Learning Mechanisms of Visual Processing of Non-salient Stimuli in Perceptual Learning

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Abstract

Research on perceptual learning with non-salient stimuli has demonstrated plasticity in the adult brain, yet how perceptual learning affects different stages of visual processing remains unclear. Here, we investigated the mechanisms of perceptual learning by partitioning eye movement metrics into three visual processing stages: search latency (early stage), defined as the interval from search array onset to the first saccade leaving the initial fixation position, representing the time required to select the first search location; number of fixations and average fixation duration (middle stage), representing the number of locations processed by fixation and the average processing time during search; and decision time (late stage), representing the judgment of whether the current stimulus is the target and the execution of a response. Results showed improved search accuracy and faster response times for trained stimuli, accompanied by a significant increase in search latency and decreases in both the number of fixations and average fixation duration. Critically, these changes in behavioral and eye movement metrics did not transfer to untrained stimuli. These findings indicate that perceptual learning affects early and middle stages of visual processing, potentially enhancing search performance by increasing search latency while concurrently reducing saccade frequency and shortening fixation duration.

Full Text

Learning of Visual Processing for Nonsalient Stimuli in Perceptual Learning

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Abstract

Perceptual learning studies with nonsalient stimuli have revealed the plasticity of the adult brain, yet how perceptual learning influences different visual processing stages remains unclear. This study investigated the mechanism of perceptual learning by dividing eye movement metrics into three visual processing stages: search initiation time (early stage), defined as the interval from search display onset to the first saccade leaving the initial fixation position, representing the time to select the first search location; number of fixations and average fixation duration (middle stage), representing the number of fixated locations and average processing time during search; and verification time (late stage), representing the process of determining whether the current stimulus is the target and making a response. Results showed improved search accuracy and faster reaction times for trained stimuli, accompanied by significantly increased search initiation time and reduced number of fixations and average fixation duration. Moreover, these changes in behavioral and eye movement indices did not transfer to untrained stimuli. These findings suggest that perceptual learning affects early and middle visual processing stages, potentially enhancing search performance by prolonging search initiation time while reducing the number of saccades and shortening fixation duration.

Keywords: perceptual learning, nonsalient stimuli, learning mechanism, visual processing, eye movement
Classification Code: B842

1 Introduction

Perceptual learning refers to the phenomenon where perceptual abilities change through training or experience (Fahle et al., 2005). Early researchers believed that brain plasticity was a capacity limited to infancy and childhood, with the adult brain lacking such capabilities (Hubel & Wiesel, 1965). Consequently, plasticity in early sensory areas was thought to be restricted to critical periods early in life. However, subsequent research has demonstrated that even primary sensory cortex remains plastic in adulthood (Gilbert et al., 2001). Studies on perceptual learning in the visual domain employing various tasks have consistently shown that human visual performance improves significantly with practice, including tasks such as visual grating detection or discrimination (Kahnt et al., 2011), motion direction discrimination (Liu & Weinshall, 2000), and texture discrimination (Karni & Sagi, 1991).

Perceptual learning exhibits two fundamental characteristics: transfer and specificity (Ma et al., 2009). Transfer refers to the phenomenon where, after training, participants' visual perceptual abilities for trained stimuli improve significantly, and this improvement also manifests for similar stimuli (Fahle et al., 2005; Ma et al., 2009). Previous studies have shown that perceptual training effects can sometimes transfer to untrained stimuli, such as in orientation (J. Y. Zhang et al., 2010), spatial location (Xiao et al., 2008), and motion direction (Liu & Weinshall, 2000). Research using conjunction feature stimuli (e.g., color and shape) has found that perceptual learning effects exhibit transferability (Ding et al., 2023; Su et al., 2014). Su et al. (2014) and Ding et al. (2023) investigated the transferability of short-term (40–50 minutes) and long-term (6–10 days) color-orientation conjunction search learning, respectively. Both studies found that learning effects did not transfer to target conditions where both color and orientation changed simultaneously, but could partially transfer to conditions where only one feature (color or orientation) changed. Ding et al. (2003) used line orientation as stimuli for perceptual learning and found that although no behavioral transfer was observed, neural activity showed transfer effects. However, perceptual learning effects are not always transferable; other studies have found specificity in perceptual learning (Fahle & Edelman, 1993; Saffell & Matthews, 2003). Specificity refers to perceptual learning effects being confined to the trained stimulus features (Saffell & Matthews, 2003). For example, in a vernier acuity discrimination task, training on horizontally oriented verniers improved discrimination ability, but this performance enhancement did not transfer to vertically oriented verniers (Fahle & Edelman, 1993). Monocular training tasks have also shown that improved discrimination does not transfer from the trained eye to the untrained eye (Fahle et al., 1995).

Salient visual stimuli are relatively conspicuous in the environment, such as bright traffic lights or colorful billboards, which attract attention more easily due to their differences from the surroundings. Nonsalient visual stimuli, by contrast, are less noticeable and more homogeneous with surrounding stimuli, such as searching for a triangle of a specific orientation among triangles of different orientations. Current evidence suggests that perceptual learning of nonsalient stimuli is associated with changes in primary sensory cortex (Maertens & Pollmann, 2005; Fang et al., 2005). Maertens and Pollmann (2005) used functional magnetic resonance imaging (fMRI) to investigate the neural correlates of perceptual learning in primary visual cortex, finding that improved perceptual learning performance was accompanied by increased neural activity in V1, with the learning effect exhibiting location specificity in the visual field. However, other evidence indicates that perceptual learning of nonsalient stimuli is related to changes in higher-level cognitive processes. For instance, researchers have argued that higher-level brain regions associated with voluntary attentional control or decision-making (such as frontal and parietal cortex) play important roles in perceptual learning (Kahnt et al., 2011; Law & Gold, 2008, 2009). The involvement of primary versus higher-level visual cortex reflects different neural mechanisms underlying the specificity and transferability of perceptual learning. For primary visual cortex, neurons have limited receptive fields, with different orientations or locations represented by different neurons. Therefore, as perceptual learning progresses, only neurons representing trained stimuli change, resulting in a lack of transferability when changes involve primary visual cortex (Sagi & Tanne, 1994). Bao et al. (2010) found that contrast detection tasks for gratings exhibited location specificity, with increased C1 component amplitude after perceptual learning; C1 is thought to originate from V1, suggesting that perceptual learning may alter receptive field properties of neurons in primary visual cortex. In contrast, higher-level visual cortex has larger receptive fields, with single neurons sensitive to different simple line orientations and locations (Desimone & Ungerleider, 1989). Therefore, when higher-level cortex is involved, perceptual learning generally shows transferability. Studies using motion direction discrimination tasks to investigate the neural mechanisms of perceptual learning have found that improved discrimination ability can transfer to untrained stimuli, accompanied by enhanced responses in the lateral intraparietal area (LIP), indicating that changes in higher-level cortex representing decision-making are associated with perceptual learning (Law & Gold, 2008).

Orientation-based perceptual learning research generally includes two types: simple line orientation (Ahissar & Hochstein, 1997) and complex shape orientation (e.g., triangles and T-shapes) (Hu et al., 2018; Qu et al., 2017). Some researchers have found that simple line orientation perceptual learning exhibits transferability (Ding et al., 2003). Fang et al. (2005) found that line orientation perceptual learning was associated with primary visual cortex, with enhanced V1 activity after training on specific orientations. Qu et al. (2017) investigated complex shape orientation perceptual learning and found increased N2pc component amplitude after training, suggesting that complex shape orientations can automatically capture attention following perceptual learning. Sigman et al. (2000) found that complex shape orientation perceptual learning exhibited location and orientation specificity, leading to the conclusion that it may be related to primary visual cortex.

Qu et al. (2017) used triangle orientation for training and found significantly improved search performance after perceptual learning, but no transferability. Previous research has shown that task difficulty affects the transferability of perceptual learning (Ahissar & Hochstein, 1997). In Qu et al. (2017), post-training search accuracy (p') was only 0.345. Therefore, the current study reduced task difficulty by decreasing search set size to investigate whether the lack of transferability in triangle orientation perceptual learning was due to task difficulty or inherent specificity of triangle orientation learning. Furthermore, actual search processes involve different cognitive processing stages and metrics, such as search initiation time, fixation duration, and number of fixations. Researchers have found that after visual search training, search initiation time increases, number of fixations decreases, scanning time shortens, and search efficiency improves (Q. Zhang et al., 2022). Studies using real-world scenes have found that when targets appear in high-probability regions, average fixation duration is shorter and verification time is reduced compared to low-probability regions (Malcolm & Henderson, 2010). Therefore, accuracy and reaction time alone cannot reflect the actual visual processing.

Drawing on previous research, we divided eye movements into three stages (Malcolm & Henderson, 2009) to investigate the mechanism of perceptual learning for nonsalient stimuli. The first stage is early visual processing, with search initiation time as the analysis metric, defined as the interval from search display onset to the first saccade leaving the initial fixation position, representing the time to select the first search location. We hypothesized that search initiation time may reflect the allocation of covert attention before saccades. Studies have found that attention is allocated to target locations before saccades occur (Casteau & Smith, 2020; Kowler et al., 1995). Q. Zhang et al. (2022) found that search initiation time increased after perceptual learning, with a target-elicited N2pc component observed before the first saccade, suggesting that participants allocated covert attention to target locations before saccades. Therefore, we hypothesized that if search initiation time (early visual processing stage) increased significantly after perceptual learning, it would indicate that participants enhanced search performance through improved covert attention. The second stage is middle visual processing, or the scanning stage, defined as the interval from the first saccade to the onset of the last fixation, including metrics such as number of fixations and average fixation duration. Researchers have found that the number of fixations changes after perceptual learning (Q. Zhang et al., 2022), indicating that participants need to search fewer locations after training. Therefore, if the number of fixations decreased significantly after perceptual learning, it would suggest that search performance was enhanced by searching fewer locations; if average fixation duration decreased significantly, it would suggest that visual processing speed at each location became faster. The third stage is late visual processing, defined as the interval from the onset of the last fixation to the keypress, or verification time, representing the process of determining whether the stimulus at the current location is the target. Studies have found that verification time is shorter when targets appear in high-probability regions (Malcolm & Henderson, 2010), indicating that participants can identify targets more quickly. Therefore, if late visual processing changed after perceptual learning, it would suggest that perceptual learning affects the judgment process of whether the current location contains a target. By analyzing metrics from these three stages and their differences between pretest and posttest, we can investigate how perceptual learning effects for nonsalient stimuli influence different visual processing stages, providing experimental evidence for further understanding the mechanisms of perceptual learning.

2.1 Participants

Based on the effect size from a similar experimental paradigm investigating perceptual learning for nonsalient stimuli (Hu et al., 2018; p = 0.373), we used MorePower 6.0 (Campbell & Thompson, 2012) to calculate that a minimum of 16 participants were required (power = 0.8, $\alpha = 0.05$). A total of 24 healthy young adults (M = 21.23 years, SD = 2.02 years; 19 females) participated as paid volunteers. All participants had normal or corrected-to-normal vision, were right-handed, and were unaware of the study's purpose. Written informed consent was obtained from all participants prior to the experiment, and the study was approved by the Ethics Committee of the School of Psychology and Education at Minnan Normal University (approval number: 2022-06-01).

2.2 Apparatus and Stimuli

An EyeLink 1000 eye tracker (SR Research, Ontario, Canada) was used to record participants' eye movements, employing a 9-point calibration procedure for calibration and validation, with drift correction performed before each block. Experimental stimuli were generated and presented using the Psychtoolbox 3.0 toolkit (Brainard, 1997) in MATLAB (MathWorks, Natick, MA, USA). A chinrest was used to stabilize participants' heads during the experiment. The monitor resolution was 1920$×1080, *withascreenlengthof*52.7*cm*, *andparticipantsviewedthescreenfromadistanceof*63*cm*.*Thestimu*
seeoriginalpaper]*A*, *withluminancemeasuredat*0.12*cd*/*m*^{2}$ using a Spyder X (Lin et al., 2023). All stimuli were presented on a gray background with a luminance of 20.9 cd/m^2. The 8 triangles had a side length of 1° and were positioned 7° from the center of the screen. Triangles could appear in four possible orientations (upward, downward, leftward, or rightward).

The experiment lasted three days, consisting of pretest, training, and posttest phases [Figure 1: see original paper]C. On Day 1, pretest and training were conducted; Day 2 involved only training; and Day 3 included training and posttest. Each participant was randomly assigned one orientation as the trained triangle (e.g., upward) and another orientation as the untrained triangle (e.g., rightward). The remaining orientations always served as distractors.

During pretest and posttest, two search tasks were administered: searching for the trained triangle (e.g., upward) and searching for the untrained triangle (e.g., rightward), each consisting of 160 trials, with eye movements recorded. For example, when searching for the trained triangle, target-absent trials (50% of trials) displayed 8 triangles with three orientations (downward, leftward, rightward) randomly presented. In target-present trials (50% of trials), one distractor was replaced by the trained triangle. When searching for the untrained triangle, target-absent trials (50% of trials) displayed 8 triangles with three orientations (downward, leftward, upward), while target-present trials (50% of trials) replaced one distractor with the untrained triangle.

The training phase comprised 1,600 trials per day (400 trials per block, 4 blocks total), with no eye movement recording. Only the trained stimulus was used during training, identical to the trained triangle search task in pretest and posttest.

The trial procedure for pretest, posttest, and training is illustrated in [Figure 1: see original paper]B. Each trial began with a central fixation cross. During eye movement recording (pretest and posttest), the search display appeared only after participants maintained fixation on the central cross for more than 500 ms (within 2° of the center). During training without eye movement recording, the central fixation cross was presented for 500 ms before the search display appeared. After search display onset, participants could move their eyes freely and were instructed to judge as quickly as possible whether the target was present (50% of trials). Participants pressed the left arrow key to report target presence or the right arrow key to report target absence. The search display disappeared immediately after the keypress or after 2,000 ms if no response was made.

Figure 1 (A) Schematic diagram of stimuli used in the experiment. (B) Flowchart of a single trial. (C) Schematic diagram of the entire experimental procedure.

2.4.1 Behavioral Analysis

Accuracy and reaction time (calculated only for correct trials) were analyzed using a 2 (target type: trained vs. untrained triangle) × 2 (test stage: pretest vs. posttest) repeated-measures ANOVA. We reported search task accuracy using the formula: $p' = (p - fp)/(1 - fp)$, where p and fp represent hit and false alarm rates, respectively (Hu et al., 2018; Qu et al., 2017). To enhance result reliability, we reported Bayesian factors BF_{10} (Wagenmakers et al., 2018; Wasserstein & Lazar, 2016). BF_{10} less than 1 indicates evidence favoring the null hypothesis (BF_{10} = 1–0.33: weak evidence; 0.33–0.1: moderate evidence; < 0.1: strong evidence for null), while BF_{10} greater than 1 indicates evidence favoring the alternative hypothesis (BF_{10} = 1–3: weak evidence; 3–10: moderate evidence; > 10: strong evidence for alternative).

2.4.2 Eye Movement Analysis

Eye movement metrics were analyzed using a 2 (target type: trained vs. untrained triangle) × 2 (test stage: pretest vs. posttest) repeated-measures ANOVA. Eye movement traces were segmented into fixations, saccades, and blinks. Saccades were defined as movements with velocity exceeding 30°/s, acceleration exceeding $8000°/s^2$, and distance exceeding 0.1°. Blinks were defined as data loss exceeding 3 ms. Remaining intervals were classified as fixations, with fixations longer than 100 ms counted as valid fixations.

We analyzed three stage-specific metrics: (1) search initiation time (early stage), defined as the interval from search display onset to the first saccade leaving the initial fixation position; (2) scanning stage (middle stage), defined as the interval from the first saccade to the onset of the last fixation, including number of fixations and average fixation duration; and (3) verification time (late stage), defined as the duration of the last fixation before response. Trials with blinks or saccades at trial onset, or with search initiation time less than 80 ms, were excluded from analysis. Incorrect trials were also excluded from eye movement analyses. The number of correct trials for trained and untrained triangles in pretest and posttest, for both target-present and target-absent conditions, is shown in [Figure 2: see original paper].

Figure 2 (A) Number of correct trials for searching trained and untrained triangles in pretest and posttest under target-present conditions. (B) Number of correct trials for searching trained and untrained triangles in pretest and posttest under target-absent conditions.

3.1 Behavioral Results

For accuracy [Figure 3: see original paper]A, the 2 (target type: trained vs. untrained triangle) × 2 (test stage: pretest vs. posttest) repeated-measures ANOVA revealed significant main effects of target type ($F(1, 23) = 83.25$, $p < 0.001$, $p^2 = 0.78$) and test stage ($F(1, 23) = 49.59$, $p < 0.001$, $p^2 = 0.68$), as well as a significant interaction ($F(1, 23) = 101.68$, $p < 0.001$, $p^2 = 0.82$). Simple effects analysis showed that posttest accuracy for trained triangles was significantly higher than pretest accuracy ($\Delta = -0.37 \pm 0.14$, $t(23) = -13.31$, $p < 0.001$, Cohen's d = 2.77, $BF_{10} = 2.99$, 95% CI = [-0.43, -0.31]), while no significant difference was found for untrained triangles between pretest and posttest ($\Delta = 0.00 \pm 0.18$, $t(23) = 0.07$, $p = 0.942$, Cohen's d = 0.02, $BF_{10} = 0.21$, 95% CI = [-0.07, 0.08]). No significant difference existed between target types at pretest ($\Delta = 0.01 \pm 0.12$, $t(23) = 0.22$, $p = 0.829$, Cohen's d = 0.05, $BF_{10} = 0.22$, 95% CI = [-0.04, 0.06]), but a significant difference emerged at posttest ($\Delta = 0.38 \pm 0.15$, $t(23) = 12.15$, $p < 0.001$, Cohen's d = 2.53, $BF_{10} = 6.05$, 95% CI = [0.32, 0.45]).

For reaction time under target-present conditions [Figure 3: see original paper]B, significant main effects of target type ($F(1, 23) = 178.68$, $p < 0.001$, $p^2 = 0.89$) and test stage ($F(1, 23) = 130.64$, $p < 0.001$, $p^2 = 0.85$) were found, along with a significant interaction ($F(1, 23) = 142.72$, $p < 0.001$, $p^2 = 0.86$). Simple effects analysis revealed that posttest reaction times for trained triangles were significantly faster than pretest ($\Delta = 0.50 \pm 0.10$ s, $t(23) = 24.26$, $p < 0.001$, Cohen's d = 5.06, $BF_{10} = 7.29$, 95% CI = [0.45, 0.54]), while no significant difference was observed for untrained triangles ($\Delta = -0.01 \pm 0.18$ s, $t(23) = -0.40$, $p = 0.696$, Cohen's d = 0.08, $BF_{10} = 0.23$, 95% CI = [-0.09, 0.06]). No significant difference existed between target types at pretest ($\Delta = 0.01 \pm 0.10$ s, $t(23) = 0.75$, $p = 0.462$, Cohen's d = 0.16, $BF_{10} = 0.28$, 95% CI = [-0.03, 0.06]), but a significant difference emerged at posttest ($\Delta = -0.50 \pm 0.16$ s, $t(23) = -14.76$, $p < 0.001$, Cohen's d = 3.08, $BF_{10} = 2.28$, 95% CI = [-0.57, -0.43]).

For reaction time under target-absent conditions [Figure 3: see original paper]C, significant main effects of target type ($F(1, 23) = 80.46$, $p < 0.001$, $p^2 = 0.78$) and test stage ($F(1, 23) = 65.62$, $p < 0.001$, $p^2 = 0.74$) were found, along with a significant interaction ($F(1, 23) = 72.00$, $p < 0.001$, $p^2 = 0.72$). Simple effects analysis showed that posttest reaction times for trained triangles were significantly faster than pretest ($\Delta = 0.45 \pm 0.20$ s, $t(23) = 11.06$, $p < 0.001$, Cohen's d = 2.28, $BF_{10} = 8.74$, 95% CI = [0.36, 0.53]), while no significant difference was found for untrained triangles ($\Delta = 0.04 \pm 0.17$ s, $t(23) = 1.13$, $p = 0.270$, Cohen's d = 0.24, $BF_{10} = 0.37$, 95% CI = [-0.03, 0.11]). No significant difference existed between target types at pretest ($\Delta = 0.04 \pm 0.11$ s, $t(23) = 1.64$, $p = 0.114$, Cohen's $d = 0.34$, $BF_{10} = 0.71$, 95% CI = [-0.01, 0.08]), but a significant difference emerged at posttest ($\Delta = -0.37 \pm 0.21$ s, $t(23) = -8.85$, $p < 0.001$, Cohen's $d = 1.84$, $BF_{10} = 1.72$, 95% CI = [-0.46, -0.28]). These results demonstrate clear perceptual learning effects for trained triangles in both accuracy and reaction time, with no transfer to untrained triangles.

Figure 3 (A) Accuracy results for pretest and posttest. (B) Reaction time results for target-present trials in pretest and posttest. (C) Reaction time results for target-absent trials in pretest and posttest.

To examine how perceptual learning effects changed with training amount, we divided the total training into 6 equal parts (training amounts 1–6). For accuracy [Figure 4: see original paper]A, repeated-measures ANOVA revealed a significant main effect of training amount ($F(1, 23) = 135.00$, $p < 0.001$, $p^2 = 0.85$). Post-hoc comparisons showed significant differences between all adjacent training amounts (ps < 0.05) except between amounts 4 and 5 ($p = 1.000$). For target-present reaction time [Figure 4: see original paper]B, repeated-measures ANOVA showed a significant main effect of training amount ($F(1, 23) = 167.38$, $p < 0.001$, $p^2 = 0.88$), with significant differences between all adjacent training amounts (ps < 0.01). For target-absent reaction time [Figure 4: see original paper]C, repeated-measures ANOVA revealed a significant main effect of training amount ($F(1, 23) = 65.96$, $p < 0.001$, $p^2 = 0.74$), with no significant differences between training amounts 2 and 3 ($p = 0.144$) or between amounts 3 and 4 ($p = 0.113$), but significant differences between all other adjacent amounts (ps < 0.01). These results indicate that participants' performance improved gradually throughout the three-day training period.

Figure 4 (A) Accuracy (p') results across different training amounts. (B) Reaction time results across different training amounts for target-present trials. (C) Reaction time results across different training amounts for target-absent trials. The horizontal axis labels 1 and 2 represent the first and second halves of Day 1 training; 3 and 4 represent the first and second halves of Day 2 training; 5 and 6 represent the first and second halves of Day 3 training.

3.2.1 Search Initiation Time

For target-present trials [Figure 5: see original paper]A, the 2 (target type: trained vs. untrained triangle) × 2 (test stage: pretest vs. posttest) repeated-measures ANOVA on search initiation time showed no significant main effects of target type ($F(1, 23) = 2.00$, $p = 0.171$, $p^2 = 0.08$) or test stage ($F(1, 23) = 1.51$, $p = 0.232$, $p^2 = 0.06$), but a significant interaction ($F(1, 23) = 4.53$, $p = 0.044$, $p^2 = 0.16$). Simple effects analysis revealed that posttest search initiation time for trained triangles was significantly longer than pretest ($\Delta = -32.43 \pm 63.95$ ms, $t(23) = -2.48$, $p = 0.021$, Cohen's $d = 0.52$, $BF_{10} = 2.65$, 95% CI = [-59.43, -5.42]), while no significant difference was found for untrained triangles ($\Delta = 0.31 \pm 83.42$ ms, $t(23) = 0.02$, $p = 0.986$, Cohen's $d < 0.01$, $BF_{10} = 0.21$, 95% CI = [-34.91, 35.53]). No significant difference existed between target types at pretest (Δ = -3.99 ± 49.91 ms, t(23) = -0.39, p = 0.699, Cohen's d = 0.08, BF_{10} = 0.23, 95% CI = [-25.07, 17.08]), but a significant difference emerged at posttest (Δ = 28.75 ± 63.51 ms, t(23) = 2.22, p = 0.037, Cohen's d = 0.46, BF_{10} = 1.66, 95% CI = [1.93, 55.57]).

For target-absent trials [Figure 5: see original paper]B, similar results were found: no significant main effects of target type (F(1, 23) = 4.52, p = 0.044, p^2 = 0.16) or test stage (F(1, 23) = 1.06, p = 0.315, p^2 = 0.04), but a significant interaction (F(1, 23) = 8.88, p = 0.007, p^2 = 0.28). Simple effects analysis showed that posttest search initiation time for trained triangles was significantly longer than pretest (Δ = -45.16 ± 75.56 ms, t(23) = -2.93, p = 0.008, Cohen's d = 0.61, BF_{10} = 6.12, 95% CI = [-77.06, -13.25]), while no significant difference was observed for untrained triangles (Δ = 13.51 ± 101.67 ms, t(23) = 0.65, p = 0.52, Cohen's d = 0.14, BF_{10} = 0.26, 95% CI = [-29.42, 56.44]). No significant difference existed between target types at pretest (Δ = -9.67 ± 65.28 ms, t(23) = -0.73, p = 0.475, Cohen's d = 0.15, BF_{10} = 0.27, 95% CI = [-37.23, 17.90]), but a significant difference emerged at posttest (Δ = 49.00 ± 67.07 ms, t(23) = 3.58, p = 0.002, Cohen's d = 0.75, BF_{10} = 23.40, 95% CI = [20.68, 77.32]). These results demonstrate that search initiation time for trained triangles increased significantly after training, regardless of target presence, with no transfer to untrained triangles.

Figure 5 (A) Search initiation time for target-present trials. (B) Search initiation time for target-absent trials.

3.2.2 Number of Fixations

For target-present trials [Figure 6: see original paper]A, the 2 (target type: trained vs. untrained triangle) × 2 (test stage: pretest vs. posttest) repeated-measures ANOVA on number of fixations revealed significant main effects of target type (F(1, 23) = 76.59, p < 0.001, p^2 = 0.77) and test stage (F(1, 23) = 79.39, p < 0.001, p^2 = 0.78), and a significant interaction (F(1, 23) = 51.74, p < 0.001, p^2 = 0.69). Simple effects analysis showed that posttest number of fixations for trained triangles was significantly lower than pretest (Δ = 2.04 ± 0.50, t(23) = 19.89, p < 0.001, Cohen's d = 4.15, BF_{10} = 9.37, 95% CI = [1.83, 2.26]), while no significant difference was found for untrained triangles (Δ = -0.02 ± 1.16, t(23) = -0.10, p = 0.919, Cohen's d = 0.02, BF_{10} = 0.22, 95% CI = [-0.52, 0.47]). No significant difference existed between target types at pretest (Δ = 0.09 ± 0.89, t(23) = 0.48, p = 0.638, Cohen's d = 0.10, BF_{10} = 0.24, 95% CI = [-0.29, 0.46]), but a significant difference emerged at posttest (Δ = -1.98 ± 0.88, t(23) = -11.10, p < 0.001, Cohen's d = 2.31, BF_{10} = 9.32, 95% CI = [-2.35, -1.61]).

For target-absent trials [Figure 6: see original paper]B, significant main effects of target type (F(1, 23) = 59.65, p < 0.001, p^2 = 0.72) and test stage (F(1, 23) = 71.24, p < 0.001, p^2 = 0.76) were found, along with a significant interaction

($F(1, 23) = 48.14$, $p < 0.001$, $p^2 = 0.68$). Simple effects analysis revealed that posttest number of fixations for trained triangles was significantly lower than pretest ($\Delta = 2.23 \pm 0.85$, $t(23) = 12.84$, $p < 0.001$, Cohen's $d = 2.68$, $BF_{10} = 1.46$, 95% CI = [1.87, 2.59]), while no significant difference was found for untrained triangles ($\Delta = 0.18 \pm 1.14$, $t(23) = 0.79$, $p = 0.437$, Cohen's $d = 0.17$, $BF_{10} = 0.28$, 95% CI = [-0.30, 0.67]). At pretest, trained triangles elicited significantly more fixations than untrained triangles ($\Delta = 0.40 \pm 0.73$, $t(23) = 2.65$, $p < 0.05$, Cohen's $d = 0.55$, $BF_{10} = 3.59$, 95% CI = [0.09, 0.70]), while at posttest, trained triangles elicited significantly fewer fixations ($\Delta = -1.65 \pm 0.91$, $t(23) = -8.92$, $p < 0.001$, Cohen's $d = 1.86$, $BF_{10} = 1.97$, 95% CI = [-2.03, -1.27]). These results demonstrate that the number of fixations decreased after training, regardless of target presence, with no transfer of this perceptual learning effect to untrained triangles.

Figure 6 (A) Number of fixations for target-present trials. (B) Number of fixations for target-absent trials.

3.2.3 Average Fixation Duration

For target-present trials [Figure 7: see original paper]A, the 2 (target type: trained vs. untrained triangle) × 2 (test stage: pretest vs. posttest) repeated-measures ANOVA on average fixation duration revealed significant main effects of target type ($F(1, 23) = 82.58$, $p < 0.001$, $p^2 = 0.78$) and test stage ($F(1, 23) = 39.63$, $p < 0.001$, $p^2 = 0.63$), and a significant interaction ($F(1, 23) = 44.05$, $p < 0.001$, $p^2 = 0.66$). Simple effects analysis showed that posttest average fixation duration for trained triangles was significantly shorter than pretest ($\Delta = 63.40 \pm 42.04$ ms, $t(23) = 7.39$, $p < 0.001$, Cohen's $d = 1.54$, $\log(BF_{10}) = 11.47$, 95% CI = [45.65, 81.16]), while no significant difference was found for untrained triangles ($\Delta = -4.82 \pm 23.23$ ms, $t(23) = -1.02$, $p = 0.321$, Cohen's $d = 0.21$, $BF_{10} = 0.34$, 95% CI = [-14.63, 5.00]). No significant difference existed between target types at pretest ($\Delta = -6.59 \pm 19.90$ ms, $t(23) = -1.62$, $p = 0.118$, Cohen's $d = 0.34$, $BF_{10} = 0.67$, 95% CI = [-15.00, 1.81]), but a significant difference emerged at posttest ($\Delta = -74.81 \pm 42.84$ ms, $t(23) = -8.56$, $p < 0.001$, Cohen's $d = 1.87$, $\log(BF_{10}) = 13.80$, 95% CI = [-92.90, -56.73]).

For target-absent trials [Figure 7: see original paper]B, a significant main effect of target type was found ($F(1, 23) = 10.06$, $p < 0.01$, $p^2 = 0.30$), while the main effect of test stage ($F(1, 23) = 1.31$, $p = 0.263$, $p^2 = 0.05$) and the interaction ($F(1, 23) = 0.29$, $p = 0.597$, $p^2 = 0.01$) were not significant. These results indicate that when targets were present, average fixation duration for trained targets decreased after training, with no transfer of this perceptual learning effect to untrained triangles.

Figure 7 (A) Average fixation duration for target-present trials. (B) Average fixation duration for target-absent trials.

3.2.4 Verification Time

For target-present trials [Figure 8: see original paper]A, verification time showed no significant main effects of target type (F(1, 23) = 0.99, p = 0.329, p^2 = 0.04) or test stage (F(1, 23) = 1.25, p = 0.274, p^2 = 0.05), and no significant interaction (F(1, 23) = 1.70, p = 0.206, p^2 = 0.07). For target-absent trials [Figure 8: see original paper]B, verification time similarly showed no significant main effects of target type (F(1, 23) = 2.68, p = 0.115, p^2 = 0.10) or test stage (F(1, 23) = 0.37, p = 0.552, p^2 = 0.02), and no significant interaction (F(1, 23) = 2.47, p = 0.129, p^2 = 0.10). These results indicate that training did not significantly affect the late stage of visual processing.

Figure 8 (A) Verification time for target-present trials. (B) Verification time for target-absent trials.

4 Discussion

Using an experimental paradigm similar to Qu et al. (2017), this study divided the visual search process into three processing stages to more intuitively investigate the effects of perceptual learning. Results revealed significant perceptual learning effects for trained stimuli in search initiation time and scanning stage, while verification time, representing late visual processing, was unaffected. This suggests that perceptual learning effects occur in relatively early and middle visual processing stages.

To further explore the relationship between increased search initiation time and decreased number of fixations after perceptual learning, we conducted a Pearson correlation analysis, finding a significant negative correlation ($r = -0.416$, $p < 0.05$), indicating that longer search initiation time was associated with fewer fixations. We also categorized target-present trials into two types based on number of fixations: trials with zero fixations during scanning (30.32 ± 20.90%) occurred when participants made only one saccade before responding, meaning the single fixation between the first saccade and keypress was counted as verification time rather than scanning; trials with more than zero fixations (69.70 ± 20.90%) involved more than one saccade before response. Results showed that search initiation time was significantly longer in trials with zero fixations than in trials with more than zero fixations ($p < 0.001$). Qu et al. (2017) found that perceptual learning of nonsalient stimuli elicited an N2pc component from the lateral occipital complex (LOC), and Q. Zhang et al. (2022) observed a significant N2pc component specific to trained targets before saccade onset, indicating that spatial attention focuses on trained target stimuli after perceptual learning, with attention allocated before saccades to optimize subsequent search. The N2pc component can only be observed before eye movements when covert attention is allocated to stimuli prior to saccade generation (Talcott & Gaspelin, 2021). The current study found reduced number of fixations and average fixation duration after perceptual learning, suggesting that covert attention may be allocated before eye movements to facilitate search.

Previous studies recording eye movements before and after perceptual learning have also found increased search initiation time and decreased number of fixations (Q. Zhang et al., 2022), consistent with our results. Q. Zhang et al. (2022) used color-orientation conjunction stimuli representing interdimensional feature binding, while the current study used triangles representing intradimensional feature binding. Both are nonsalient stimuli, suggesting that geometric shape and conjunction feature perceptual learning may share similar learning mechanisms in early visual processing. However, in middle visual processing, although both types of learning showed reduced fixation counts, Q. Zhang et al. (2022) found no significant difference in average fixation duration between pretest and posttest for conjunction features, inconsistent with our geometric shape results. This suggests that while geometric shape and conjunction feature perceptual learning may share some mechanisms in middle visual processing, they are not identical.

The Dual-Plasticity model proposes two types of perceptual learning plasticity (Watanabe & Sasaki, 2015): feature-based plasticity and task-based plasticity. Feature-based plasticity involves changes in neural responses to trained features, while task-based plasticity involves improved task-related processing associated with changes in connectivity between visual representation and cognitive regions (Shibata et al., 2016). These two plasticity types suggest different mechanisms of perceptual learning. If perceptual learning in this study were feature-based, learning effects should differ between target-present and target-absent conditions. However, our results showed consistent learning effects for search initiation time, number of fixations, and verification time regardless of target presence, suggesting that perceptual learning for nonsalient stimuli may be task-based.

Task difficulty also influences perceptual learning outcomes. Easier tasks generally involve changes in higher-level visual cortex and thus show transferability, while more difficult and precise tasks involve changes in primary visual cortex and exhibit specificity (Ahissar & Hochstein, 1997). Qu et al. (2017) found no transferability under difficult conditions. The current study reduced task difficulty by decreasing search set size, yet perceptual learning effects for trained triangle orientations still did not transfer to untrained triangles, showing specificity. Researchers attribute the lack of transferability to neural bases of learning effects residing in early sensory processing stages (Karni & Sagi, 1991), with plasticity changes possibly occurring in primary visual cortex. Early visual cortex neurons have small receptive fields and are selective for simple stimulus features (e.g., orientation), making them more likely to show specificity. Although some attribute perceptual learning specificity to V1 plasticity, the neural mechanisms may be more complex, involving not only primary cortex but also networks of brain regions engaged in sensory processing, decision-making, top-down task relevance, and action selection (Law & Gold, 2008, 2009). These sensory and cognitive processes may all change during task performance, suggesting that perceptual learning involves multiple processes, levels, and brain regions. Future research should view perceptual learning as a process-based change and investigate the involvement of different brain regions at different learning stages from neurophysiological perspectives, rather than simply attributing specificity to V1 plasticity.

In addition to task difficulty, training duration affects perceptual learning. Building on Qu et al. (2017), this study reduced task difficulty while shortening training duration, yet pretest-posttest comparisons still showed significant improvements in search ability. Research has found rapid performance improvements after just one hour of training (Fahle et al., 1995), and Ahissar and Hochstein (1996) observed significant behavioral improvements after 1,400 trials in pop-out detection perceptual learning. Karni and Sagi (1993) proposed that perceptual learning may involve fast and slow learning phases: fast learning shows significant improvement shortly after training, while slow learning shows improvement 6–8 hours after the final training session, often related to sleep. Ding et al. (2023) trained participants on color-orientation conjunction search and found significant perceptual learning effects that partially transferred to new targets sharing color or orientation features with trained targets. When retested several months later, search performance for color features decreased significantly compared to the first posttest, while orientation performance showed no significant difference. The researchers concluded that orientation feature improvements were relatively difficult to achieve and that slow learning effects are generally long-lasting, suggesting that orientation learning primarily results from slow learning, while color feature learning may involve fast learning.

Ding et al. (2023) also found that conjunction feature learning effects could partially transfer to new targets sharing either color or orientation with trained targets, with the total learning effect approximately equal to the sum of individual feature transfer effects. This suggests that conjunction feature perceptual learning does not form a new functional unit but rather learns individual features, supporting a feature-based attentional enhancement mechanism (Ding et al., 2023; Su et al., 2014). According to the unitization hypothesis, intradimensional conjunction features (e.g., triangles) form a new functional unit corresponding to the conjunction after perception (Czerwinski et al., 1992), with perceptual learning effects specific to trained targets and no transfer to any new targets (Su et al., 2014). Future research requires more electrophysiological evidence to investigate the learning mechanisms of these two types of features from deeper brain processing perspectives.

5 Conclusion

This study investigated the mechanism by which perceptual learning facilitates search by examining different eye movement metrics representing distinct visual processing stages. Results showed that triangle orientation perceptual learning effects occurred primarily in early and middle visual processing stages, with specificity. Perceptual learning may enhance search performance by increasing search initiation time before the first saccade, thereby reducing the number of searched locations and accelerating processing at each location.

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The mechanism of visual processing for nonsalient stimuli in perceptual learning

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Previous studies have found that perceptual learning can improve performance on visual search tasks. However, many cognitive processes are involved in visual search, and it is unclear at which visual processing stage perceptual learning facilitates search performance. The current study explored the mechanism of perceptual learning by dividing eye movement metrics into three visual processing stages: search initiation time (early visual processing stage), which represents the cognitive process of processing the current location and selecting the next search location; scanning time (middle visual processing stage), which includes the number and processing time of fixation positions; and verification time (late visual processing stage), which represents determining whether the current stimulus is the target and making a verification.

A 2 (target type: trained vs. untrained triangle) × 2 (pretest vs. posttest) within-subjects design was used to address this issue. Twenty-four healthy young adults (5 males; mean age: 21.23 ± 2.02 years) participated as paid volunteers. We randomly selected one of the four triangle orientations (up, down, left, or right) as the trained triangle, which received three days of training. To ensure visual search training was specific to the trained triangle, we tested both trained and untrained triangles by recording behavioral results and eye movements before and after training (the untrained triangle was randomly selected from distractors). Each trial began with a fixation cross (during eye movement recording, the search display appeared only after participants fixated the center cross for more than 500 ms; during training without eye movement recording, the central fixation cross was presented for 500 ms before the search display). The search display was presented until response or until 2000 ms elapsed. Participants pressed the left arrow key to report target presence or the right arrow key to report target absence.

A two-way repeated-measures ANOVA with factors of target type (trained vs. untrained triangle) and test stage (pretest vs. posttest) was conducted. Behavioral results showed reduced response time and increased accuracy when searching for trained stimuli after training. However, no significant differences in response time or accuracy were found between pretest and posttest for untrained stimuli. Eye movement tracking results were as follows: (1) In the early visual processing stage, search initiation time for trained stimuli increased significantly after training, with no significant difference for untrained stimuli. (2) In the middle visual processing stage, the number of fixations and average fixation duration for trained stimuli decreased significantly after training, with no significant difference for untrained stimuli. (3) In the late visual processing stage, no significant difference in verification time was found between pretest and posttest for either trained or untrained stimuli.

In conclusion, accuracy and search initiation time for trained stimuli increased, while the number of fixations and fixation duration decreased. Moreover, changes in behavioral and eye movement indices did not transfer to untrained stimuli. This suggests that perceptual learning can affect early and middle visual processing stages, and that search performance may be improved by increasing search initiation time, reducing the number of saccades, and reducing fixation duration.

Key words: Perceptual learning, nonsalient stimuli, learning mechanism, visual processing, eye movement

Note: Figure translations are in progress. See original paper for figures.