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# Temporal Dynamics of Implicit Attentional Guidance by Binary Categorization of Numerical Stimuli in Visual Search

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# Abstract

The binary categorization of numerical sequential information can produce a category effect in visual search, with faster and more accurate performance in between-category than within-category. However, it remains unclear how the binary categorization guides attention during the searching process. To clarify this, we conducted one behavioral experiment and one eye-tracking experiment to explore the category effect in a dynamic temporal view. Experiment 1 used eight numbers as stimuli (1,2,3,4,6,7,8,9), and two conditions of within-category and between-category were divided according to midpoint-precedent (1,2,3,4) and midpoint-antecedent (6,7,8,9) numbers. Results showed a stable category effect that participants' reaction times were faster in the between-category condition. Further temporal dynamics analysis showed this category effect increased as the reaction time prolonged, which indicates that the category information exerts a gradually amplifying, late-stage influence on attentional selection rather than an early fixed perceptual effect. Experiment 2 adopted the eye-tracking technology to further analyze the temporal distribution of fixation proportions on target versus distractor arrays. Results showed a fixation dominance on target versus distractor arrays earlier in the between-category condition (401–500 ms) than that in the within-category condition (501–600 ms). During the subsequent time course, target fixation proportion was greater than distractor in the between-category condition, while the within-category condition showed a comparable pattern with a smaller, non-significant difference. Collectively, these findings confirm that binary categorization of numerical sequential information exerts a temporally specific regulatory effect on visual search by modulating early attentional orienting efficiency and late maintenance stability, thus determining overall search performance.


# Introduction

Visual search is a critical topic in attention research. Studies have shown that when individuals search for a target, category information has an influence on the speed of visual search, the phenomenon is known as the “category effect” (Brand, 1971; Gleitman & Jonides, 1978; Ingling, 1972; Jonides & Gleitman, 1972). When the target and distractors belong to the same category (within category), search speed slows down significantly compared to when they belong to different categories (between category). For instance, Brand’s (1971) classic research demonstrated that participants searching for letters or numbers were more efficient when the target and distractors belonged to different categories (e.g., letter in numbers or number in letters). In addition to letters and numbers, other feature differences, such as color and shape, can also guide attention, resulting in similar category effects (Daoutis et al., 2006; Lindsey et al., 2010). Overall, these studies suggest that categorization becomes more efficient and easier in visual search tasks when targets differ significantly from nontargets on one or more features (e.g., shape, size, color, etc.) (Duncan, 1983).

Recent researches have further revealed that the category effect is not limited to physical feature differences. Long et al. (2017) found that in visual search tasks involving living and non-living objects, when the target and distractor belonged to different categories (e.g., searching for living objects among

non-living objects), the search speed increased significantly. Similarly, Wu et al. (2018) also found that category effects persist even when individuals are unaware of category differences between targets and distractors. For example, they observed significant category effects in social media and manufacturing company logos. These studies suggest that a priori knowledge such as category can significantly affect individuals' search efficiency and accuracy. Moreover, it has been shown that searching among non-targets with homogeneous concepts is more efficient than searching among non-targets with heterogeneous concepts (Lupyan, 2008). This phenomenon further suggests that categorization is not only based on physical characteristics but also relies on the modulation of conceptual knowledge.

In addition to the above categories, numbers have implicit polarity categorization (Proctor & Cho, 2006). Proctor and Cho suggested that the size of numbers itself has a polarity categorization, and the categorization feature that can be explained through polarity correspondence theory. The theory suggests that there is a polarity matching relationship between numbers and dimensions such as spatial relations, and this relationship may influence cognitive processes. Several studies have explored that implicit information about numbers can produce category effects that can direct the participants' attention. For example, numerical distance can be implicitly categorized as close, medium, and long. Schwarz and Eiselt (2012) found that participants' reaction times were significantly shorter when the numerical distance between the target and distractor digits was large. Moreover, numerical sequences can be categorized as "small" and "large", activating of spatial representations associated with the numbers. Fischer (2013) used four numbers (1, 2, 8, 9) as cues and found participants associated small numbers (1, 2) with the spatial left and large numbers (8, 9) with the spatial right. This is consistent with the mental number line theory, which suggests that numbers are not encoded discretely, but along a continuous mental number line (Dehaene et al., 1993). Furthermore, the polarity of the numbers not only correlates with spatial dimensionality, but also directs attention, thus improving the efficiency of the visual search task.

Beyond the category effect of numerical distance, implicit sequential information of numbers can also contribute to such effect. Yan et al. (2024) further explored the binary categorization of sequential stimuli (numbers/letters), and investigated whether individuals unconsciously classify numbers/letters as "midpoint-precedent numbers/letters" and "midpoint-antecedent numbers/letters" categories, and thus produce the category effect. By ruling out the influence of distance and stimulus frequency effects, their results showed a stable category effect that visual search was significantly faster in the between-category condition than that in the with-category condition, and the category effect gradually increased as the reaction time prolonged. Their finding indicated that binary categorization of sequential stimuli, including numbers, could implicitly modulate search efficiency and it is mainly induced by late knowledge-guided category information processing.

However, it remains unclear how the binary categorization of numerical sequences directs attention during the search process. Previous researches have shown that eye-tracking plays a significant role in investigating the category effect (Yang & Zelinsky, 2009; Guo et al., 2020). For example, Guo et al. (2020) conducted experiments using hardness classification. Their study found that when participants

searched for a soft object among hard objects, their fixation times and the number of distractors fixated upon were significantly reduced, which in turn led to faster search speeds. This suggests that the category effect may arise because individuals are able to suppress the interference from distractors more effectively, rather than enhanced recognition of the target. However, this conclusion does not clarify the category effect's temporal change characteristics during the dynamic search process. To address the above questions, the present study also utilized eye-tracking technology to delve into the temporal change characteristics of the category effect.

In eye-tracking studies, traditional analysis methods often focus on comparing fixation counts and durations in areas of interest (AOIs) (Carter & Luke, 2020). However, these analyses overlook the instantaneous changes in fixation behavior during visual search. Exploring short-term changes in fixation to different stimuli can reveal more clearly which stimuli an individual is responding to at a specific moment. It also provides new perspectives for understanding temporal change characteristics during the dynamic search process in different category conditions. Several previous studies have attempted to convert eye-tracking data into time-series formats, revealing participants' moment-by-moment responses while performing cognitive tasks (Chakraborty & Han Wu, 2017; Constantino et al., 2017; Liu et al., 2024a; Salverda & Tanenhaus, 2010; Shen et al., 2016). Therefore, this study utilized time-series analysis to investigate the differences of fixation proportion on target and distractor numbers at specific time points in within and between-category conditions. We hypothesized that, when the target and distractor numbers were between different categories, participants would locate target numbers more quickly or suppress distractor interference more effectively, thereby improving their search efficiency.

The goal of this study is to provide deeper insights into how category information dynamically guides attention allocation during visual search. In Experiment 1, we used four two-digits number arrays as stimuli and required participants to find the target number array (both odds or evens) in the other three non-target number arrays. And we hypothesized that participants would search faster when the target and distractor arrays were between different categories. In Experiment 2, we further used eye-tracking technology to analyze the fixation proportion on target and distractor in within-category and between-category conditions. We hypothesized that the fixation proportion on target and distractor in between-category condition would be more dissociated than that in the within-category condition during the dynamic search.

# Materials and Methods

### Experiment 1

We adopted the experimental paradigm of Vestner et al. (2019) to verify whether there is a binary categorization relationship for numerical sequences and whether it can influence individual search. We hypothesized that Experiment 1 would repeat the results of Yan (2024) that showing a category effect.

#### *Participants*

Sample size estimates for all experiments in this study were calculated using G*power 3.1. Based on a stringent criterion, the statistical test power (1-β) was set to 0.95, and the effect size was 0.74 (Brand, 1971). A minimum of 26 participants would be needed to reach the actual power of 0.95. Based on this calculation and the possible loss of participants, the actual sample size for each experiment (26) to ensure that actual -power could be achieved.

Twenty-six undergraduate students (18-24 years old, Mage=19.5 years old, 10 males) were recruited. All participants had no history of neurological or psychiatric disorders and did not have color blindness or color vision deficiency. All of them were right-handed and had a normal or corrected-to-normal vision. Each participant volunteered to take part in the experiment and signed an informed consent form before the experiment, and was compensated a certain amount of money after the experiment. This study was approved by the Institutional Review Board of XXX University.

***Apparatus, materials, and design***

The stimuli were presented on a 27-inch LCD monitor (resolution: 1,024 × 768 pixels, vertical refresh rate: 60 Hz). Participants' eyes were level with the center of the monitor and 50 cm away from it. Stimulus presentation and response recording were controlled by E-prime 2.0 software.

List the numbers 1 through 9 (except 5) to form four pairs of numbers, each containing only four different numbers (Figure 1). In each pair, two of the numbers are either from the midpoint-precedent numbers (less than 5) or from the midpoint-antecedent numbers (larger than 5). One of the four pairs has the same parity as the target and the other three pairs have different parities. All stimuli were presented on a white background (480 × 270 pixels), which was divided equally into 2 × 2 grids (4 locations in total), with each grid measuring 240 × 135 pixels in size. In each search array, four pairs of two numbers were displayed at the center of each grid as search items. One pair is the target and the other three pairs are distractors (size 0.3 × 0.2°, font Courier New, and spacing of 1 cm between each set of digits) (Figure 1). The positions at which the target array appears are balanced to have both a 25% probability of appearing in any of the grids.

The task consisted of three conditions, the between-category condition, and the within-category condition and absent-group condition (Figure 1). In the between-category condition, the target and distractors were in the different types of sequences: the distractors were in midpoint-precedent numbers and the target were in the midpoint-antecedent numbers (with the target such as “11” and distractors such as “66”, “56”, “68”), or vice versa, with same percentage in both conditions. In the within-category condition, the target and distractors were the same sequence numbers: both of them were the midpoint-precedent numbers or the midpoint-antecedent numbers (with the target such as “11” and distractors such as “22”, “24”, “23”).

The formal experiment consisted of 8 blocks of 120 trials each, resulting in a total of 960 trials randomly selected from them as experimental stimuli. Of these, 10% were allocated to the absent-group condition, while the remaining trials were evenly divided between the between-category and within-category

conditions. Prior to the formal experiment, participants completed 20 practice trials to familiarize themselves with the task.

### *Procedures*

First, a blank 500 ms grid appeared in the center of the screen for 500 ms, following by a 500ms red cue in the center of the grid displaying either "□" or "□", which mean "Odd" or "Even", instructing participants to locate the corresponding array with the same parity. Then four pairs of arrays appeared on each grid. The search display was presented for 5000 ms or until the participants responded. Participants needed to press the space bar as quickly as possible after searching for the target array or determining it did not exist. After that, the four pairs of arrays were replaced by four letters (V, B, N, and M). At this point, participants needed to identify the location of the target number and press the corresponding letter on the keyboard; if the target array did not exist, they needed to press the space bar one more time (Figure 1). After the experiment, none of the participants reported being aware of the number or order of categories between the target and the distractors.

### *Statistical analysis*

In the analysis of response times (RTs) for searching, 4.3% of the trials were removed due to either incorrect identification of array position or RTs beyond 3 standard deviations in each condition. To determine whether participants' response speed was significantly different in the between-category versus within-category conditions, RTs were averaged across all trials for each condition and a two-tailed paired-samples *t*-test was performed. To further quantify the evidence, we conducted a Bayesian paired t-test using the BayesFactor package in R with the default JZS prior (Cauchy scale = 0.707). To assess the strength of this effect, we calculated the posterior distribution of the mean difference ($RT_{within}$ - $RT_{between}$) and the standardized effect size (δ).

In addition to the above analysis, to explore how the strength of category effects evolves, we employed a Vincentizing procedure (Ratcliff, 1979) for the distribution of RT. Specifically, the ranking RT distribution of each subject under each condition was divided into four equal bins (i.e. the 25th, 50th, 75th, and 100th percentiles). Calculated the category effect ($RT_{within}$ □ $RT_{between}$) for each bin. Subsequently, a linear mixed effects model (LMM) was used to test the linear trend of category effects within four RT bins, where the intervals were used as fixed effects (with the mean as the center representing the average effect at the intercept) and the subjects were used as a random effect (including random intercept and interval random skewness).

### *Results*

For all trials (Figure 2-A), the mean RT in the between-category condition (1061 ± 29 ms) was shorter than that in the within-category condition (1145 ± 32 ms), $t(25) = -8.23$, $p < 0.001$, Cohen's $d = -1.61$, 95% confidence interval [CI: -1.21, -2.02]. After the experiment, none of the participants reported being aware of the number or order of categories between the target and the distractors.

We employed the Bayesian paired t-test, yielding a Bayes factor $BF_{10}$ = 9.48×10⁵, which provided strong evidence for differences between the two conditions. Posterior parameter estimates further confirmed this effect, with the posterior mean of the standardized effect size δ = 1.535 (95% CrI [0.953, 2.137]). Despite some variability, the posterior mean of the estimated mean difference was 82.15 ms (95% CrI [60.54, 103.25] ms), consistent with the overall pattern of category effects observed across the entire dataset. These results provide extreme evidence that response was significantly slower for within-category trials than for between-category trials, suggesting a strong category effect.

Based on the average RT findings, the LMM analysis (Figure 2-B) revealed the temporal progression of category effect. The significant intercept confirms the existence of stable overall category interference (β = 84.48, $t(25) = 8.24$, $p < .001$), and, the primary interest was the linear trend across bins. A significant positive slope was observed (β = 31.51, $t(25) = 5.08$, $p < .001$), indicating that the magnitude of the category effect linearly increased as reaction times grew longer.

***Discussion***

In Experiment 1, participants were required to search for the target array among three pairs of distractor arrays. The results showed that although participants were not aware of the categories of the numerical sequences, their search rates still differed significantly across conditions: participants' search speed in the between-category condition was significantly faster than that in the within-category condition, which further supported the existence of implicit binary categorization of numerical sequences and it could guide participants' attention (Brand, 1971; Pilling et al., 2003; Holmes & Regier, 2017; Yan et al.,2024).

The binning analysis revealed that the category effect increased gradually with longer reaction times, replicating the findings of Yan (2024). This indicates that the influence of category information exhibits a clear temporal dynamic profile: the category effect is not fixed early in perceptual processing, but amplifies progressively as processing time extends and attentional resources are continuously allocated.

**Experiment 2**

In Experiment 1, it was verified that binary categorization of numerical sequences guided participants' attention, and it remains unclear about the category effect’s temporal change characteristics during the dynamic search process.

Eye tracking techniques can record participants' gaze position, gaze duration, and gaze variability by measuring the position of infrared light reflecting off the cornea. This makes eye tracking techniques useful for most studies exploring mental processes (Carter & Luke, 2020). The number of arrays participants attend to, and the number and duration of their gaze, may reflect how their attention is affected by the array condition. For example, participants tend to attend to distractor arrays more in the within-category condition (Guo et al., 2020). Furthermore, Eye-tracking also allows for the precise measurement of how long individuals fixate on specific areas during visual search, thereby revealing

their attentional focus on different stimuli (Brams et al., 2019; Plummer et al., 2017). It could be used for revealing the temporal change characteristics during the dynamic search process. Based on it, experiment 2 used eye tracking techniques to determine how participants shifted attention during search. We hypothesized that binary categorization guides attention in at least two ways: (1) the target is more readily salient among distractors which is manifested by the target receiving earlier and more fixations than distractors in the between-category condition compared to the within-category condition; (2) this dissociation is stable during the searching process which facilitates participants' target identification, processing and decision-making, thus leading to shorter response times in the between-category condition

***Participants***

Sample size estimates for all experiments in this study were calculated using G*power 3.1. Based on a stringent criterion, the statistical test power (1-$\beta$) was set to 0.95, and the effect size was 0.74 (Brand, 1971). A minimum of 26 participants would be needed to reach the actual power of 0.95. Based on this calculation and the possible loss of participants, the actual sample size for each experiment (26) to ensure that actual -power could be achieved.

Twenty-six undergraduate students (18-23 years old, Mage=20.6 years old, 7 males) were recruited. All participants had no neurological or psychiatric history, were not color-blind or color-frail. All of them were right-handed and had a normal or corrected-to-normal vision. Each participant volunteered to take part in the experiment and signed an informed consent form before the experiment, and was paid a certain amount of money after the experiment. This study was approved by the Institutional Review Board of XXX University.

***Apparatus, materials, design, and procedure***

The basic equipment, stimuli, and design of Experiment 2 were essentially identical to Experiment 1, with the addition of tracking each participant's right eye with an SR Research Eyelink 1000 plus desktop eye tracker sampled at 2000 Hz. Prior to the start of each experiment, we used a 9-point calibration and validation procedure and then performed the visualization search task as described in Experiment 1.

Prior to the start of the experiment, a gaze point was presented in the center of the screen, and participants were told to look at its center for the experiment to begin. The follow-up process was consistent with Experiment 1. After the experiment, none of the participants reported being aware of the number or order of categories between the target and the distractors.

***Statistical analysis and Eye tracking analysis***

The RT analysis procedure of Experiment 2 was the same as that of Experiment 1. 11.6% of the trials were removed due to incorrect responses or RTs outside of 3 standard deviations. Then, a two-tailed, paired-samples t-test, a Bayesian paired t-test, and a linear mixed effects model (LMM) were conducted to test the category effect.

Standard eye-tracking metrics focus on calculating gaze duration and gaze count within Areas of Interest (AOI). (Carter & Luke, 2020). To collect complete eye movement data for the analysis task, we designated four large rectangular grids as the AOIs (Figure 3). Each AOI was 240 × 135 pixels in size and completely covered the grid presented in the tasks. To explore momentary changes of gaze during visual search, we further partitioned the whole trial duration into several 100-ms bins (Liu et al., 2024b). And the total number of fixations each participant looked at each AOI in each condition and each bin were counted. Then the participants' fixation proportion to the target and distractor arrays were calculated for each bin (Figure 4). To compare the temporal distribution of gaze on the target and distractor arrays in the between-category and within-category conditions, a two-tailed paired-samples t-test was conducted for them in each bin (Table 1).

***Results***

For the RT (Figure 2-C), the results showed that the average RTs for the between-category condition (1266 ± 86 ms) was shorter than the average RTs for the within-category condition (1300 ± 75 ms) while it was not significant, $t(25) = -0.42$, $p = 0.676$, Cohen's $d = -0.08$, 95% confidence interval [CI: -0.49, 0.32]. The Bayes factor $BF_{10}$ was 0.22, which provided moderate evidence for differences between the conditions. The posterior mean of the raw mean difference was 29.64 ms (95% CrI [-119.28, 179.84] ms). The posterior mean of the standardized effect size δ was 0.074 (95% CrI [-0.287, 0.433]). The LMM analysis did not reveal the temporal progression of category effect. The intercept was not significant (β = 33.69, $t(25) = 0.42$, $p = .676$). A slope was observed (β = -18.62, $t(25) = -0.25$, $p = .803$), indicating that the magnitude of the category effect linearly did not increase as RT grew longer.

For the fixation proportion (see Table 1), the results showed that at first the distractor received more fixations than the target because the distractor has three AOIs while the target only has one AOI. Then participants switched their attention to the target showing that the fixation proportion of the target increased and the fixation proportion of the cannons decreased (). The difference between them became non-significant at 301-400 ms in the between-category condition (1-100 ms: $t(25) = -4.14$, $p < 0.001$; 101-200 ms: $t(25) = -4.98$, $p < 0.001$; 201-300 ms: $t(25) = -2.62$, $p = 0.015$; 301-400 ms: $t(25) = -1.98$, $p = 0.059$) while at 401-500 ms in the within-category condition (1-100 ms: $t(25) = -3.30$, $p = 0.003$; 101-200 ms: $t(25) = -4.35$, $p < 0.001$; 201-300 ms: $t(25) = -3.92$, $p < 0.001$; 301-400 ms: $t(25) = -3.51$, $p = 0.002$; 401-500 ms: $t=-0.28$, $p=0.785$). Then, the fixation proportion of the target changed to be larger than the distractor in the 401-500 ms in the between-category condition ($t(25) = 2.22$, $p = 0.035$) while at the 501-600 ms in the within-category condition ($t(25) = 1.59$, $p = 0.123$). The difference gradually increased and then keep stably significant in the between-category condition until to the response was made in the between-category condition (401-500 ms: $t(25) = 2.22$, $p = 0.035$; 501-600 ms: $t(25) = 3.14$, $p = 0.004$; 601-700 ms: $t(25) = 2.65$, $p = 0.008$; 701-800 ms: $t(25) = 2.87$, $p = 0.008$; 801-900 ms: $t(25) = 2.51$, $p = 0.019$; 901-1000 ms: $t(25) = 1.97$, $p = 0.060$; 1001-1100 ms: $t(25) = 0.87$, $p = 0.395$; 1101-1200 ms: $t(25) = 0.24$, $p = 0.811$), while the within-category condition showed a comparable pattern with a smaller, non-significant difference (501-600 ms: $t(25) = 1.59$, $p = 0.123$; 601-700 ms: $t(25) = 0.76$, $p = 0.455$; 701-800

ms: $t(25) = 0.84$, $p = 0.411$; 801-900 ms: $t(25) = 0.93$, $p = 0.362$; 901-1000 ms: $t(25) = 0.57$, $p = 0.576$; 1001-1100 ms: $t(25) = -0.34$, $p = 0.734$; 1101-1200 ms: $t(25) = -0.89$, $p = 0.381$).

***Discussion***

The RT results in Experiment 2 showed a category effect trend of faster average RT for the participants in between-category but was not significant, which may be due to interference from the eye-tracking technology with participants, resulting in inflated standard errors (Keith, 2009; Risko & Kingstone, 2011). The eye-tracking results primarily revealed two key findings: (1) The shift from a larger fixation proportion on distractors to a larger proportion on the target occurred faster in the between-category condition than in the within-category condition, as evidenced by an earlier emergence of the crossover point (green dashed line in Figure 4). The transition occurred in the 301–400 ms bin for the between-category condition, versus the 401–500 ms bin for the within-category condition. This indicates that participants were able to detect the target and shift their attention to it more rapidly (Wolfe, 1994). (2) Following target identification, the between-category condition exhibited greater stability relative to the within-category condition, characterized by a larger and more stable disparity in fixation proportion between the target and distractors. In contrast, although the fixation proportion on the target was higher than that on distractors in the within-category condition, this difference was not statistically significant. This indicates that participants were less confident in their target identification, leading to more frequent saccadic shifts of fixations between the target and distractors and longer response time, which is consistent with the findings of Guo et al. (2020).

# General Discussion

The present study aimed to replicate and verify whether binary classification of numerical sequence could guide individuals' attention and how numerical binary classification affects participants' visual search, by adopting the visual search paradigm of Vestner et al. (2019) and eye-tracking technology. Experiment 1 replicated and confirmed that the categorization of number sequence can implicitly guide attention by showing a category effect with a faster response time in the between-category condition compared to the within-category condition. In Experiment 2, the eye-tracking results further revealed a temporal dynamic pattern of the category effect: participants could fixate on the target earlier and maintain a more stable focus on it in the between-category condition compared to the within-category condition.

Based on Polarity Coding Theory (Proctor & Cho, 2006), we categorized number sequences into "midpoint-precedent numbers" (1-4) and "midpoint-antecedent numbers" (6-9). This mechanism may be related to joint number-spatial representations: the "midpoint-precedent numbers" sequence of digits has similar category correspondences to the "left-right" polarity of space (D'Ascenzo et al., 2022; Wiemers et al., 2017).

Based on the Polarity Coding Theory (Proctor & Cho, 2006), we classified numerical sequences into midpoint-precedent numbers (1–4) and midpoint-antecedent numbers (6–9), a categorization linked to

joint numerical-spatial representations that align midpoint-precedent numbers with left-right spatial polarity (D'Ascenzo et al., 2022; Wiemers et al., 2017). In the present study, when the target and distractor were distributed on the same category (e.g., both "midpoint-antecedent") or different category (e.g., target "midpoint-precedent" and distractor "midpoint-antecedent"). Targets are more difficult to discriminate from the distractors within the same category than across different categories, thus showing the category effect in our study.. This result is also supported by the Discrete Semantic System (DSS; Krajcsi et al., 2016), which proposes independent semantic nodes for individual numbers with connection strength reflecting semantic association. Krajcsi et al. (2016) found stronger connections between proximal small numbers (e.g., 3 and 4) than between distant numbers (e.g., 3 and 8. This semantic characteristic resulted the emergence of the category effect. Future research could try to verify whether numerical sequence categorization is fully implicit automatic processing by shortening the stimulus presentation time (e.g., 30 ms) and examine the category effect in an unconscious condition in conjunction with masking techniques.

Although category effect on RT was not observed in Experiment 2, a modulation mechanism of visual search by category information was revealed by eye-movement data. In the between-category condition, participants showed a significant and sustained target gaze advantage from 401-500 ms onwards, which persisted up to 1000 ms. This suggests that binary categorization of numerical sequence enhances search efficiency through enhanced inhibition. The long-term maintenance of the target's gaze dominance (until to 1000 ms) suggests that the target's gaze dominance can be maintained. This temporal pattern directly reflects enhanced and persistent inhibition of distractors: binary categorization of numerical sequences strengthens the active suppression of irrelevant distractors, and this robust inhibitory control eliminates distractor interference early and maintains it over time. Consequently, attentional resources are not wasted on processing distractors, and are instead allocated stably to the target, enabling more persistent and precise target recognition and localization (Driver et al., 1992). In contrast, in the within-category search condition, the gaze dominance of the target array was delayed until 501-600 ms to emerge and fail to reach statistically significant. This finding indicates impaired and delayed distractor inhibition: within-category distractors share high numerical sequential similarity with the target, which weakens the ability to suppress irrelevant information; the ineffective inhibition of similar distractors means they continue to compete for attentional resources, interfering with target selection (Treisman, 1988; Treisman & Sato, 1990). This forces participants to adopt a serial scanning strategy to discriminate the target from non-inhibited distractors, ultimately leading to reduced search efficiency. In summary, eye-movement data confirmed, from a temporal dynamic perspective, that categorical information guides visual attention by facilitating early perceptual discrimination and enhancing the efficiency and persistence of distractor inhibition to produce the category effect in visual search.

Although the present study reveals the attentional guidance mechanism for categorization of numerical sequences, there are still some limitations. Currently using only numerical 1-9 sequences, it could be extended to non-numerical categories such as letters in the future to verify whether the effect is consistent with numeric classification (Yan, 2024). The moderating role of working memory capacity or

executive function on distractor suppression was not examined in the study, which may affect the stability of the effect. Additionally, investigating the role of executive functions in suppressive control would further clarify the underlying mechanisms of category information's influence on visual attention.

# Conclusion

In summary, this study reveals the attentional guidance mechanism of number sequence categorization from both behavioral and temporal dynamic perspectives. Binary categorization of numerical sequential information exerts a temporally specific regulatory effect on visual search by modulating early attentional orienting efficiency and late attentional maintenance stability.

# Declarations

***Open Practices Statement***

The data and materials supporting the reported experiments are publicly available. None of the experiments were preregistered. All procedures were conducted in accordance with open science practices.

***Funding***

This research received no external funding.

***Conflicts of interest***

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

***Ethics approval***

This study was approved by the Institutional Review Board of XXX University. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee.

***Consent for publication***

Informed consent for publication was obtained from all individual participants included in the study.

***Availability of data and materials***

The datasets analyzed during the current study has been deposited in OSF with the repository URL: https://osf.io/hkfr6/overview?view_only=5c526c7dd8de4a0abb2371df0c09b2c4. All materials used in this study can be provided by the authors upon reasonable request.

***Code availability***

The code used in this study has been deposited in OSF with the repository URL: https://osf.io/hkfr6/overview?view_only=5c526c7dd8de4a0abb2371df0c09b2c4.

***Authors' contributions***

This study was designed by ZL, LY, and WN. ZL created the stimuli. ZL programmed the experiment. ZL, LY, and WN oversaw the data collection and analyzed the data. ZL, LY, and WN wrote the manuscript. All authors have read and agreed to the published version of the manuscript.

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# Table

Table 1 *Comparison of the fixation proportion between the target and the distractor across different bins. The p-value of the t-test for each condition is listed in parentheses.*

| Time Distribution (ms) | Condition | |
|---|---|---|
| | between-category | within-category |
| 1-100 | -4.14(<0.001) | -3.30(0.003) |
| 101-200 | -4.98 (<0.001) | -4.35(<0.001) |
| 201-300 | -2.62 (0.015) | -3.92(<0.001) |
| 301-400 | -1.98 (0.059) | -3.51(0.002) |
| 401-500 | 2.22 (0.035) | -0.28(0.785) |
| 501-600 | 3.14(0.004) | 1.59(0.123) |
| 601-700 | 2.65(0.014) | 0.76(0.455) |
| 701-800 | 2.87(0.008) | 0.84(0.411) |
| 801-900 | 2.51(0.019) | 0.93(0.362) |
| 901-1000 | 1.97(0.060) | 0.57(0.576) |
| 1001-1100 | 0.87(0.395) | -0.34(0.734) |
| 1101-1200 | 0.24(0.811) | -0.89(0.381) |
| 1201-1300 | -0.26(0.794) | -1.61(0.120) |

# Figures

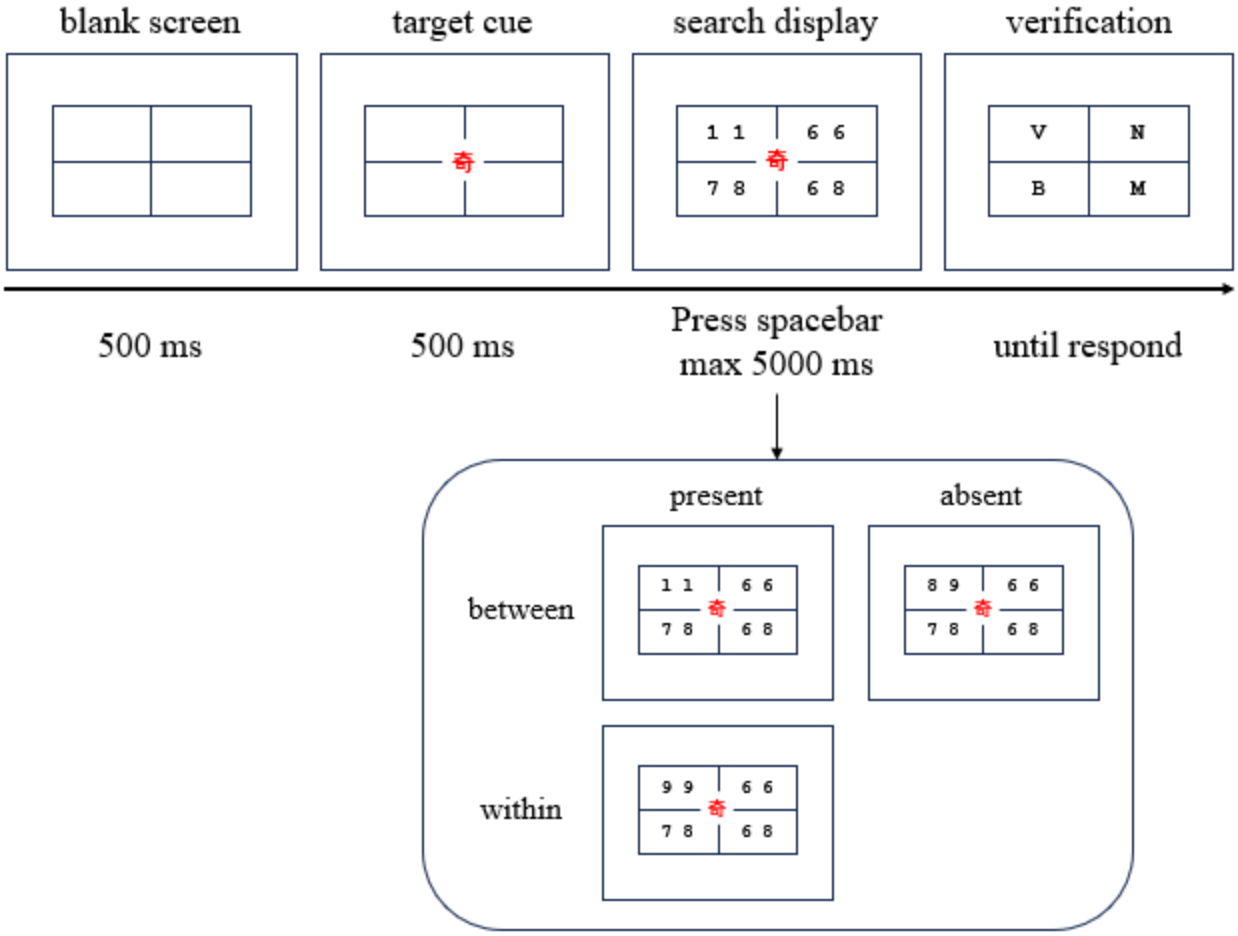



**Figure 1**

*Conditions and schematic for Experiment 1. Trials began with a 500 ms blank screen, followed by a 500 ms target cue. The search array then appeared in the grid, and participants were required to press the space bar after finding the target. Finally, in the verification screen, participants were required to press the corresponding position ("VBNM") on the keyboard to determine the location of the target. In this example, the target was is a number pair in which both numbers are odd: 11. In the between-category condition, the distractor was 678, and in the within-category condition, the distractor was 234, presenting even groups in the absence conditions.*

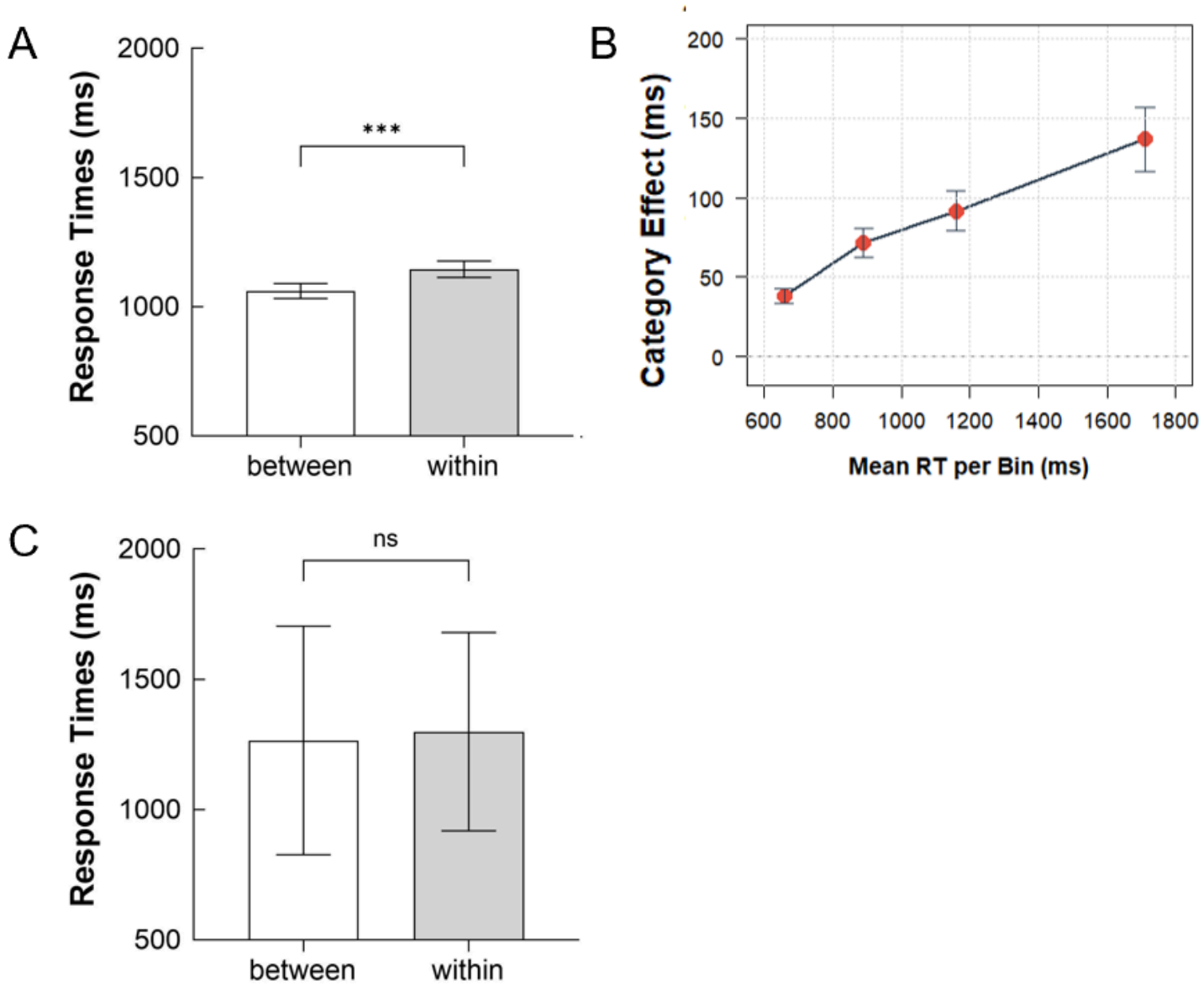



**Figure 2**

*(A) Category effect on RTs in Experiment 1. The x-axis shows the conditions, and the y-axis shows RTs (ms). (B) The temporal progression of category effect in Experiment 1. The effect size as a function of response speed. The x-axis shows the mean RT per bin, and the y-axis shows the corresponding category effect (ms).*

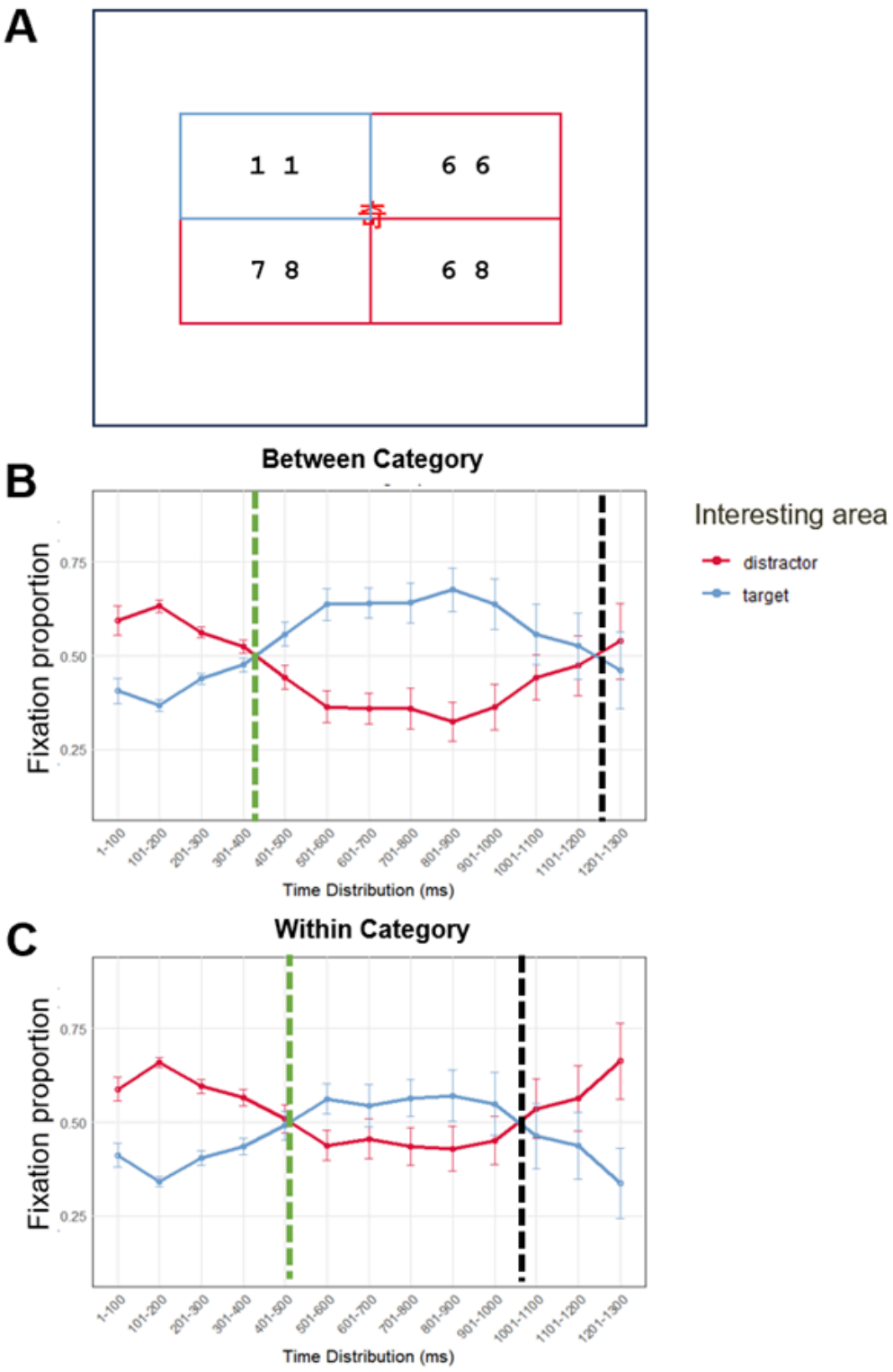



**Figure 3**

*(A) The four colored boxes indicate the Areas of Interest (AOIs) employed in the eye-tracking analysis, which are used to record participants' fixation. The blue AOI is for the target, the three red AOIs are for the distractors. (B) The fixation proportion between the target and the distractor across bins in the between-category condition. The blue dash line represents the fixation proportion participants attended to the target and the red dash line represents the fixation proportion participants attended to the distractors. The green*

*dashed line corresponds to the time point that participants attending to the distractor array versus the target array reach the same proportion, and the black dashed line corresponds to the average response time. (C) The fixation proportion between the target and the distractor across bins in the within-category condition.*