



# Double training promotes retinotopic transfer of category learning



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Perceptual learning is traditionally retinotopically constrained, whereas category learning is thought to generalize across the visual field. Recent evidence challenges this distinction by showing that information-integration (II) category learning can also exhibit visual-field specificity. We investigated whether II learning transfers across retinal locations using a double-training paradigm. Participants learned to categorize gratings at one peripheral location, and transfer was tested at the opposite hemifield. We replicated visual-field specificity and found that transfer depended on the temporal order of training. Double training, with simultaneous or subsequent passive exposure to an irrelevant task at the untrained location, enabled robust transfer, whereas performing the irrelevant task before category training abolished it. This order-dependent pattern mirrors double-training effects in perceptual learning, suggesting that II category learning and perceptual learning share principles of location-specific plasticity and flexible transfer. These findings shed light on mechanisms of visual learning and inform strategies to enhance transfer.

Categorization is fundamental to human cognition, allowing individuals to efficiently interpret and respond to a wide range of sensory inputs, from object recognition to complex decision-making. Traditional models, such as prototype and exemplar theories, emphasize high-level cognitive processes and propose that categorization relies on abstract representations largely independent of low-level sensory inputs<sup>1</sup>. However, accumulating evidence suggests that category learning can be divided into two distinct forms: rule-based (RB) and information-integration (II) learning, supported by partially dissociable cognitive and neural systems<sup>2,3</sup>.

Rule-based category learning engages explicit reasoning, as participants identify a single relevant stimulus dimension (e.g., spatial frequency or orientation) and apply verbalizable rules to assign category membership. Success in RB learning depends critically on declarative memory systems, particularly working memory and executive attention, which support hypothesis testing and rule maintenance<sup>4,5</sup>. In contrast, information-integration learning requires combining multiple, often incommensurable, stimulus dimensions before making a categorical decision<sup>4</sup>. This process operates largely implicitly and depends on procedural learning mechanisms, with stimulus–response associations reinforced through striatal-based feedback learning<sup>6–8</sup>.

Recent studies have shown that information-integration category learning exhibits a striking specificity to retinal location, suggesting a close dependency on low-level perceptual processes<sup>9,10</sup>. Participants trained to categorize stimuli presented on one side of fixation

performed worse when the same stimuli appeared on the opposite side, whereas rule-based learning remained unaffected, highlighting its abstract nature. This location specificity parallels that observed in perceptual learning, where improvements are typically confined to the trained retinal location or feature<sup>11–13</sup>. The specificity of perceptual learning has been attributed either to plasticity within early visual areas, such as V1 neurons tuned to the trained stimulus<sup>14–19</sup>, or to changes in higher-level visual and decision-related regions<sup>20–24</sup>. The latter account aligns with reweighting theories, which propose that perceptual learning primarily adjusts how sensory inputs are read out, rather than altering sensory tuning itself<sup>25,26</sup>.

The specificity of learning poses a major challenge in practical applications, motivating extensive research on how to overcome this limitation<sup>12</sup>. For example, our previous studies have demonstrated complete transfer of learning across retinal locations or stimulus features using double-training paradigms<sup>27–33</sup>. In these paradigms, participants are trained at one location or orientation in a task that is typically location- or orientation-specific, while simultaneously or subsequently being passively exposed to the transfer location or orientation in an irrelevant task. This procedure enables complete transfer to untrained locations or orientations, challenging specificity-based models and suggesting the operation of a more general learning mechanism. Learning specificity may result from the underactivation of untrained visual neurons due to insufficient bottom-up stimulation

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and/or limited top-down attention during training<sup>31</sup>. Moreover, we have shown mutual and complete transfer between physically distinct orientations or motion stimuli<sup>34</sup>, indicating that perceptual learning may involve the formation of abstract sensory representations<sup>30,34,35</sup>. Such findings point to the engagement of higher-level brain areas that process complex information, a principle that may also apply to information-integration learning.

Although most research on transfer has focused on perceptual learning, similar questions about generalization and system-level mechanisms are equally critical for category learning. The influential Competition between Verbal and Implicit Systems (COVIS) framework posits two partially distinct systems: an explicit, prefrontal-dependent rule-based (RB) system and an implicit, basal ganglia-dependent information-integration (II) system<sup>6</sup>. COVIS further predicts differential basal ganglia involvement, with the head of the caudate supporting RB learning and the putamen and body of the caudate supporting II learning<sup>7,8</sup>. Overlapping activations in sensory and motor cortices across tasks are consistent with this account<sup>36</sup>, suggesting that the separation between systems is relative rather than absolute.

Building on this foundation, recent evidence refines rather than refutes the dual-system view. Neuroimaging and neuropsychological studies have revealed partially overlapping neural activations during RB and II learning<sup>7,37</sup> and show that lesions to either the basal ganglia or prefrontal cortex can impair both types of tasks<sup>38,39</sup>. Computational models such as SUSTAIN<sup>40</sup> likewise suggest that exemplar- and prototype-based representations may emerge from shared mechanisms. More recent perspectives conceptualize category learning along a continuum, emphasizing the dynamic, context-dependent interaction between explicit and implicit processes<sup>41–43</sup>. This integrative view reconciles earlier theoretical divisions and provides a more nuanced understanding of how multiple learning systems jointly contribute to category acquisition.

This continuum perspective of learning raises an important question: do location-specific effects in II category learning<sup>9,10</sup> reflect rigid low-level constraints, or can they be modified through targeted training, as observed in perceptual learning? To address this question, we examined whether the double-training paradigm, previously shown to facilitate transfer in perceptual learning, can overcome retinal location specificity in II category learning. Specifically, we systematically compared several training paradigms: (1) simultaneous double training with an interleaved irrelevant task, and (2) sequential double training in which either the II task or the irrelevant task was trained first. This design allowed us to evaluate the relative effectiveness of these paradigms in promoting transfer across retinal locations.

## Results

In the information-integration (II) category-learning task, participants learned to classify stimuli based on trial-by-trial feedback (category structure shown in Fig. 1a; an example trial in Fig. 1b; see the “Methods” section for details). The study consisted of four experiments, each with a distinct group of participants, differing in the temporal arrangement of II category learning and an irrelevant grating contrast discrimination task (Fig. 1c). In Experiment 1 (baseline), participants completed only the II category-learning task at the trained location, allowing assessment of the magnitude and location specificity of II learning. Experiment 2 employed a simultaneous double-training paradigm, pairing II learning at the trained location with contrast discrimination training at the transfer location. Experiment 3 used a sequential double-training design, where contrast discrimination training at the transfer location was completed first, followed by II category learning at the trained location. Experiment 4 implemented a reversed sequential design, with II category learning first, followed by contrast discrimination training at the transfer location. Across all experiments, the post-test phase was identical and consisted of two blocks of the II category task performed without feedback, one at the trained location and one at the transfer location.

To provide an overall assessment of learning and transfer effects across these different training regimes, we first conducted linear mixed-effects (LME) analyses on the pooled II task data from Experiments 1–4. This approach allowed us to test common effects of post-test location and experimental group, as well as their interaction, before examining experiment-specific patterns in subsequent within-group analyses. The LME analysis revealed a significant main effect of post-test location ( $F_{(1, 68)} = 38.67, p < 0.0001$ ), but no significant main effect of group ( $F_{(3, 68)} = 0.72, p = 0.54$ ). Importantly, there was a significant interaction between group and post-test location ( $F_{(3, 68)} = 7.47, p = 0.0002$ ). Post hoc comparisons showed that, at the trained location, post-test accuracy did not differ significantly among the four groups ( $ps > 0.17$ ), suggesting comparable II task learning across experiments. Additional post hoc analyses examining location-specific effects and transfer are reported in the within-group analyses below.

In addition, an LME analysis of the pooled data from the grating contrast discrimination task (the “irrelevant task” in Experiments 2–4) showed that accuracy in the final block was significantly higher than in the first block across all three experiments ( $ps < 0.002$ ), demonstrating robust learning in this task.

### Experiment 1: Location specificity of information-integration category learning

In Experiment 1, we sought to replicate previous findings demonstrating retinal location specificity in II category learning<sup>9,10</sup>. Twenty participants completed 10 blocks of the II category-learning task with trial-by-trial feedback. Following training, they performed two post-test blocks without feedback: one at the trained location and the other at an untrained transfer location in the opposite visual hemifield (Fig. 2a).

As shown in Fig. 2b, both average and individual learning curves indicated steady improvement during training. Post-test analyses revealed clear location specificity: accuracy at the transfer location was significantly lower than at the trained location (Fig. 2c; trained:  $0.78 \pm 0.02$ ; transfer:  $0.66 \pm 0.02$ ; difference =  $0.127 \pm 0.02, t = 6.22, p < 0.0001$ , 95% confidence interval (CI) [0.09, 0.17], Cohen’s  $d = 1.34$ ).

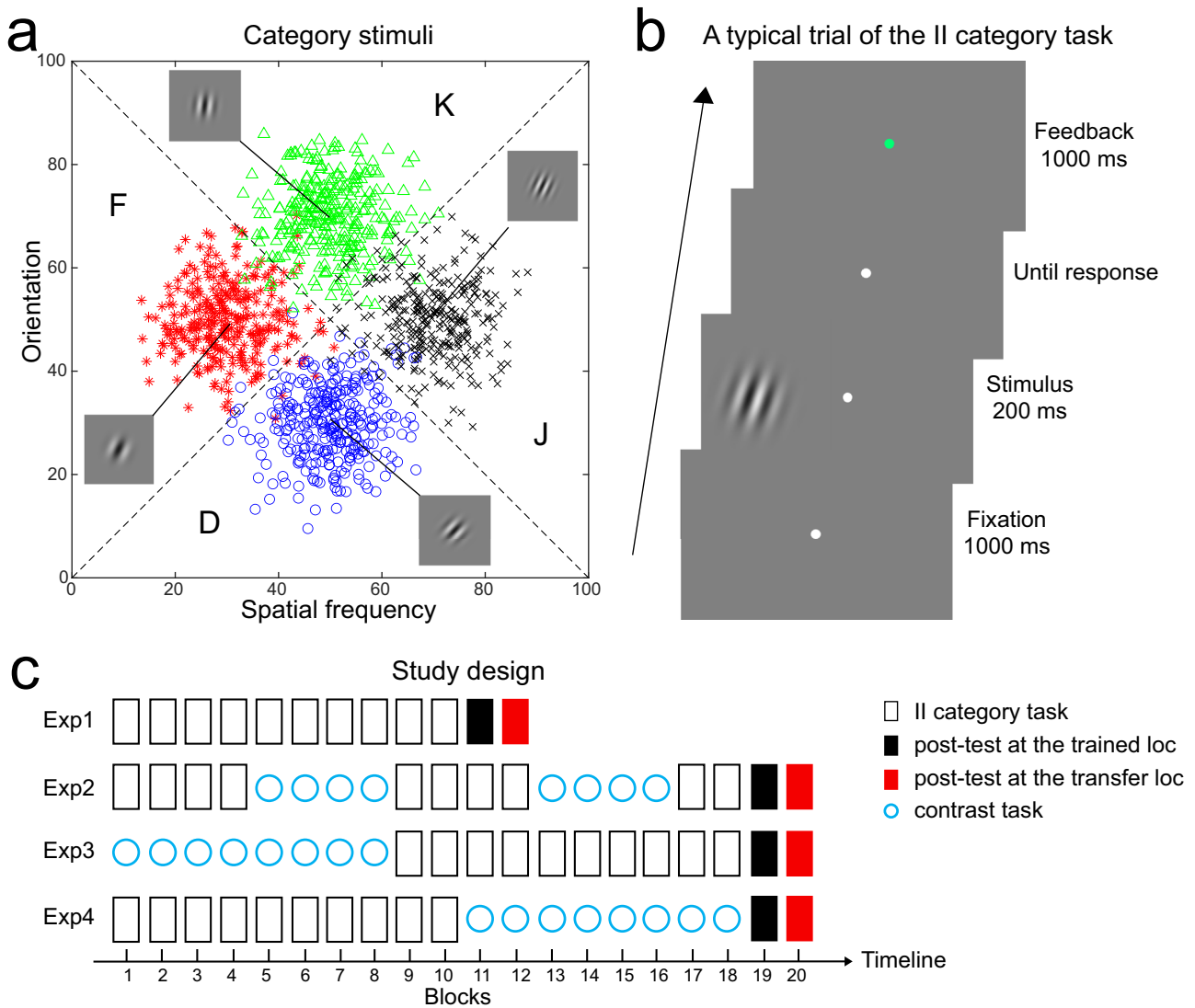
Transfer indices (TIs) were computed to further quantify learning transfer. A one-sample t-test showed TIs were significantly below 1 (mean TI =  $0.77 \pm 0.04, t_{19} = 5.64, p < 0.001$ , Cohen’s  $d = 1.26$ ), confirming incomplete transfer. These results provide robust evidence that II category learning is retinotopically specific, replicating previous studies<sup>9,10</sup>.

### Experiment 2: Simultaneous double training reduces location specificity in II category learning

Building on prior findings from perceptual learning showing substantial interhemispheric transfer through double-training paradigms<sup>27,31–33</sup>, we tested whether simultaneous double training could similarly reduce location specificity in II category learning. Twenty participants performed the II category task at one peripheral location ( $5^\circ$  eccentricity) while simultaneously completing eight blocks of an irrelevant contrast discrimination task at the mirror-symmetric transfer location. The two tasks used identical Gabor stimuli and were interleaved in four-block segments (Fig. 3a).

Training led to robust improvements in both categorization accuracy and contrast discrimination task performance (Fig. 3b). Importantly, post-test analyses indicated no significant difference in II task accuracy between trained and transfer locations (trained:  $0.81 \pm 0.02$ ; transfer:  $0.78 \pm 0.02$ ; difference =  $0.029 \pm 0.02, t = 1.42, p = 0.16$ , 95% CI [−0.01, 0.07], Cohen’s  $d = 0.38$ ; Fig. 3c). Transfer indices (TIs) did not differ significantly from 1 (mean TI =  $0.95 \pm 0.03, t_{19} = 1.54, p = 0.14$ , Cohen’s  $d = 0.35, BF_{10} = 0.64$ ), providing only anecdotal evidence for equivalent performance across locations.

These results indicate that simultaneous double training with an interleaved contrast discrimination task substantially reduces location specificity in II category learning. Although the data do not conclusively demonstrate complete transfer, the pattern suggests that interleaved exposure at the transfer location can effectively promote generalization.



**Fig. 1 | Stimuli and study design.** **a** Sample stimuli and categories. The stimuli were adapted from Rosedahl et al.<sup>10</sup> and consisted of Gabor patches. In the II category task, Gabor stimuli were categorized into four groups according to their spatial frequency and orientation: F (30, 50), D (50, 30), K (50, 70), and J (70, 50). Dashed lines indicate nominal category boundaries and are shown for visualization purposes only. Because categories were defined as overlapping normal distributions, some stimuli from one category may fall within the nominal region of another. **b** Trial structure. Each II category trial began with a 1000 ms fixation, followed by a stimulus presented for

200 ms at 5° left or right of fixation (locations balanced across participants). Participants categorized the stimulus using the keys D, F, J, or K. Feedback was provided via a change in the fixation point color: green for correct and red for incorrect responses, displayed for 1000 ms. **c** Study design. Four experiments were conducted with separate participant groups: the baseline group (Experiment 1) completed 10 blocks of the II category task; double-training groups (Experiments 2–4) additionally completed 8 blocks of an irrelevant contrast discrimination task in different temporal arrangements. Post-test phases included II category blocks at both the trained and transfer locations.

**Experiment 3: Incomplete transfer in sequential double-training with prior exposure to the irrelevant task**

Previous studies in perceptual learning have shown that double-training paradigms can involve either simultaneous or sequential task presentation, with the temporal order of tasks critically determining transfer efficacy<sup>27,28</sup>. In category learning, Rosedahl and Watanabe<sup>9</sup> reported that sequential double training, when the irrelevant contrast discrimination task precedes the II category task, fails to produce complete location transfer.

We replicated this paradigm with 16 participants (Fig. 4a). Training began with contrast discrimination at the transfer location, followed by II category training at the mirror-symmetric location. Learning curves (Fig. 4b) confirmed successful acquisition of the category task. However, post-test performance revealed pronounced location specificity: accuracy at the transfer location ( $0.67 \pm 0.04$ ) was significantly lower than at the trained location ( $0.77 \pm 0.03$ ; difference =  $0.106 \pm 0.02$ ,  $t = 4.65$ ,  $p < 0.0001$ , 95% CI [0.06, 0.15], Cohen’s  $d = 1.24$ ; Fig. 4c). Transfer indices (TIs) were

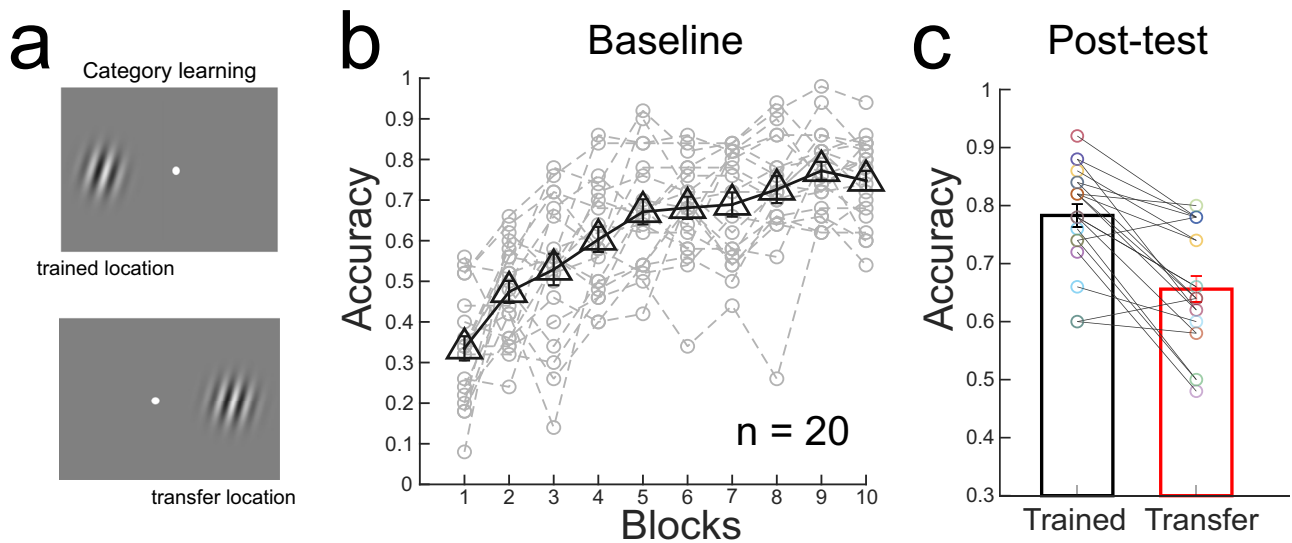
significantly below 1 (mean TI =  $0.78 \pm 0.05$ ,  $t_{15} = 4.70$ ,  $p < 0.001$ , Cohen’s  $d = 1.18$ ), indicating incomplete transfer.

These results demonstrate that sequential double training, when the irrelevant task is administered first, does not overcome retinotopic constraints in II category learning, consistent with the findings of Rosedahl and Watanabe<sup>9</sup>.

**Experiment 4: Sequential double training with initial category learning reduces location specificity**

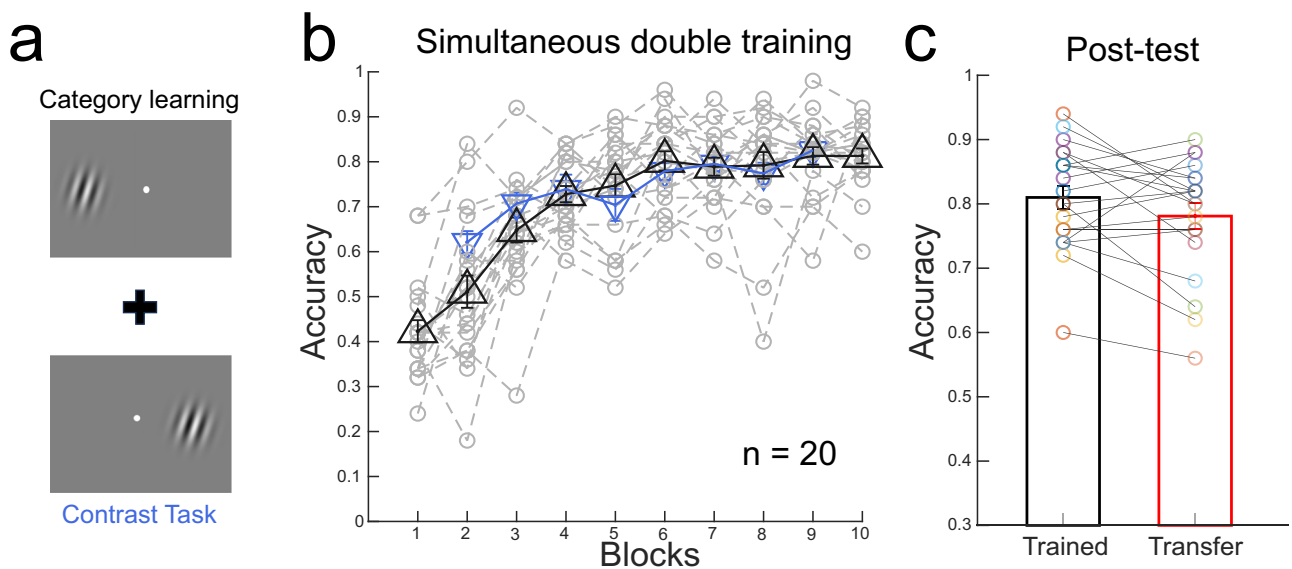
Previous work in perceptual learning has shown that sequential training facilitates transfer when the primary task precedes exposure to an irrelevant task<sup>27,44,45</sup>. Based on this, we hypothesized that the same temporal order would promote location transfer in II category learning.

Sixteen participants completed a sequential double-training protocol (Fig. 5a), performing the II category task at one peripheral location (5° eccentricity) first, followed by an irrelevant contrast discrimination task at



**Fig. 2 | Behavioral results from the baseline group.** **a** Schematic of the experimental design. During training, participants performed the II category task at a peripheral location (5° eccentricity from central fixation). Post-tests were conducted at both the trained location and the mirror-symmetric transfer location in the opposite visual hemifield. **b** Learning curves showing categorization accuracy across training blocks.

Black triangles indicate block-wise mean accuracy (large dots) with individual participant data (small dots). **c** Post-test performance at trained versus transfer locations. Each data point represents an individual participant's accuracy (small dots). Error bars indicate  $\pm 1$  SEM.



**Fig. 3 | Behavioral results for the simultaneous double-training group.** **a** Schematic of the training paradigm. Participants performed the II category task at the trained location (5° eccentricity) while simultaneously completing an irrelevant contrast discrimination task at the mirror-symmetric transfer location. Both tasks used identical Gabor stimuli. **b** Block-by-block accuracy for the II category task

(black triangles) and the contrast discrimination task (blue triangles). Large dots indicate group mean; small dots represent individual participants. **c** Post-test performance at trained versus transfer locations. Each data point represents an individual participant's accuracy (small dots). Error bars indicate  $\pm 1$  SEM.

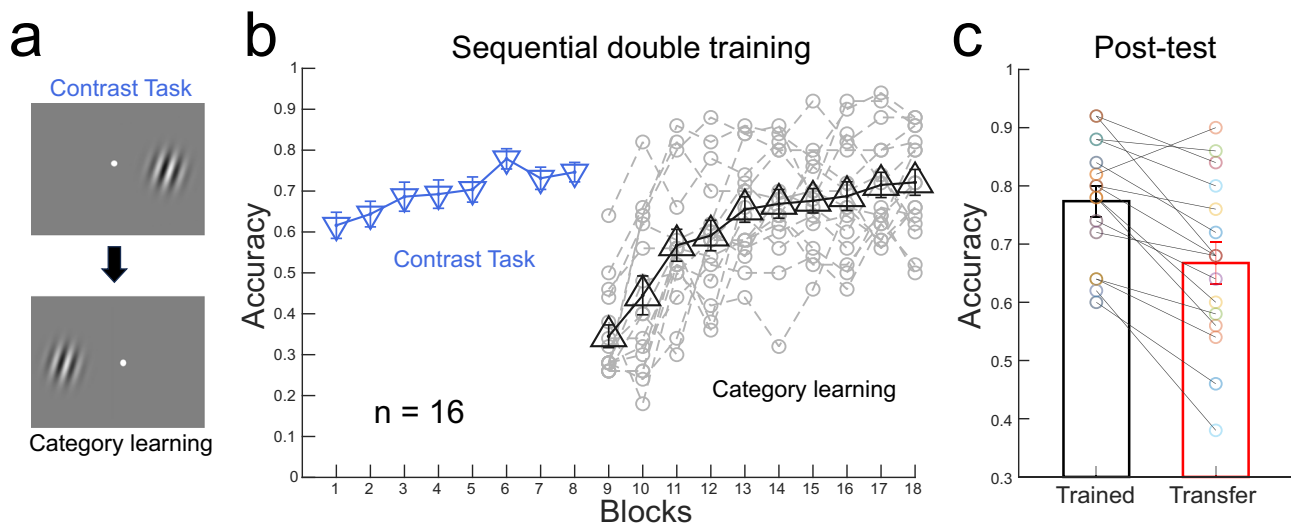
the mirror-symmetric transfer location. Learning curves confirmed successful acquisition of the category task (Fig. 5b). Post-test performance showed comparable accuracy between trained and transfer locations (Fig. 5c; trained:  $0.76 \pm 0.03$ ; transfer:  $0.76 \pm 0.03$ ; difference =  $0.005 \pm 0.02$ ,  $t = 0.22$ ,  $p = 0.83$ , 95% CI  $[-0.04, 0.05]$ , Cohen's  $d = 0.05$ ). Transfer indices (TIs) did not differ significantly from 1 (mean TI =  $1.01 \pm 0.06$ ,  $t_{15} = 0.19$ ,  $p = 0.86$ , Cohen's  $d = 0.05$ ,  $BF_{10} = 0.26$ ), providing moderate evidence for equivalent performance across locations.

These results indicate that sequential double training, when the II category task is performed before the irrelevant task, effectively reduces

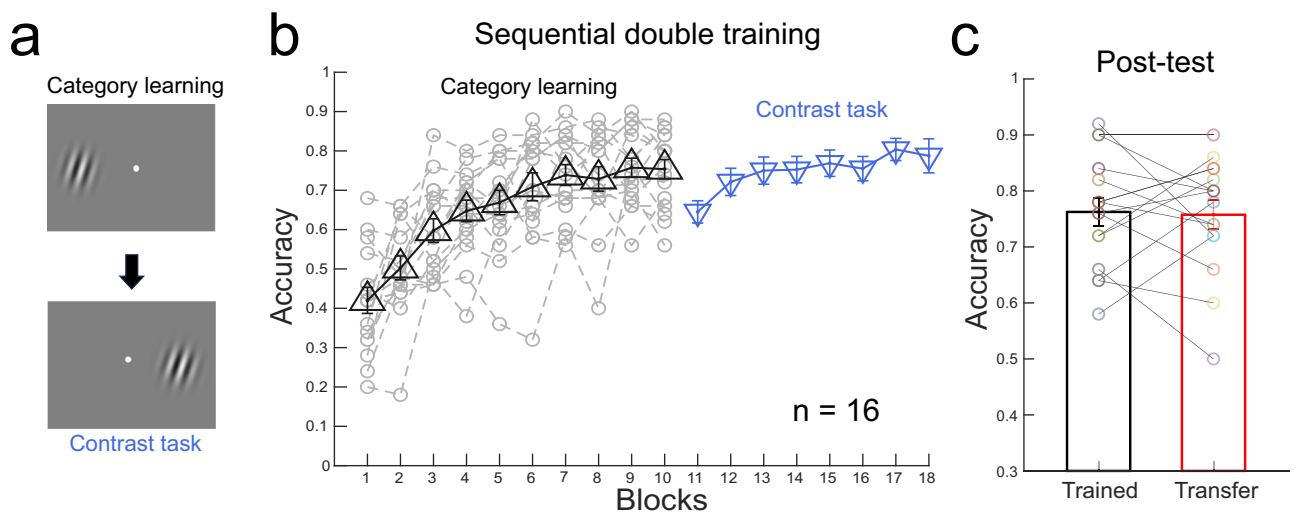
retinotopic constraints in II category learning. The Bayesian analysis, however, suggests that the evidence for complete transfer is moderate rather than conclusive.

**Summary: Comparison of transfer indices across experiments**

The transfer index (TI) was calculated for each experimental group, with higher values indicating better transfer effects. To evaluate these effects systematically, we compared the TIs of Experiments 1–4, using Experiment 1 as the baseline reference (Fig. 6). Statistical analysis revealed a significant effect of experimental condition on TI (A one-



**Fig. 4 | Behavioral results for sequential double training group 1.** **a** Schematic of the sequential double-training paradigm. Participants first performed the irrelevant Gabor contrast discrimination task at the transfer location, followed by the II category task at the trained location. **b** Learning curves across training phases. Blue triangles: contrast discrimination accuracy (phase 1); black triangles: II category task accuracy (phase 2). Large dots: group mean; small dots: individual participants. **c** Post-test comparison of categorization accuracy between trained and transfer locations. Small dots: individual participants. Error bars:  $\pm 1$  SEM.



**Fig. 5 | Behavioral results for sequential double training group 2.** **a** Schematic of the sequential double-training paradigm. Participants first performed the II category task at the trained location, followed by the irrelevant contrast discrimination task at the transfer location. **b** Learning curves across training phases. Black triangles: II category accuracy (phase 1); blue triangles: contrast discrimination accuracy (phase 2). Large dots: group mean; small dots: individual participants. **c** Post-test comparison of categorization accuracy between trained and transfer locations. Small dots: individual participants. Error bars:  $\pm 1$  SEM.

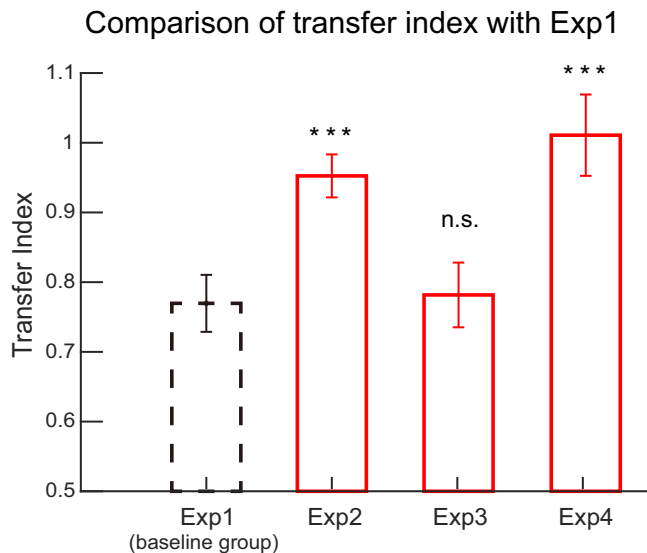
way ANOVA:  $F_{(3, 68)} = 7.552, p < 0.001, \eta_p^2 = 0.25$ ). Post hoc comparisons with Bonferroni correction showed that both Experiment 2 ( $p = 0.016$ ) and Experiment 4 ( $p < 0.001$ ) showed significantly higher TI values than Experiment 1, indicating enhanced transfer performance. In contrast, no significant difference was found between Experiment 3 and Experiment 1 ( $p > 0.99$ ). These results corroborate our previous analyses, providing further evidence that specific training paradigms can effectively facilitate location transfer in the II category task.

**Discussion**

The present study demonstrates that the double-training paradigm, previously shown to facilitate broad transfer in perceptual learning, can also overcome the retinal location specificity observed in II category learning. Transfer across retinal locations critically depended on the temporal order

of the training tasks: it was robust when exposure to the transfer location occurred concurrently with or after II learning, but markedly weaker when such exposure preceded II category learning. These findings suggest that II category learning, like perceptual learning, exhibits both constraints and flexibility in location-specific learning.

Consistent with Rosedahl et al.<sup>10</sup>, who reported strong retinotopic specificity in visual category learning, we replicated the finding that performance deteriorates when stimuli appear at untrained retinal locations. Applying the double-training paradigm, we found that simultaneous exposure to the transfer location through an irrelevant task effectively reduced location specificity, whereas prior exposure to the irrelevant task alone had little effect, consistent with Rosedahl and Watanabe<sup>9</sup>. Importantly, a task-order effect emerged: transfer was strongest when II category learning preceded the irrelevant task, but weaker when the irrelevant task came first. This asymmetry may reflect the formation of higher-level,



**Fig. 6 | Comparison of transfer indices across experiments.** Transfer indices of Experiments 2–4 compared to the baseline group (Experiment 1). \*\*\*Indicates  $p < 0.001$ ; n.s. indicates  $p > 0.05$  (not significant). Error bars represent  $\pm 1$  SEM.

location-invariant representations during initial category learning that later generalize through exposure. In contrast, early exposure to the irrelevant task may not effectively support the integration of information across locations, leading to weaker transfer. Similar order-dependent effects have been observed in visual and auditory learning<sup>27,28,44,45</sup>, suggesting that transfer efficacy may depend on the interaction between temporal order and representational variability, where exposure to diverse exemplars promotes abstraction of invariant features<sup>46–49</sup>.

The observed modulation of location specificity by double training likely reflects dynamic interactions among sensory encoding, spatial attention, and higher-order cognitive mechanisms such as decision processes<sup>11</sup>. Repeated learning may bias attention toward the trained location, whereas exposure at an untrained location can recruit attention there, enabling learned decision rules to generalize across spatial representations<sup>28,32,33</sup>. Because participants were unaware of any “main” or “irrelevant” task, the observed order-dependent effects are unlikely to reflect explicit strategies and instead likely arise from the intrinsic functional structure of the learning process. When the contrast task precedes II learning, the categorization rules acquired during II learning fail to integrate with the representations associated with the previously exposed location, thereby constraining transfer. Both exogenous and endogenous attention may modulate transfer, as attentional allocation, whether bottom-up or top-down, has been shown to facilitate performance<sup>31,50,51</sup>. Converging ERP evidence indicates that perceptual learning alters early visual components (C1, P1–N1), reflecting interactions between low-level visual areas and higher-order cortical regions<sup>52–54</sup>. This attentional account is further supported by neuroimaging and computational findings demonstrating coordinated activation between visual and prefrontal areas during transfer<sup>55–57</sup>. The observed order-dependent modulation of location transfer may therefore arise from the temporal sensitivity of attentional deployment, which can be shaped by prior cues and temporal preparation<sup>58,59</sup>.

II category learning exhibits not only spatial specificity but also response- and stimulus-level specificity: performance declines when response-key mappings are reversed, and transfer to novel stimulus regions is more limited compared to RB learning<sup>60–62</sup>. These constraints suggest that II learning is tightly linked to the specific stimulus-response associations formed during training. However, evidence from perceptual learning indicates that such constraints may not be intrinsic to the learning system: double training has been shown to reduce location-, feature-, and stimulus-

level specificity<sup>27,29–32,34</sup>. This suggests a possible mechanism whereby attentional bias and co-activation across locations or features could facilitate transfer in II learning. Because II learning requires integration across multiple stimulus dimensions and the formation of implicit decision boundaries<sup>2</sup>, double training may promote the establishment of more abstract, flexible representations that are less tied to specific stimulus–response mappings. Future studies could examine whether manipulating spatial attention or feature co-activation further enhances transfer in II tasks, bridging perceptual learning frameworks with computational theories of category learning, such as SUSTAIN or COVIS<sup>4,40</sup>.

Beyond transfer effects, RB and II learning differ in cognitive demands: RB learning is highly sensitive to concurrent working-memory load yet relatively robust to delayed or blocked feedback, whereas II learning exhibits the opposite pattern<sup>5,63–66</sup>. Perceptual learning shows a more mixed profile: it can proceed without explicit external feedback<sup>67–69</sup>, yet performance often depends on attention or working memory, particularly in early stages or for fine discriminations<sup>70</sup>. These findings suggest that perceptual, RB, and II learning share partially overlapping mechanisms that interact flexibly according to task demands rather than operating as fully distinct systems. This flexibility supports the formation of abstract category representations and aligns with models like SUSTAIN, which dynamically cluster stimulus features to generate flexible representational units<sup>40,71</sup>. Neuroimaging evidence further supports this continuum view, showing overlapping activation across visual, prefrontal, and striatal regions during both perceptual and category learning<sup>7,36,37,72,73</sup>.

These findings advance our understanding of learning transfer and suggest practical strategies for promoting flexible, generalizable training. Double training can enhance the robustness and transferability of learning, allowing skills acquired in one context to generalize to untrained tasks or locations. In clinical settings, this approach promotes functional recovery by encouraging skill generalization to untrained conditions<sup>44,74–76</sup>; for example, double-training with endogenous spatial attention has been shown to significantly improve visual recovery in cortically blinded fields<sup>76</sup>. In educational contexts, varying stimulus presentation and incorporating spaced, multi-context practice can strengthen abstract memory traces, reduce context dependence, and foster flexible knowledge transfer<sup>77</sup>. Insights from human cognitive flexibility may also inform the design of adaptive artificial learning systems<sup>78</sup>, bridging neuroscience and computational applications.

Some limitations of the present study should be acknowledged. First, the post-tests of the II category task at the trained location were always administered before those at the untrained location to maintain comparability with prior studies<sup>10</sup>; counterbalancing this order could provide a more direct control for potential order effects. Second, we did not assess whether learning in the contrast discrimination task transferred across retinal locations. Future research should examine whether the order-dependent modulation generalizes to other category learning tasks. Third, all experiments were conducted within a single 1–1.5-h session, shorter than typical multi-day perceptual learning protocols, suggesting potential differences in underlying learning dynamics. Therefore, the apparent similarity in principles between perceptual and category learning should be interpreted cautiously. Finally, although this study did not investigate response- or stimulus-level specificity, future work could systematically examine whether double training alleviates these constraints, thereby revealing general principles of learning transfer across perceptual and cognitive domains.

## Methods

### Participants and apparatus

Seventy-two students from Peking University participated in a 1–1.5-h experiment. All had normal or corrected-to-normal vision, were naive to psychophysical experiments, and were unaware of the study’s objectives. The study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board of Peking University and the Human Research Protection Committee of East China Normal University. Written informed consent was obtained from all participants.

Experiments 1 and 2 each included 20 participants, whereas Experiments 3 and 4 included 16 participants. Sample sizes were guided by prior studies (Rosdahl et al.<sup>10</sup>: 20–23 participants; Rosdahl and Watanabe<sup>9</sup>: 14–15 participants) and were confirmed via a G\*Power analysis<sup>79</sup>, assuming an effect size of 0.75,  $\alpha = 0.05$ , and power = 0.80, which indicated that 16 participants would be sufficient. All participants performed significantly above chance on the trained location blocks, and no participants were excluded from the analyses.

Stimuli were generated using Psychtoolbox-3 software<sup>80</sup> and displayed on a 21-inch Sony G520 color monitor (1024 × 768 pixels; 0.39 × 0.39 mm per pixel; 60 Hz frame rate; 50 cd/m<sup>2</sup> mean luminance). A chin-and-head rest stabilized participants' heads, and viewing was binocular at a distance of one meter in a dimly lit room. Responses were collected via a computer keyboard, and eye movements were monitored using an EyeLink-1000 eye tracker (SR Research, Kanata, Ontario, Canada) at a 1000-Hz sampling rate. Each session began with a nine-point calibration, with additional recalibration performed before each test block and during training as needed. Trials were aborted if eye movements exceeded 2° from fixation or if saccades were detected (velocity threshold: 35°/s; acceleration threshold: 9500°/s<sup>2</sup>).

### Stimuli and procedures

The stimuli were adapted from Rosdahl et al.<sup>10</sup> and consisted of Gabor patches (Gaussian-windowed sinusoidal gratings). For II category learning, Gabor gratings had a standard deviation of 0.68° and a contrast of 80%, varying only in spatial frequency and orientation. The category structure was defined by a bivariate normal distribution with means for spatial frequency and orientation as follows: category F (30, 50), D (50, 30), K (50, 70), and J (70, 50) (see Fig. 1a). The variance for both dimensions was set to 50 across all distributions, with covariances at 0, ensuring distributions differed only by their means. Because each category was defined as a probabilistic distribution centered around its mean rather than as a region with hard boundaries, some stimuli sampled from a given category could fall near or across the nominal boundary of another category in feature space. We did not enforce hard reassignment or correction of such samples, as this overlap reflects the inherent fuzziness typically observed in category boundaries in perceptual categorization. Gabor stimuli were generated by: (1) drawing 300 random samples from each bivariate normal distribution; (2) linearly transforming the samples to match population parameters, and (3) generating Gabor stimuli with spatial frequency:  $x_1^* = \frac{x_1}{30} + 0.25$  cycle per degree of visual angle and orientation  $x_2^* = 0.9x_2 + 20$  degrees anticlockwise rotation from horizontal.

For the II category task, participants were instructed to classify disk-like images into one of four categories (D, F, J, K) with feedback provided during training. A white fixation point was presented at the center of a gray screen, and participants were instructed to maintain fixation. Each trial began with a central fixation presented for 1000 ms, followed by a Gabor stimulus displayed for 200 ms at 5° to the left or right of fixation (locations balanced across participants). After stimulus offset, only the fixation remained on the screen, and participants responded at their own pace (self-paced; no time-out). Feedback was delivered immediately upon keypress by changing the fixation point to green (correct) or red (incorrect) for 1000 ms, after which the fixation returned to its neutral color. In transfer trials, stimuli appeared at the opposite location. Each block, in both the training and transfer phases, consisted of 50 trials and took approximately 5 minutes to complete.

In the double training groups, the irrelevant tasks involved a contrast discrimination task using Gabor stimuli. Each stimulus had one of two contrast levels (70% and 90%), and participants were instructed that the classification rule depended on contrast or luminance. Participants categorized each stimulus into one of two categories using the “F” or “J” key. The trial and block structure for these tasks mirrored that of the II category task.

### Experimental design

This study comprised four experiments, each involving a separate group of participants (Fig. 1c). Every experiment included a training phase followed by a post-test phase, all completed within a single session lasting approximately 1–1.5 h. The post-test phase consisted of two blocks of the II category

task performed without feedback: one at the trained location and one at the untrained location in the opposite visual field. Following the procedure of Rosdahl et al.<sup>10</sup>, the post-test at the trained location was always administered before that at the untrained location.

While the post-test phase was identical across all experiments, the training phase varied as follows. Experiment 1 (Baseline Group): Participants completed 10 blocks of the II category task with feedback. Experiment 2 (Simultaneous Double-Training Group): Participants completed 8 blocks of an irrelevant contrast discrimination task at the transfer location, interleaved with the II category task at the trained location, alternating every four blocks. Experiment 3 (Sequential Double-Training Group 1): Participants first practiced the contrast discrimination task at the transfer location, followed by the II category task at the trained location. Experiment 4 (Sequential Double-Training Group 2): Participants completed the II category task at the trained location, followed by the contrast discrimination task at the transfer location. This design enabled a systematic assessment of how different double-training schedules influence location-specific learning and transfer across retinal locations.

### Statistical analyses

Data were analyzed using the R software<sup>81</sup>. A linear mixed-effects (LME) model was applied to the pooled data of the II category task across Experiments 1–4, using the `lme` function from the “nlme” package<sup>82</sup> with Restricted maximum likelihood (REML) estimation. Response accuracy served as the dependent variable, with post-test location (trained vs. transfer) and experimental group (Experiments 1–4) as fixed effects. Their interaction was modeled according to the following formula:

$$\text{accuracy} \sim \text{location} * \text{group} + (1|\text{participant}) \quad (1)$$

Random intercepts were included to account for individual variability in baseline accuracy. Likelihood ratio tests comparing models with and without random slopes revealed no improvement in model fit, indicating that random intercepts alone were sufficient. Post hoc pairwise comparisons were conducted using the “emmeans” package<sup>83</sup>. Degrees of freedom for fixed effects were estimated using Satterthwaite's approximation, as implemented in `nlme::lme()`.

To quantify transfer, a transfer index (TI) was computed following Rosdahl et al.<sup>10</sup>.

$$TI = \frac{P_{\text{Transfer}} - 0.25}{P_{\text{Trained}} - 0.25} \quad (2)$$

where  $P_{\text{Transfer}}$  and  $P_{\text{Trained}}$  denote accuracy at the transfer and trained locations, respectively. TI values approaching 1 indicate full transfer, whereas values near 0 indicate complete location specificity. Each TI was compared against 0 and 1 using one-sample *t*-tests. Between-group differences in TI were assessed via one-way ANOVA, followed by post hoc comparisons against Experiment 1 (baseline condition). When frequentist analyses yielded non-significant results, Bayesian *t*-tests were performed to assess evidence for the null hypothesis. Bayes factors (BF<sub>10</sub>) were interpreted according to conventional guidelines<sup>84</sup>, with BF<sub>10</sub> < 0.33 (or equivalently BF<sub>01</sub> ≥ 3) taken as moderate evidence supporting the null hypothesis.

### Data availability

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

### Code availability

Custom scripts used for stimulus presentation and data analysis are available from the corresponding author upon reasonable request.

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**Author contributions**

X.Y.X., J.Y.Z., and C.Y. conceived and designed the study. J.P.Z., X.Y.X., and J.Y.Z. performed the experiments. J.P.Z., X.Y.X., and J.Y.Z. analyzed the data and wrote the manuscript. All authors read and approved the manuscript.

**Competing interests**

The authors declare no competing interests.

**Additional information**

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