compared to larger subjective categories (e.g., healthy food; Wu, Pruitt et al., 2017). An alternative explanation is that small categories containing only a few items may allow for individual representations of each item to be maintained simultaneously. Although this may be the case for categories containing only a handful of items (e.g., "my family" or "numerals 0–9"), this explanation is strained for categories containing more items than can be held in working memory (e.g., categories larger than about 8–10 items), such as the company logo categories used in our study. Additionally, if the maintenance of individual exemplars included in the study (i.e., eight possible targets) was an advantageous strategy for the visual search task with the smaller category, the same strategy could be applied to the eight items from the larger category (e.g., manufacturing companies).

There are a few important limitations to note in our study. Our conclusions on smaller versus larger categories may depend on this specific stimulus set of company logos. One potential issue is that perhaps social media logos themselves may capture attention more readily than other logos because they frequently appear in the experimental setting (a computer screen) and often serve to grab the user's attention when updates become available throughout the day. However, if this issue drove our results, our findings across both behavioral and neural levels, including the familiarity and naming data, and between both experiments would support this explanation. However, the behavioral responses during search and the familiarity and naming responses revealed no difference and perhaps even a slight advantage for manufacturing company logos. This sensitivity to context (e.g., typically appearing on a computer vs. on a product) and use (e.g., interacting with the logo many times per day or encountering it for specific activities), although not supported by our data, supports the more general theme that high level knowledge about a category may bear on rapid neural responses in visual search. Using novel stimuli that are not subject to these concerns about where and how participants typically encountered the stimulus prior to the experiment, a previous study (Wu et al., 2016) demonstrated similar findings to Experiment 1, although the research question in that study was not specifically related to perceived category size, and no perceived category size measure was obtained.

Another limitation to the present study is that it is unclear if the participants considered these stimuli as categories in the same way that they do more universally accepted, familiar categories, such as letters and numbers. In other words, real-world categories can vary in their degree of unitization in the natural environment. Unitization may be facilitated by explicit rules (e.g., Wu et al., 2016) or implicit information, such as co-occurrence (e.g., Facebook, Pinterest, and Instagram logos are commonly displayed together; see also Wu, Gopnik, Richardson, & Kirkham, 2011; Wu et al., 2013). Real-world categories also may be fluid. Indeed, although PlayStation and Xbox logos were included in the manufacturing category, they also include gaming social media platforms. Therefore, perhaps participants did not unitize these logos in a manufacturing category as readily as logos in the social media category. Despite the possibility of confusion over the category boundaries, our participants were able to complete the task quickly and accurately, suggesting that even if they did not initially consider the items in the sets as categories or were initially unsure of category boundaries, they quickly adapted to the task demands. Future studies could investigate whether more naturally unitized categories may enhance the effects that we found in the present study.

One aspect that is still unclear is the magnitude of the perceived size difference that is needed to generate the effect that we showed in this study, especially given the somewhat inconsistent results that we obtained between Experiment 1 and Experiment 2. Participants in the second experiment reported that the number of social media companies was larger than participants in the first experiment, and participants in the first experiment reported that the difference in the perceived category size between social media and manufacturing companies was larger compared to participants in the second experiment. Furthermore, in terms of a possible interaction between perceived size and task demands, the number of items included in the visual array and in the task set may have influenced search outcomes. In terms of number of items in the array, scaling up from two to four items, even when two of the four items were placeholders in Experiment 2, eliminated differences between company type in target-present trials in our study, although the differences in the target-absent trials remained. In terms of the number of items in the task set, future studies could investigate whether including only a few items versus dozens in each category set would encourage participants to use different strategies to complete the task. Despite these limitations, our results support a growing literature on how prior knowledge of categories facilitates task-relevant selection, but also affects attentional capture to task-irrelevant items during visual search (Cunningham & Wolfe, 2014; Egeth et al., 1972; Karlin & Bower, 1976; Nako, Wu, Smith, & Eimer, 2014; Wu et al., 2013, 2015; Wu, Pruitt et al., 2017; Yang & Zelinksy, 2009).

Another unresolved aspect of our study is the discrepancy between the neural and behavioral data, namely, the positive results in the N2pc measure and the null results in the response times across both experiments. Typically, with highly familiar or simple stimuli as exemplars (e.g., the letter *A* or a red square) or highly constrained categories (e.g., letters), behavioral effects tended to follow N2pc effects (see Nako, Wu, & Eimer, 2014, for a study using a similar paradigm as the present study with letters and numbers). However, our recent studies have revealed interesting dissociations between the brain and behavior when searching for more complex stimuli, such as anthropomorphic figures. With these complex stimuli, it appears that ERP measures may be more sensitive than behavioral measures to cognitive influences on search (in this case, prior knowledge of category size). One of our recent studies using a similar search paradigm (Wu et al., 2016), which included novel alien stimuli, produced positive results in the N2pc effects and null results in the response times, similar to the present study. In another study (Wu et al., 2015), we showed that behavioral responses and the N2pc component are affected by different factors. In that study, participants were slower and less accurate in selecting less familiar ape faces compared to more familiar human faces. However, their N2pc components were almost identical across face types. It may be the case that the N2pc reflects more automatic (but still top-down) search processes, whereas behavioral responses are influenced more by later and higher-level decision-making processes (cf. guidance vs. verification; Maxfield & Zelinsky, 2012). Future studies could clarify how the mechanisms involved in neural search efficiency are different from those involved in behavioral search efficiency.

Moreover, although prior behavioral studies (e.g., Maxfield & Zelinksy, 2012) have found differences in reaction time based on category size, these categories were based on groupings at different levels (subordinate, basic, or superordinate levels), which differ on similarity between items within a category. Items in subordinate categories (e.g., jeans) tend to be more similar to other items in that category compared to items in basic categories (e.g., pants), and even more so compared to items in superordinate categories (e.g., clothing). In terms of visual search, items that are more similar to each other typically allow for better search performance. In the present study, our categories were chosen because they included dissimilar logos within the categories. The specific logos were chosen based on how dissimilar they were to other logos in the same category, as well as how similar they were to other logos in the other category. Perhaps behavioral differences found in prior studies were driven by the similarity between category items, and when similarity is comparable between categories, behavioral effects may not be as apparent.

In terms of the theoretical and methodological advances of the present study, given that visual search is a standard cognitive task that can be included in batteries of cognitive assessments and used for cognitive training (e.g., Ball et al., 2002), our findings have important implications for cognitive tasks used for cognitive assessments and training in general. In line with other studies (e.g., Brady et al., 2016; Orhan & Jacobs, 2014), our findings suggest that many aspects of implicit and explicit prior knowledge of stimulus characteristics matter when performing cognitive tasks. Even after equating the bottom-up properties of task stimuli, prior knowledge may still impact search because a participant interacts with the experimental stimuli based on their real-world significance. These issues are especially important for developmental research because prior knowledge about objects and their relationships with other objects continues to increase across the lifespan. More research is needed to investigate the development of the costs and benefits of prior knowledge on visual search, as well as other fluid cognitive abilities. Developmental research, in particular, may provide insight into the issue of how fluid and crystallized abilities interact in developmental mechanisms and for assessments (e.g., Kievet et al., 2017). It may be the case that, although fluid and crystallized abilities are distinguishable via cognitive tasks using specified stimuli, they may also constructively support or interfere with each other, especially in the natural environment. Studies investigating these issues would help us understand optimal approaches to measuring and training cognitive abilities across the lifespan as underlying prior knowledge changes and increases over time.

In conclusion, we have provided evidence that perceived size of categories may impact visual search. We found that smaller categories increase obligatory attentional capture to task-irrelevant items in the same category as the target, and they also may increase neural search efficiency for the smaller category in general. Future research on the costs and benefits of different types of prior knowledge on attentional selection and other cognitive abilities will provide invaluable information on the bidirectional nature of attention and learning, informing research on cognitive training, cognitive development, and cognitive aging (Wu, Rebok, & Lin, 2017).

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