

**Intermixed levels of visual search difficulty produce asymmetric probability
learning**

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Abstract

When performing novel tasks, we often apply the rules we have learned from previous, similar tasks. Knowing when to generalize previous knowledge, however, is a complex challenge. In this study, we investigated the properties of learning generalization in a visual search task, focusing on the role of search difficulty. We used a spatial probability learning paradigm in which individuals learn to prioritize their search toward the locations where a target appears more often (i.e., high probable location) than others (i.e., low probable location) in a search display. In the first experiment, during a training phase, we intermixed the easy and difficult search trials within blocks, and each was respectively paired with a distinct high probable location. Then, during a testing phase, we removed the probability manipulation and assessed any generalization of spatial biases to a novel, intermediate difficulty task. Results showed that, as training progressed, the easy search evoked a stronger spatial bias to its high probable location than the difficult search. Moreover, there was greater generalization of the easy search learning than difficult search learning at test, revealed by a stronger bias toward the former's high probable location. Two additional experiments ruled out alternatives that learning during difficult search itself is weak and learning during easy search specifically weakens learning of the difficult search. Overall, the results demonstrate that easy search interferes with difficult search learning and generalizability when the two levels of search difficulty are intermixed.

Key words: Spatial attention, probability cueing, search difficulty, generalizability

Introduction

We use past experience to improve our visual search performance, but doing so is not a trivial matter. Each unique visual search we engage in is virtually never identical to previous searches, so how do we know when to generalize what we have learned? When we buy apples in our regular supermarket, we might have learned the probable location of the apple display. Will this information help or hurt us when we seek apples in a different supermarket?

A long line of research has explored the non-conscious influences of long-term past experience on behavior (Nissen & Bullemer, 1987; Reber, 1967, 1989; Reber et al., 1991; Rossetti & Revonsuo, 2000), with a growing number of studies focusing specifically on visual search (Chun & Jiang, 2003; Geng & Behrmann, 2005; Howard & Howard, 1997). This body of research paints the picture of a vast arrangement of implicit cognitive machinery that is ever-active, continuously monitoring environments in the world and robustly influencing our search behavior. However, much remains unknown about the *generalizability* of such learning phenomena. The scope and extent of learning generalizability is of great consequence in the practical world; what is the use of such a sophisticated cognitive mechanism if it over or under-generalizes across task conditions?

In this study, we focus on *search difficulty* as a factor that may modulate generalizability. There are several reasons why we focus on this variable. From an ecological perspective, task difficulty may serve to differentiate distinct task contexts, in which separate behavioral approaches to the task may apply. Cognitive control research has demonstrated we have a dedicated neural system that is sensitive to task demands,

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which can alert a person to adopt a different task processing mode than when the task is easy (Botvinick et al., 2001). Specific to the domain of visual search, difficulty is a universal feature in every search task. Therefore, investigation of search difficulty may apply to many search behaviors. Also, the underlying mechanism of search difficulty has been thoroughly examined in the fundamental visual search literature (Duncan & Humphreys, 1989; Treisman & Gelade, 1980; Wolfe, 1994). Practically, search difficulty is easily manipulated by only minimal changes of search items, which helps us keep the task identical in various search difficulties (see Figure 1A). Suppose observers search for a letter T among many letters Ls. The search task difficulty depends on how similar the letter L looks to the letter T. As the offset of two lines of letter L is bigger; the search becomes harder. Regardless of the letter Ls' shapes, the task is always “searching for a letter T quickly.”

This study is not the first one examining how search difficulty relates to learning generalizability. Several previous studies showed that implicit learning is generalizable across two search tasks having two different contexts (Hong et al., 2020; de Waard et al., 2022) or two different levels of search difficulty – easy search to difficult search and vice versa (contextual cueing: Chun & Jiang, 1998; Jiang & Song, 2005; probability cueing: Jiang et al., 2014). For example, Jiang et al. (2014) trained participants in an easy (or difficult) search task in which the target T more often appeared in a specific location in a search display than any of other locations. As the experiment progressed, participants implicitly learned target location probabilities and found the target faster when it appeared in high probable locations vs. when it appeared in low probable locations, called *probability cueing*. After training, participants engaged in the same search task

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during the testing phase. Here, the target was distributed evenly, while the distractors either became more akin to the target (resulting in a difficult search task) or diverged further from the target (yielding an easy search task). Nonetheless, participants consistently exhibited a bias toward the preceding high probable location, offering compelling evidence of the generalization of probability cueing across variations in task difficulty.

While the previous studies examined whether experience with one search that has a fixed difficulty is transferred to a new search that has the same or a different level of difficulty, here we question whether observers learn specific difficulty-based task contexts or whether they generalize learning across them. In particular, we created distinct contingencies between probable target locations and task difficulty (e.g., difficult search trials are associated with probable targets in the upper left quadrant of the display while easy trials are associated with probable targets in the lower right). Will observers demonstrate learning specificity, in which they prioritize the relevant high-probable locations during visual search, depending on the task difficulty? Or, will they simply generalize the probability information across the two levels of difficulty and prioritize both high-probable quadrants similarly across both levels of task difficulty? Further, we question how such learned contingencies may transfer to novel search tasks, either with a neutral difficulty level or one matching one of the original tasks.

We adopted the same probability cueing paradigm as Jiang et al. (2014; see also Geng & Behrmann, 2005). Observers were shown a search display that contains a target T and several non-target Ls. During a training phase, to create distinct contingencies between search difficulty and high-probable target locations, we presented two types of

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search trials during a training phase – easy and difficult – which were randomly intermixed. Unbeknownst to participants, the target T more frequently appeared in a specific quadrant (called “easy / high probable quadrant” hereafter, easy HPQ) during the easy search task and more frequently appears in another specific quadrant (called “difficult / high probable quadrant”, hereafter, difficult HPQ) during difficult search. The other two quadrants are considered “low probable quadrants” (hereafter LPQ). In a subsequent testing phase, we tested participants in an intermediate search, the difficulty of which was approximated to be in the middle of the difficulty levels of the two training tasks on the search difficulty scale. Using an intermediate search after two searches represents an attempt to equitably compare the respective influences from two training-phase searches.

We examined learning during easy and difficult search when these conditions were intermixed during training, and we assessed whether one of these search types demonstrates stronger generalization than the other to the intermediate test trials (Experiment 1). To better understand the impact of intermixing the trials during training, we also examined learning and generalization for the easy and difficult conditions when they were completed in pure blocks (Experiment 2). Lastly, we tested whether having two competing quadrants or just intermixing the trials influences learning and generalizability for the difficult condition using only a difficult HPQ without an easy HPQ during training while two types of search trials were still intermixed (Experiment 3).

Experiment 1

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In Experiment 1, we randomly intermixed two types of search trials – easy search and difficult search – during training. Each search type had its own high-probable location, easy HPQ and difficult HPQ, respectively. Then, we presented an intermediate difficulty of search trials during testing, in which the target appeared with equal frequency across the four quadrants. This design allowed us to address several questions.

First, can individuals learn and exploit the associations between search difficulty level and the relevant high-probable location in a context-specific fashion? If so, then during training, when trials are intermixed, participants will selectively prioritize the easy HPQ during easy trials and the difficult HPQ during difficult trials. Otherwise, during training, participants will prioritize either or both HPQs similarly.

Second, is there any asymmetry in the learning during easy and difficult search? If so, during the training phase, participants will show greater prioritization toward the easy or difficult HPQ during training.

Third, is there an asymmetry in generalization of learning from easy vs. difficult search to the intermediate search during testing? If so, then participants will show greater prioritization toward the easy or difficult HPQ during testing.

Method

Participants. A pre-determined sample size of 12 student participants (10 women and 2 men; mean age 18.3 years) with normal or corrected-to-normal visual acuity, who were naïve to the purpose of the study, were used in all experiments. The sample size was determined based on the previous study (Jiang, Won, et al., 2014), which the current

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paradigm was adopted from. While our sample size was somewhat limited, we employed a post-hoc power analysis based on prior studies, which consistently demonstrated a robust effect size in probability cueing. Specifically, to gauge if 12 participants produced a sufficient power, we conducted a power analysis for the difference between the high probable condition and low probable condition (i.e., probability cueing effect) using G*Power (Version 3.1). This analysis yielded .99 of power with two-tails and $\alpha = .05$ with sample size of 12. However, it is worth noting that post-hoc power analysis often produces less accurate estimates than pre-study calculations (Althouse 2021; Zhang et al., 2019), requiring careful use. Participation was compensated with course credit. The Ohio State University IRB approved the study protocol.

Materials. Participants were tested in a dimly lit room. Stimuli were presented on 24-inch LCD monitor (vertical refresh rate: 60 Hz; 1920 x 1080) and generated using MATLAB (www.mathworks.com), with Psychtoolbox extensions (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). Head position was not fixed, and visual angles are reported assuming a typical viewing distance of 60 centimeters.

Stimuli. Eight, 12, or 16 search items were presented ($1.02^\circ \times 1.02^\circ$), including one target (a white T rotated to the left or right), and seven, 11, or 15 distractors (white Ls rotated 0° , 90° , 180° , or 270°) against a gray background. A set size manipulation was added to assess the effectiveness of our search difficulty manipulation (easy, intermediate, and difficult search). The search items' locations were randomly chosen from a 10x10 invisible matrix ($15.28^\circ \times 15.28^\circ$), with a constraint that each quadrant had an equal

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number of items (two, three, or four items). Target and distractor orientations were all randomly selected with replacement on each trial, so the target identity and motor response did not correlate with any experimental variables. Search difficulty was manipulated by adjusting the offset of the junction between the two line segments forming the L: easy search contained a small offset (0.05° ; 2 pixels), the intermediate search had a medium offset (0.15° ; 6px), and difficult search had a large offset (0.26° ; 10px). Larger offsets increased the similarity between the Ls and Ts, thus increasing search difficulty (Duncan & Humphreys, 1989, see Figure 1A).

Design. After 12 practice trials, each participant completed a 360-trial training phase, followed by a 360-trial testing phase. In the training phase, easy and difficult search trials were randomly but equally intermixed. Among the *easy search trials*, the target T more frequently appeared in one quadrant than any of the other three quadrants (50% in *easy HPQ* vs. 16.7% in each of the other three quadrants). Among the *difficult search trials*, the target T more frequently appeared in one quadrant than any other three quadrants (50% in *difficult HPQ* vs. 16.7% in each of the other three quadrants). Note that *easy HPQ* and *difficult HPQ* were never the same. In the testing phase, only *intermediate search trials* were presented, in which the target T now appeared equally often in all four quadrants (i.e., 25% per quadrant). In the training phase, three factors – two types of search (*easy and difficult search*), three types target location (*easy HPQ, difficult HPQ, and LPQ*), and set size (8, 12, and 16) – were all orthogonally counterbalanced and randomly intermixed during the experiment. The two HPQ (*easy HPQ* and *difficult HPQ*)

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were counterbalanced across participants but were held constant for a given participant.

Participants were not informed of the target's spatial distribution.

Procedure. Each trial began with the presentation of a small white square (0.51°x0.51°), whose position was randomly jittered within a range of .77° both vertically and horizontally from the center of the monitor and initiated by a mouse click on the jittered square, which required eye-hand coordination and enforced fixation at the center before the search began. After the mouse click, the screen was blank for 500-msec, after which the search display appeared, containing eight, 12, or 16 items. Participants were asked to report the orientation of the target T's stem (left or right) using computer keyboard. When participants responded to the target T's orientation, auditory feedback was given (three rising tones for 300-ms for a correct response; a low-tone buzz for 200-msec for an incorrect response). To discourage incorrect responses, participants were presented with a 2-sec blank screen following errors. After 720 main search trials (both training and testing), participants were asked to answer two recognition questions that appeared on the screen. The first question asked whether the target was evenly or unevenly distributed across all four quadrants. Regardless of the first answer, a message informed participants that the target was unevenly distributed, and the second question asked them to select one quadrant where the target more often appeared. The task took approximately 1 hour.

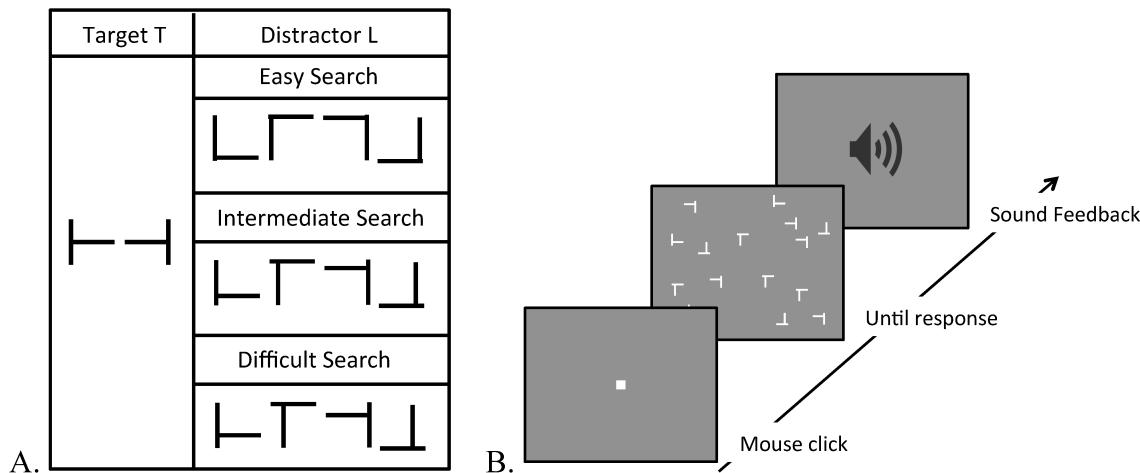
Figure 1B shows a schematic procedure of Experiment 1. All data have been made publicly available via OSF and can be accessed at

https://osf.io/3jy68/?view_only=855f727c076a43d89da1e211b1c3b2d8.

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Figure 1.

Schematic stimuli and procedure of Experiment 1.



Note. A. two targets and three types of four distractors Ls were used in easy search, intermediate search, or difficult search. B. An example search trial (the example display is difficult search with a set size of 16). The set size varied among 8, 12, and 16 items.

Results

Because accuracy of all conditions was high (the lowest = 96.1%) in all of four experiments (Experiment 1-Experiment 3; Table 1), we focus on RT data for the remaining analyses.

Table 1. Mean accuracy (%) of search tasks in four experiments.

phase	Training phase						Testing phase		
	Easy search			Difficult search			Intermediate search		
search	Easy	difficult	LPQ	easy	difficult	LPQ	Easy	difficult	LPQ
	HPQ	HPQ		HPQ	HPQ		HPQ	HPQ	
quadrant									

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Exp.1	99.4	99.4	99.2	96.1	96.1	96.3	98.8	98.3	97.7
Exp.2a	98.9	N/A	98.5	N/A			97.6	N/A	96.4
Exp.2b				N/A	97.8	97.9	N/A	98.4	98/1
Exp.3	N/A	98.1	98.3	N/A	95.6	94.7	N/A	96.5	97.5

RT. We removed 3.8% of trials from RT analyses as incorrect trials and RT outliers (trials with RTs slower than 3SD above each individual's mean). When the assumption of sphericity was violated ($p < .05$), Greenhouse-Geisser correction was applied.

Training phase.

A search difficulty (easy search, difficult search) x quadrant type (easy HPQ, difficult HPQ, LPQ) x set size (8, 12, 16) ANOVA showed that RTs for easy search were considerably faster than in difficult search, $F(1, 11) = 175.04, p < .001, \eta_p^2 = .93$, and a significant interaction between search difficulty and set size was also significant, $F(2, 22) = 27.68, p < .001, \eta_p^2 = .76$, demonstrating that the difficulty manipulation was effective (mean search slope for easy search: 81 msec/item, mean search slope for difficult search: 245 msec/item). We also found main effects of quadrant type, $F(2, 22) = 11.63, p = .002, \eta_p^2 = .51$, and set size, $F(2, 22) = 156.32, p < .001, \eta_p^2 = .93$. The interaction between search difficulty and quadrant type was significant, $F(2, 22) = 4.75, p = .045, \eta_p^2 = .30$. Quadrant type and set size didn't interact each other, $F(4, 44) = 1.33, p = .27$. We didn't find a significant 3-way interaction among search difficult, quadrant type, and set size, $F < 1$.

To characterize the significant interaction between search difficulty and quadrant type, we did a further pairwise t-test among the conditions of quadrant type in easy and difficult search tasks, separately. In the easy search, we found that the RT for the easy HPQ was significantly faster than that of the difficult HPQ, $t(11) = 2.68, p = .02, d = .77$, $BF_{10} = 3.23^1$, and also than that of the LPQ, $t(11) = 2.92, p = .014, d = .84, BF_{10} = 4.49$. However, the RT for the difficult HPQ was not faster than that for the LPQ, $t(11) = .44, p = .667, d = .13, BF_{10} = .31$.

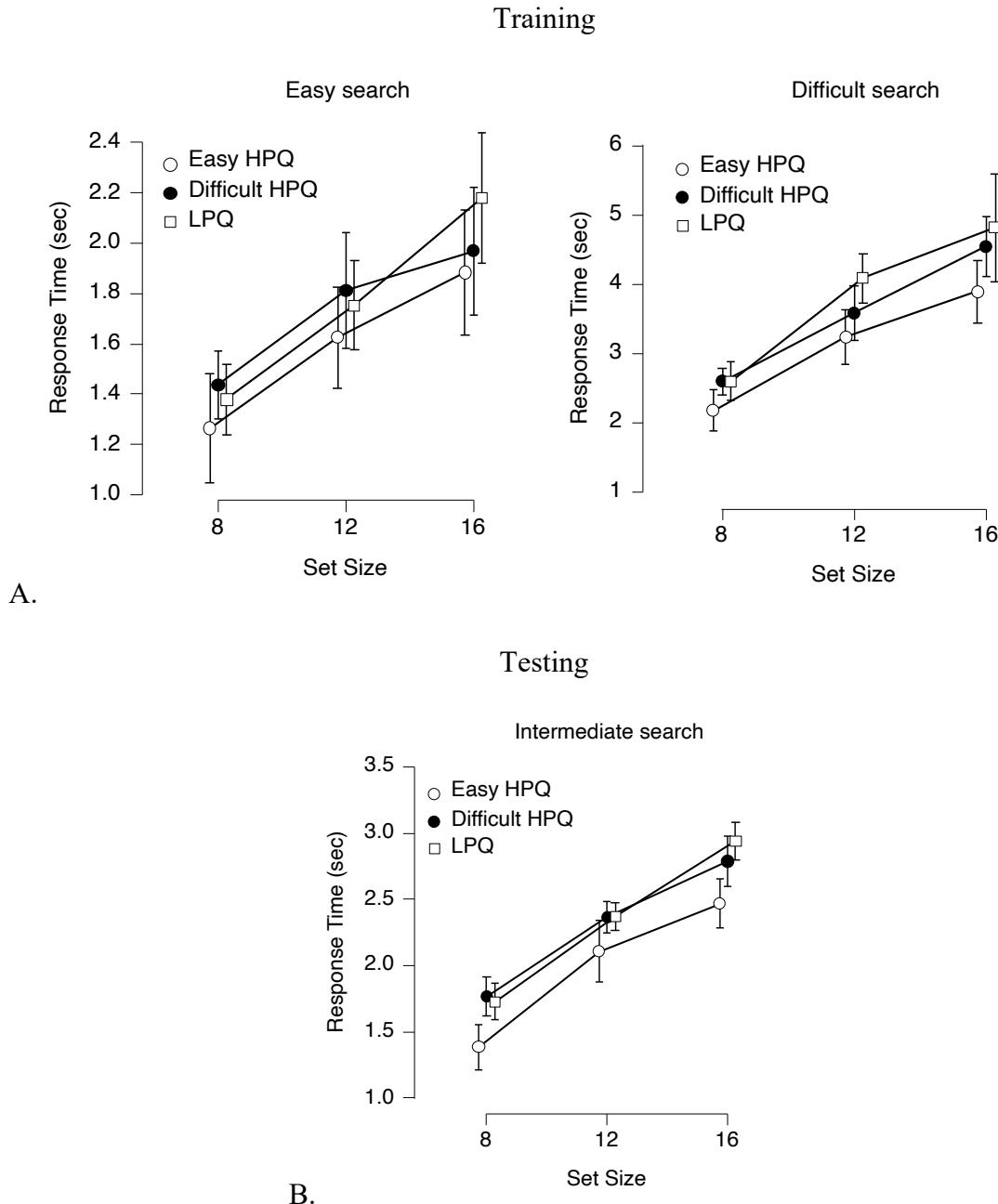
In the difficult search, we found that participants responded more rapidly to targets appearing in the easy HPQ than difficult HPQ, $t(11) = 2.59, p = .025, d = .75, BF_{10} = 2.82$, and also than that of the LPQ, $t(11) = 3.17, p = .009, d = .92, BF_{10} = 6.50$. The targets that appeared in the difficult HPQ were also found faster than the targets that appeared in the LPQ, $t(11) = 3.293, p = .007, d = .95, BF_{10} = 7.77$.

Testing phase. A quadrant type x set size ANOVA revealed a significant main effect of quadrant type, $F(2, 22) = 19.22, p < .001, \eta_p^2 = .64$, and set size, $F(2, 22) = 100.73, p < .001, \eta_p^2 = .90$. Quadrant type and set size did not interact each other, $F(4, 44) = 1.17, p = .34, \eta_p^2 = .096$. Taking a closer look at quadrant, a pairwise t-test showed that RTs to targets in the easy HPQ were faster than targets in the difficult HPQ, $t(11) = 4.98, p < .001, \eta_p^2 = 1.44, BF_{10} = 84.62$, and the LPQ, $t(11) = 5.10, p < .001, d = 1.47, BF_{10} = 99.63$. However, the RTs were not different for targets in the difficult HPQ and LPQ, $t(11) = .69, p = .51, d = .20, BF_{10} = .35$. Figure 2 shows the RT results of Experiment 1.

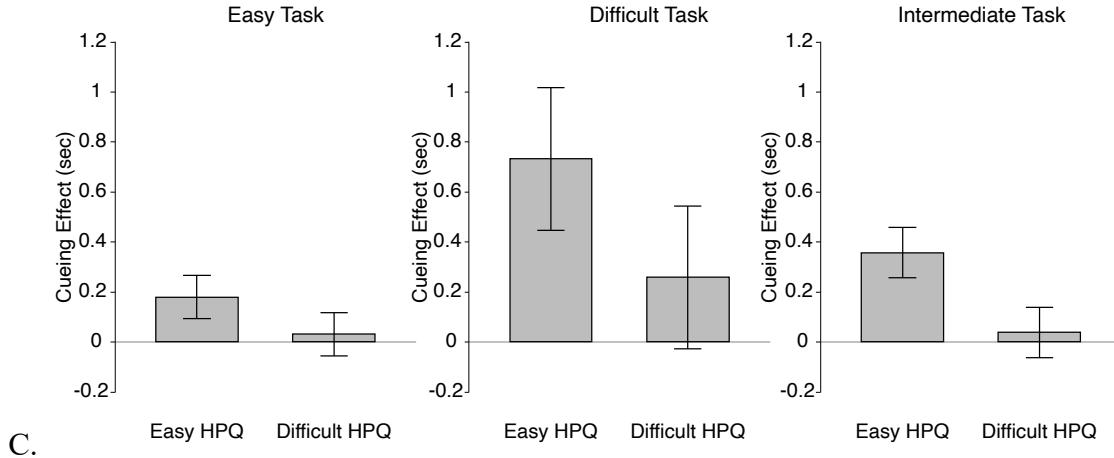
¹ We provided Bayes factors (BF), which quantify the relative likelihood of obtaining the observed data under the alternative hypothesis compared to the null hypothesis (BF_{10}) (Rouder et al., 2009).

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Figure 2. Experiment 1 RT result



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Note. A. RTs in the training phase separated on search difficulty, quadrant type, and set size in Experiment 1. In both searches, search RTs were the shortest for the target in Easy HPQ. In Easy Search, search RTs for target in difficult HPQ and that in LPQ were comparable. In Difficult Search, search RTs for target in difficult HPQ was shorter than that in LPQ. B. RTs in testing phase separated on quadrant type and set size in Experiment 1. Search RT for the target in easy HPQ was shorter than that in LPQ and Difficult HPQ, but search RT for the target in difficult HPQ was comparable with that in LPQ. LPQ stands for low probability quadrant and HPQ means high probability quadrant. C. Cueing effects (RTs in LPQ – RTs in HPQ) of two search difficulty levels in training and testing phases. Error bars show 95% confidence interval.

Discussion

There were three main findings in this experiment. First, there was a significant interaction between search difficulty and quadrant type, suggesting that prioritization to the different HPQs differed during easy and difficult search.

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Second, we found a clear asymmetry in the learning of HPQs: in both easy and difficult trials, the easy HPQ was prioritized more than the difficult HPQ. Thus, in the intermixed conditions during training, the easy trial condition produced stronger learning.

Asymmetric learning has been noted in similar visual search paradigms, illustrating how one form of learning may overshadow or block another. For instance, Rosenbaum and Jiang (2013) observed that in the context of contextual cueing, scene-based cues can overshadow array-based cues. Likewise, Kunar et al. (2013) showed that configural cues have the capacity to overshadow color cues within the same contextual cueing framework.

We can conceive of two basic reasons for the asymmetry in search difficulty observed in Experiment 1. On the one hand, easy search simply produces stronger probability learning than difficult search. On the other hand, both search types can produce robust learning in isolation, but the easy search dominates difficult search in probability learning when the two are placed in competition with one another (as in the case of the intermixed trials of this experiment). We test these alternatives in Experiment 2.

Third, the generalization of learning to the intermediate trials of test was asymmetric. Given that learning was asymmetric during training, it may not be surprising that easy trials showed greater generalization during testing. Experiment 2 will test if easy and difficult search truly show asymmetric learning during training even in isolation. If we observe similarly robust learning in the easy and difficult trials during training, we can then suggest the asymmetric learning and generalization are due to “intermixed” trials of easy and difficult task.

Experiment 2

Here, we assess the robustness of learning and generalization when the easy and difficult search trials are presented in isolation (i.e., not in competition with one another). Participants first performed a training phase containing blocks of only easy (Experiment 2A) or difficult search (Experiment 2B). Like Experiment 1, each participant had two HPQs, but they were now both presented only in the context of a fixed level of difficulty during training. Then, for both Experiments 2A and 2B, participants completed a testing phase identical to Experiment 1, consisting of intermediate trials in which the target appeared equiprobably at all quadrants.

If learning and/or generalization is simply more robust for easy than difficult trials, we will observe greater learning for the easy than the difficult trials during training and/or stronger transfer of the easy HPQ to the intermediate trials of test than that of difficult HPQ. Alternatively, if easy and difficult learning and generalization are similarly robust in isolation, we will observe significant learning effects during training as well as comparable transfer to the intermediate trials of the testing phase in both search tasks.

Method

Participants. Another 12 participants (8 women, and 4 men; mean age: 18.6 years) participated in Experiment 2A; another 12 participants (6 females and 6 males; mean age: 18.9 years) participated in Experiment 2B.

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Materials, Design, and Procedure. All aspects of the experiment were the same as those of Experiment 1 except the following: we replaced difficult search trials with easy search trials in Experiment 2A (i.e., only easy search trials in the training phase), and easy search trials with difficult search trials in Experiment 2B (i.e., only difficult search trials in the training phase), which results in two easy HPQs in Experiment 2A, and two difficult HPQs in Experiment 2B (each HPQ has a target on 33% of trials, which is matched to Experiment 1).

Results

Experiment 2A

RT. We eliminated 3.8% of trials in Experiment 2A as incorrect trials and RT outliers.

Training phase. A quadrant type (easy HPQ and LPQ) x set size (8, 12, 16) ANOVA showed that participants found the target faster when it appeared in any of easy HPQ than when it appeared in any of LPQ, $F(1, 11) = 24.50, p < .001, \eta_p^2 = .69$, that is, the cueing effect was significant, $t(11) = 4.95, p < .001, \text{BF}_{10} = 81.14$. Also, the participants made longer RTs as set size increased, $F(2, 22) = 69.70, p < .001, \eta_p^2 = .86$. The two way interaction between quadrant type and set size was significant, $F(4, 44) = 8.01, p = .002, \eta_p^2 = .42$.

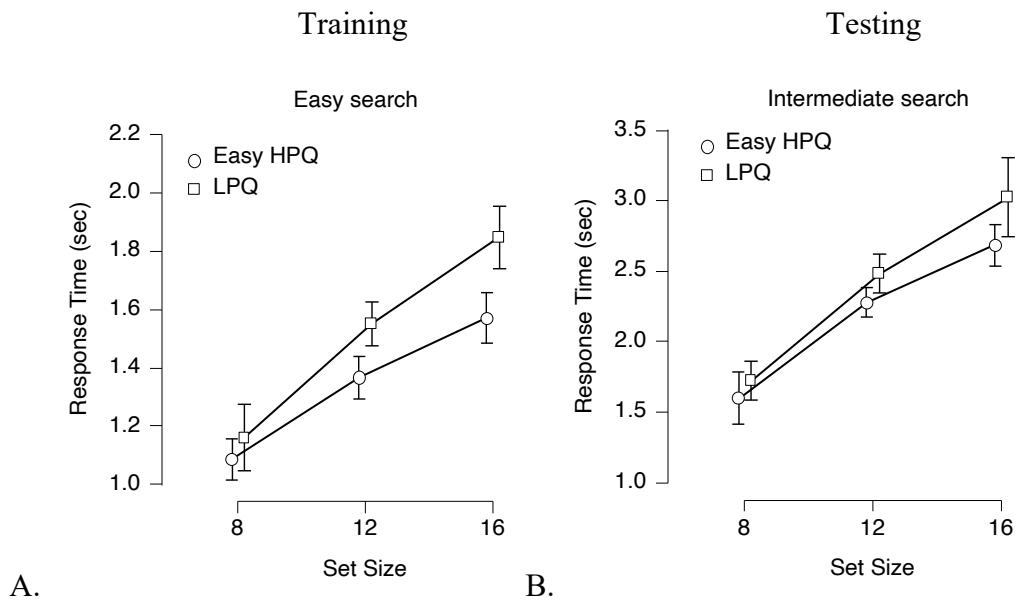
Testing. A quadrant type x set size ANOVA revealed that the target in any of easy HPQ was found faster than that in any of LPQs, $F(1, 11) = 8.88, p = .013, \eta_p^2 = .4$, that is, the cueing effect was significant, $t(11) = 2.98, p = .013, \text{BF}_{10} = 4.93$. Also, the participants made longer RTs as set size increased, $F(2, 22) = 86.39, p < .001, \eta_p^2 = .89$. The two-way

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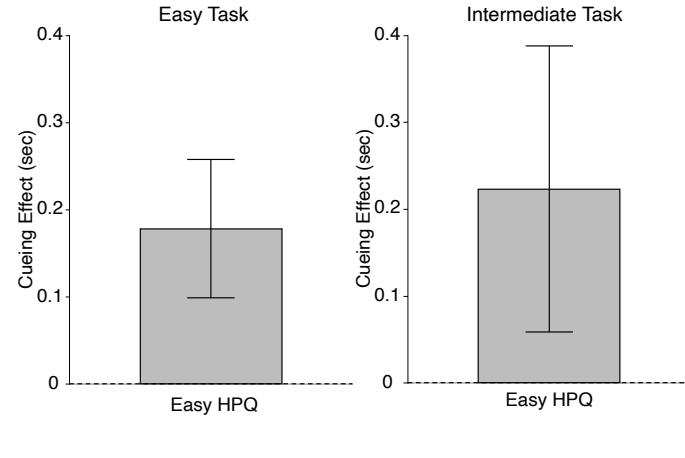
interaction between two factors was not significant, $F(2, 22) = 1.71$, $p = .22$, $\eta_p^2 = .14$.

Figure 3 shows the RT results of Experiment 2A.

Figure 3. Experiment 2A RT result



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C.

Note. A. RTs in the training phase separated on quadrant type and set size in Experiment 2A. Search RT was shorter for the target in Easy HPQ than that in LPQ. B. RTs in testing phase separated on quadrant type and set size in Experiment 2A. Search RT for the target in easy HPQ was shorter than that in LPQ. LPQ stands for low probability quadrant and HPQ means high probability quadrant. C. Cueing effects (RTs in LPQ – RTs in HPQ) in training and testing phases. Error bars show 95% confidence interval.

Experiment 2B

RT. We removed 3.9% of trials in Experiment 2B as incorrect trials and RT outliers.

Training phase. A quadrant type (difficult HPQs and LPQs) x set size (8, 12, 16) ANOVA revealed that participants found the target in any of difficult HPQs faster than that in any of LPQs, $F(1, 11) = 7.20, p = .021, \eta_p^2 = .40$, that is, the cueing effect was significant, $t(11) = 2.68, p = .021, \text{BF}_{10} = 3.22$. Also, participants made longer RTs as the set size increased, $F(2, 22) = 97.69, p < .001, \eta_p^2 = .90$. The two factors did not interact, $F < 1$.

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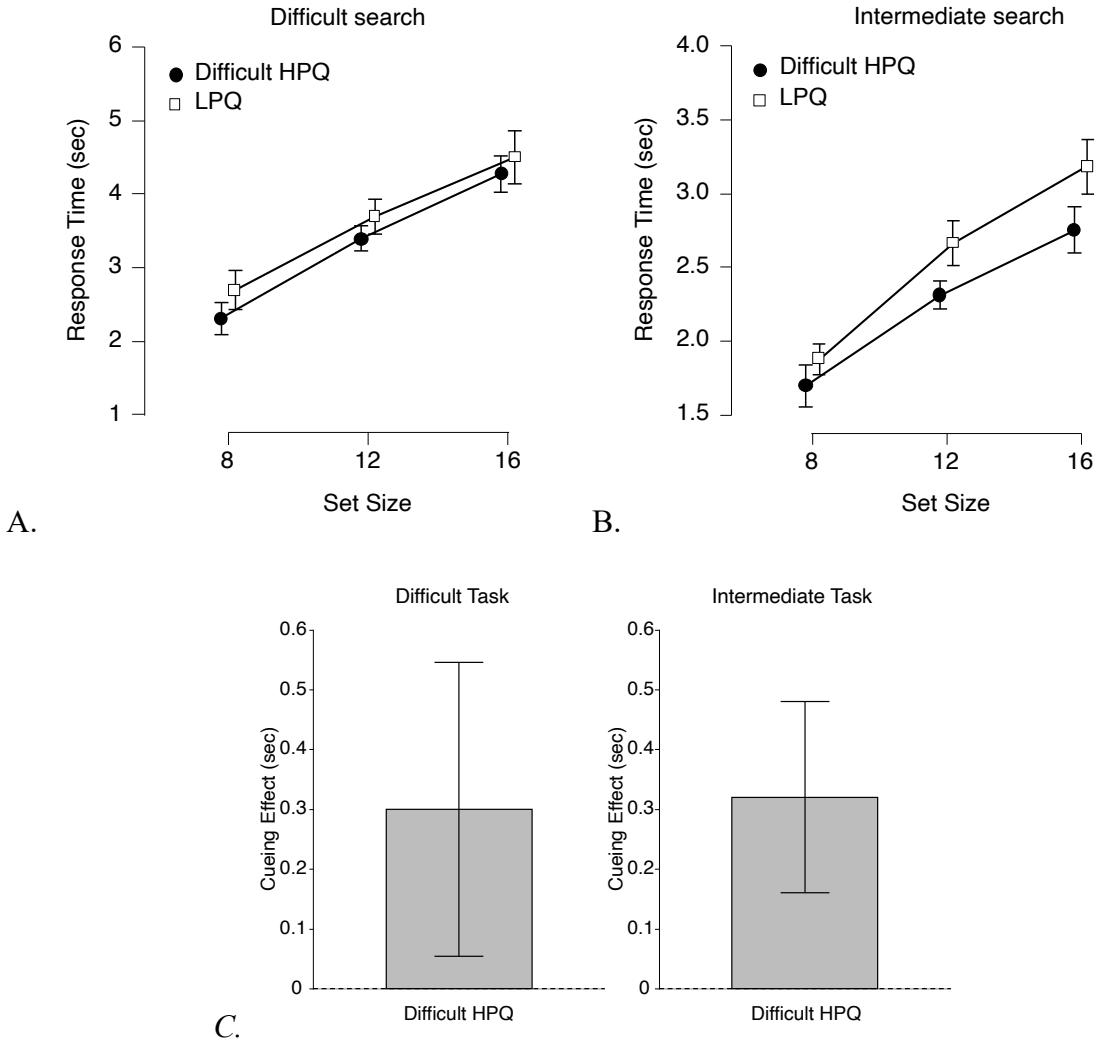
Testing phase. A quadrant type x epoch ANOVA showed that, unlike Experiment 1, participants found the target faster when it appeared in any of the difficult HPQs than in any of the LPQs, $F(1, 11) = 19.43, p = .001, \eta_p^2 = .64$, that is, the cueing effect was significant, $t(11) = 4.41, p = .001, \text{BF}_{10} = 38.47$. The RTs were longer as the set size increased, $F(2, 22) = 158.45, p < .001, \eta_p^2 = .94$. The two factors did interact each other, $F(2, 22) = 4.12, p = .030, \eta_p^2 = .27$. Figure 4 shows the RT results of Experiment 2B.

Figure 4. Experiment 2B RT result

Training

Testing

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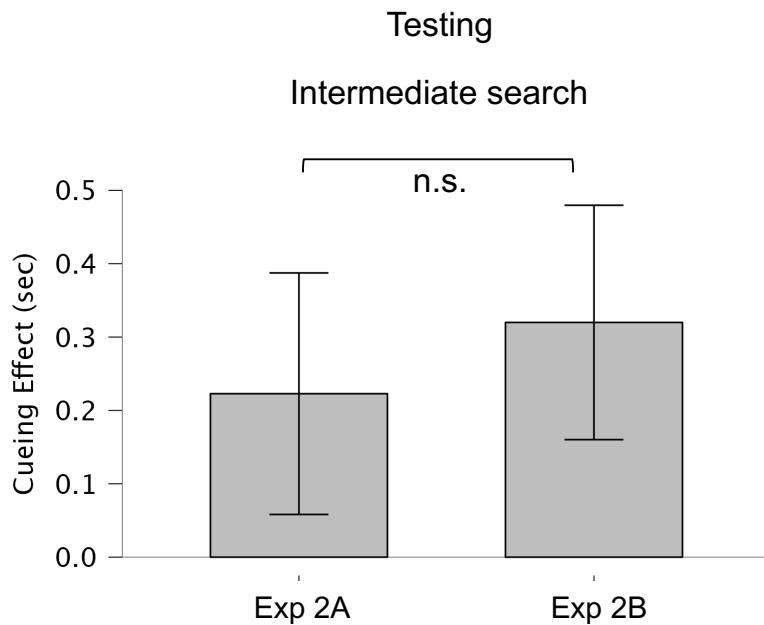
Note. A. RTs in the training phase separated on quadrant type and set size in Experiment 2B. Search RT was shorter for the target in difficult HPQ than that in LPQ. *B.* RTs in testing phase separated on quadrant type and set size in Experiment 2B. Search RT for the target in difficult HPQ was shorter than that in LPQ. LPQ stands for low probability quadrant and HPQ means high probability quadrant. *C.* Cueing effects (RTs in LPQ – RTs in HPQ) in training and testing phases. Error bars show 95% confidence interval.

Experiment 2A vs. Experiment 2B. We compared the results of testing phase between Experiment 2A (easy search during training) and Experiment 2B (difficult search during

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training). An quadrant type (HPQ, LPQ) x set size (8, 12, 16) x experiment (Experiment 2A, Experiment 2B) ANOVA (quadrant type and set size as within-groups factors and experiment as between-group factor) revealed significant main effects of quadrant, $F(1, 22) = 27.12, p = .001, \eta_p^2 = .55$, set size, $F(2, 44) = 222.82, p < .001, \eta_p^2 = .91$, and a significant interaction between quadrant type and set size, $F(2, 44) = 5.03, p = .019, \eta_p^2 = .19$. However, there was no main effect of the experiment, and more importantly, no factor interacted with experiment, $Fs < 1$, which suggests that we did not find any statistically significant difference in cueing effect during testing between the two experiments. Figure 5 shows cueing effects in the testing phase from Experiment 2.

Figure 5. Experiment 2 Cueing effect ($RT \text{ in LPQ} - RT \text{ in HPQ}$)



Note. Cueing effects of the testing phase in Experiment 2A containing only easy search trials during training (Easy HPQ) and Experiment 2B containing only difficult search

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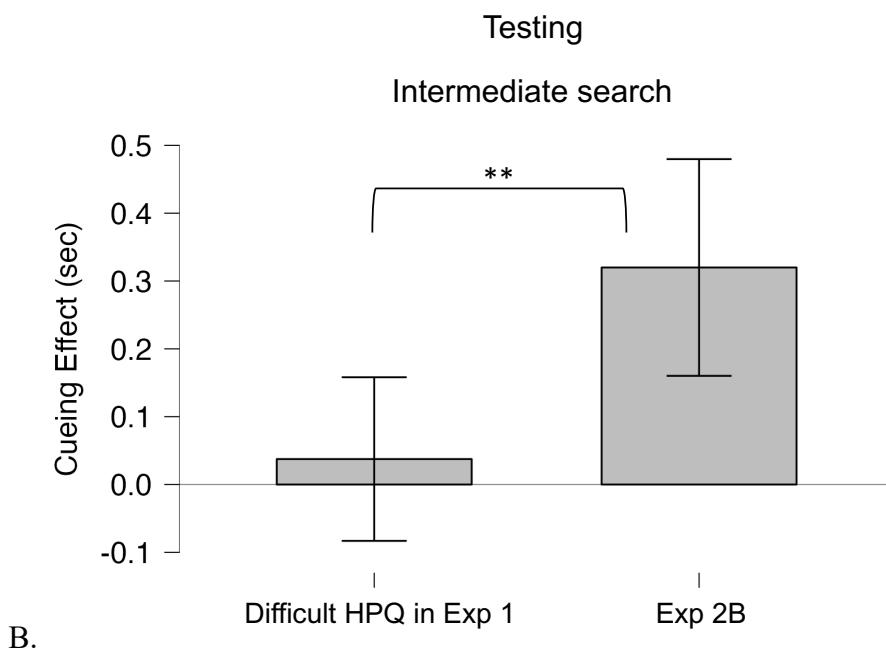
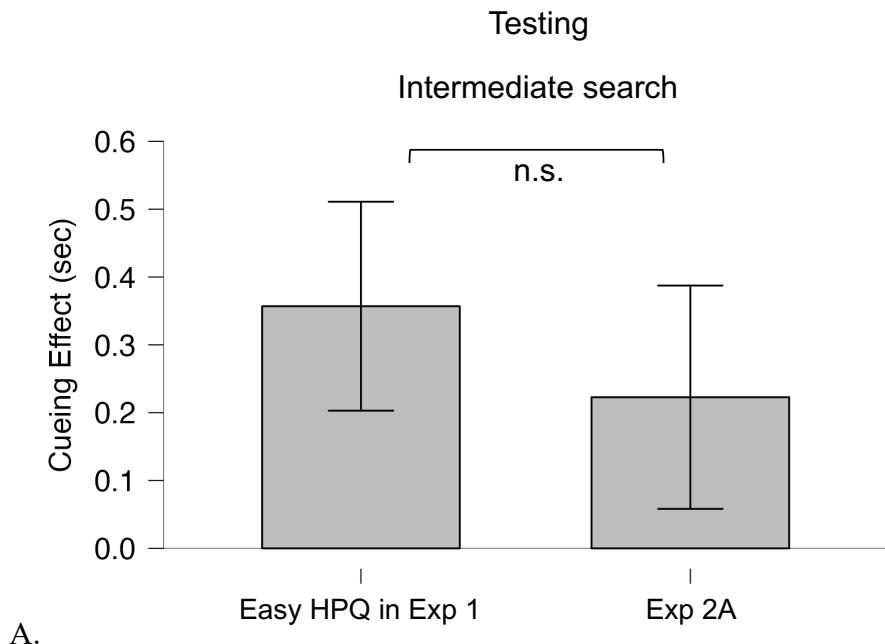
trials during training (Difficult HPQ). The cueing effects were comparable between two experiments. LPQ stands for low probability quadrant and HPQ means high probability quadrant. Error bars show 95% confidence interval.

Experiment 1 vs. Experiment 2. We next compared the results of testing phase between Experiment 1 and Experiment 2 by conducting a quadrant type (easy HPQ, LPQ) x set size x experiment (Experiment 1, Experiment 2A) ANOVA and a quadrant type (difficult HPQ, LPQ) x set size x experiment (Experiment 1, Experiment 2B) ANOVA. First, in comparison of cueing effect of easy HPQ, we found two significant main effects of quadrant type, $F(1, 22) = 32.05, p < .001, \eta_p^2 = .59$ and set size, $F(2, 44) = 166.77, p < .001, \eta_p^2 = .88$, but did not find any significant interaction effects, $ps > .07$. Especially, the lack of interaction between quadrant type and experiment suggests that easy HPQ produces a comparable cueing effect regardless of easy and difficult search trials intermixed or in isolation. Secondly, when comparing the testing phase between difficult HPQ in Experiment 1 and Experiment 2B, we found significant main effects of quadrant type, $F(1, 22) = 15.45, p < .001, \eta_p^2 = .41$ and set size, $F(2, 44) = 303.23, p < .001, \eta_p^2 = .93$, and a significant interaction between quadrant type and set size. However, more importantly, a significant interaction between quadrant type and experiment was found, $F(1, 22) = 9.64, p = .005, \eta_p^2 = .31$, which suggests that Experiment 1 where difficult search trials were intermixed with easy trials showed a weaker cueing effect in difficult HPQ than Experiment 2B where difficult search trials were presented in isolation. Other

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effects did not reach to significance, $Fs < 1$. Figure 6 shows cueing effects in the testing phase from Experiment 1 and Experiment 2.

Figure 6. Experiment 1 and Experiment 2 Cueing effects (RT in LPQ – RT in HPQ)



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Note: A. Cueing effects of easy HPQ in the testing phase in Experiment 1 and Experiment 2A. The cueing effects were comparable between two experiments. B. Cueing effects of difficult HPQ in the testing phase in Experiment 1 and Experiment 2B. The cueing effect in Experiment 2B was greater than that in Experiment 1. LPQ stands for low probability quadrant and HPQ means high probability quadrant. Error bars show 95% confidence interval.

Discussion

The results are clear and stand in contrast to Experiment 1. Whereas we found asymmetric learning and generalization favoring the easy trials in Experiment 1, we now found robust learning and generalization in both the easy and difficult conditions of Experiment 2. The prioritization of the HPQs during testing was equivalent for the easy and difficult groups. These results rule out the account that learning is simply more robust in easy than difficult search. It instead supports the notion that the *intermixing* of easy and difficult trials during training creates a competition in which learning during easy search dominates learning during difficult search.

Why does easy search dominate difficult search when they are placed in competition with one another? We consider two possibilities: 1) the *mere presence* of interleaved easy search interferes with learning during difficult search and generalization; 2) the *learning* that occurs during easy search interferes with learning during difficult search. Experiment 1 cannot differentiate these possibilities because both easy and difficult search were each paired with distinct HPQs. Experiment 3 was designed to differentiate the two alternative accounts.

Experiment 3

Here we test whether the mere presence of easy trials or the learning during easy search could explain the weak learning during difficult trials in Experiment 1. To do so, we returned to the Experiment 1 design but removed the easy HPQ during training; that is, the target evenly appeared across four quadrants when easy search was presented. The difficult HPQ remained. If learning of the easy HPQ dominated learning of the difficult HPQ in Experiment 1, then we should observe a robust learning effect from difficult search. Additionally, this learning should transfer to the intermediate trials of the testing phase. If the mere presence of easy trials during training disrupts learning during difficult trials, then we should find poor learning and generalization of the difficult HPQ, as we found in Experiment 1.

Method

Participants. Another 12 participants (8 women and 4 men; mean age 20.3 years) participated in Experiment 3.

Materials, Design, and Procedure. All materials, design, and procedure were identical with those in Experiment 1 except the following change: the target evenly (25%) appeared across four quadrants in easy search (i.e., no easy HPQ).

Results

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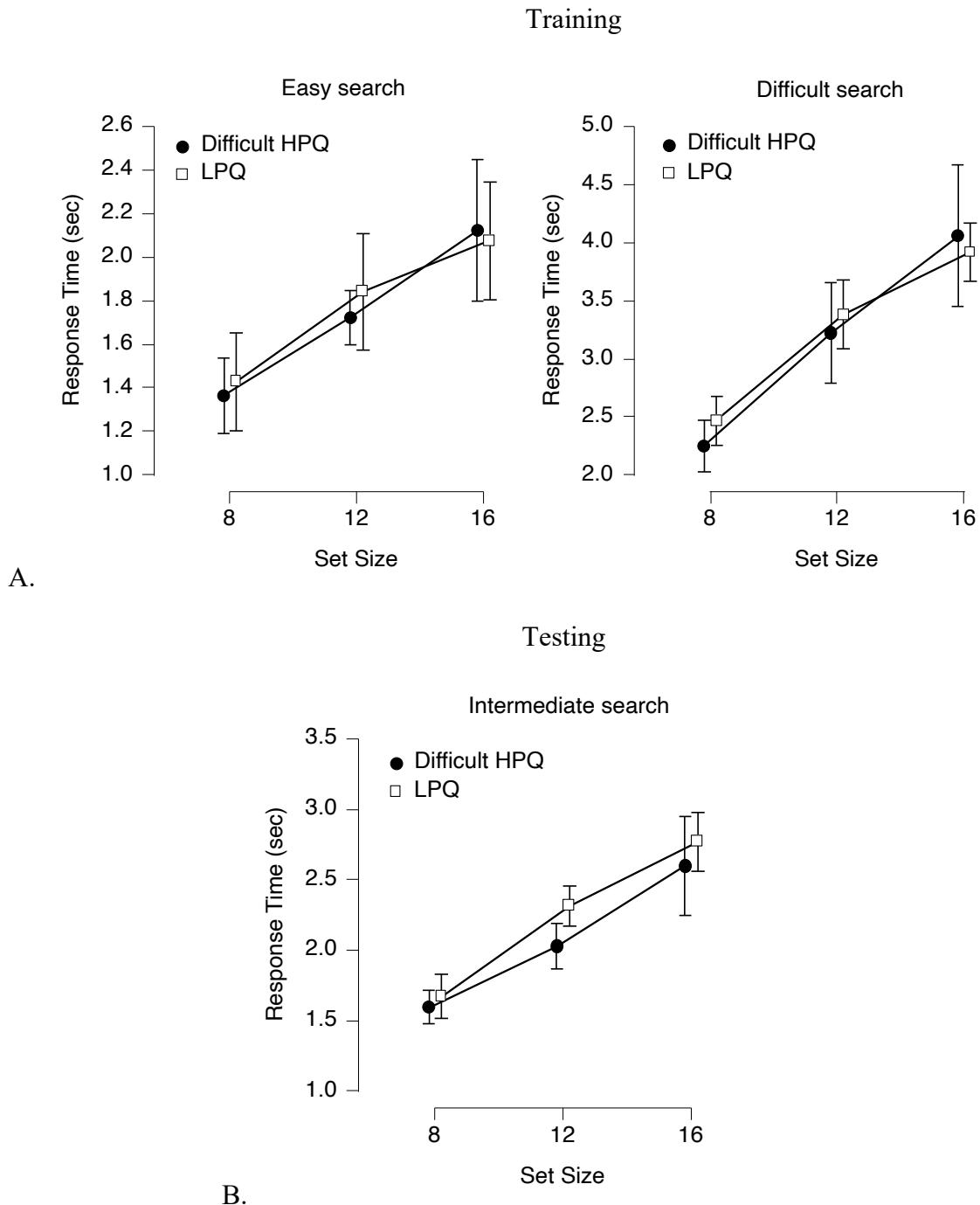
RT. We removed 4.7% of trials as incorrect trials and RT outliers in Experiment 3.

Training phase. A search difficulty x quadrant type x set size ANOVA revealed two significant main effects. That is, easy search was faster than difficult search, $F(1, 11) = 88.38, p < .001, \eta_p^2 = .89$, and search became slower as set size increased, $F(2, 22) = 90.32, p < .001, \eta_p^2 = .89$. There was a significant interaction between task and set size, $F(2, 22) = 12.37, p < .001, \eta_p^2 = .53$ (mean search slope for easy search: 88 msec/item, mean search slope for difficult search: 204 msec/item). However, critically, we did not find a significant difference between quadrant type, $F < 1$, which means the cueing effect was not significant, $t(11) = .55, p = .60, \text{BF}_{10} = .33$ for the easy task; $t(11) = .47, p = .65, \text{BF}_{10} = .32$. Also, any other interaction was not significant, $ps > .17$.

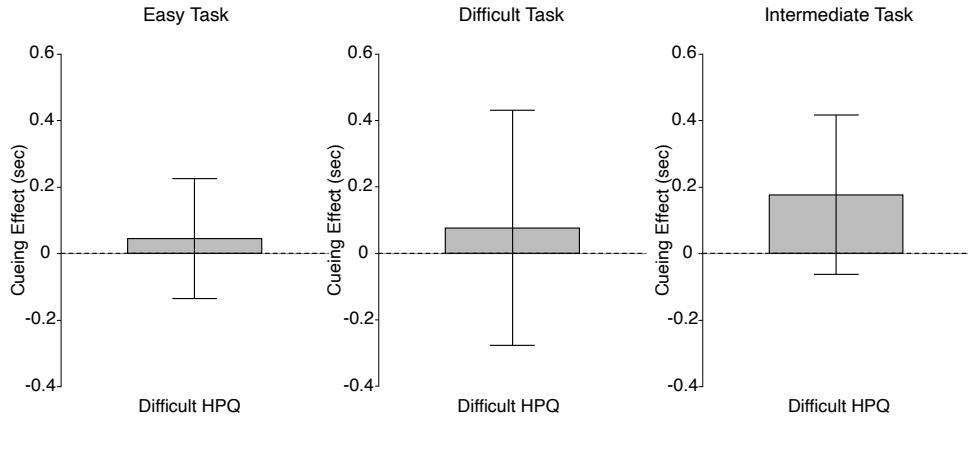
Testing phase. An ANOVA on quadrant type x set size showed a main effect of set size, $F(2, 22) = 122.47, p < .001, \eta_p^2 = .92$, however, neither that of quadrant type, $F(1, 11) = 2.65, p = .13, \eta_p^2 = .19$, nor an interaction between quadrant type and set size, $F < 1$, was significant which means the cueing effect was not significant, $t(11) = 1.63, p = .13, \text{BF}_{10} = .81$. It is important to exercise caution in interpreting the results, given the weak Bayes Factor (BF) value. Figure 7 shows the RT results of Experiment 3.

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Figure 7. Experiment 3 RT results



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C.

Note. A. RTs in the training phase separated on search difficulty, quadrant type, and set size in Experiment 3. No learning of difficult HPQ was found in the training phase. B. RTs in testing phase separated on quadrant type and set size in Experiment 3. No learning of difficult HPQ was found in the testing phase. LPQ stands for low probability quadrant and HPQ means high probability quadrant. C. Cueing effects (RTs in LPQ – RTs in HPQ) of two search difficulty in training and testing phases. Error bars show 95% confidence interval.

Discussion

Here, even though we removed the easy HPQ during easy search, we didn't observe significant learning or generalization of the difficult HPQ. In fact, though we found significant prioritization of the difficult HPQ during the difficult trials of the training phase in Experiment 1, we do not see it during the training phase in Experiment 3. For the testing phase, there is no significant prioritization of the HPQ. Overall, the present experiment suggests that the mere presence of easy search trials during training

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interferes with the learning of the difficult HPQ during difficult search and generalization to the intermediate trials of test.

Awareness of spatial probability

Previous studies have gauged the role of awareness in probability learning by asking several recognition questionnaires at the end of the experiment. They found that participants rarely reported their awareness of uneven target probability and the high probable locations no better than chance level. (Jiang et al., 2014) showed that once the bias has been established, the bias is automatic and not changed even when the participants are explicitly told that the target evenly appeared across all quadrants during the testing phase.

We also gauged the awareness of the target probability manipulation during the task by asking participants to complete questionnaires after each experiment.

The first question was whether the location of the target was evenly distributed all over the place or it was more often found in some places than others. Regardless of their first answer, they were informed that the target more often appeared in some places than in others and asked to choose one quadrant where the target most frequently appeared. Although there were two high probable locations (easy and difficult HPQs) in Experiment 1, participants were asked to choose one quadrant because we were curious which HPQ they would pick. All recognition results are reported in Table 2.

Table 2. Recognition results. Each value indicates the number of participants.

Question 1	Even	Uneven

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Question 2	Easy-high probable	Difficult-high probable	Low probable	Easy-high probable	Difficult-high probable	Low probable
Exp1	4	0	4	1	0	3
Exp2a	5	N/A	2	3	N/A	2
Exp2b	N/A	4	4	N/A	3	1
Exp3	N/A	2	4	N/A	2	4

In all experiments, 29 out of 48 participants reported the target was evenly distributed. Also, among the 19 participants who answered the target unevenly appeared, only 9 participants (47.3%) chose one of the two HPQs. Among the 29 participants who answered the target evenly appeared, 15 participants (51.7%) chose one of the HPQs. Based on these numbers, the explicit awareness about target probability did not seem to play a critical role in this study. However, considering that the questionnaires were presented after the testing phase where the target was evenly distributed, the awareness of high probable locations right after the training phase may have been higher than what we measured (Giménez-Fernández et al., 2020).

General Discussion

In this study, we set out to investigate how search difficulty impacts spatial probability learning. We investigated context specificity of learning, as well as asymmetries in the acquisition of learning and generalization of it to a novel context.

To review, in Experiment 1, we found strong learning and generalizability of easy search and weak learning and negligible generalizability of difficult search when two

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search trials were randomly interleaved. These results show that easy search learning dominates difficult search learning, which promotes greater generalizing to a novel difficulty level. It is worth noting that interpreting the lack of generalizability of difficult search learning in the training phase to the intermediate search in testing requires caution, given the weak Bayes Factor ($BF_{10} = 0.35$).

In Experiment 2, we ruled out an alternative that difficult search itself might produce a weaker cueing effect than easy search in isolation, such that it could not survive during testing. Indeed, we found a robust spatial bias of difficult search during training and robust generalizability during testing, comparable with that of easy search in isolation. These results show that the lack of learning and generalization from difficult search found in Experiment 1 was due to competition from the intermixed easy trials.

Despite intentionally matching the number of HPQs in Experiments 1 and 2, with two HPQs each, there was a notable difference: Experiment 1 had one 'difficult' HPQ, akin to Experiment 3, whereas Experiment 2 featured two 'difficult' HPQs. This inconsistency raised the possibility that the quantity of HPQs might influence learning effectiveness and, consequently, generalization in the testing phase. However, we conducted a pilot study in which participants engaged in a difficult search task that was identical to Experiment 2B, with the sole difference being the inclusion of only one difficult-HPQ. The outcomes were similar to those of Experiment 2B, indicating that the number of HPQs did not account for the observed differences across experiments.

Also, some might wonder why we chose a between-subject design for Experiment 2 instead of a within-subject design involving three blocks of easy-only search followed by three blocks of difficult-only search, and vice versa. Previous studies have

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demonstrated that probability learning can be long-lasting and persistent, even after a change in probability (Jiang et al., 2013; Golan & Lamy, 2023). Therefore, our choice aimed to mitigate any potential lingering learning effects from the previous blocks (e.g., easy search blocks), which could occur with a within-subject design. Furthermore, we considered that adopting a within-subject design might make it challenging to assess the full extent of generalizability due to possible interference between these two types of learning.

In Experiment 3, we ruled out the alternative that learning during easy search specifically weakened learning of the difficult HPQ. We tested this alternative by including easy trials without its HPQ. However, again, we saw neither learning during training nor generalizability during testing. These results suggest that the lack of learning from difficult search was not due to the competition for attention between two HPQs, but due to the mere presence of easy search trials that were intermixed during training.

The absence of learning regarding difficult HPQ during training in Experiment 3, where intermixed easy trials did not include any HPQ, is intriguing when compared to the robust learning of difficult HPQ during training in Experiment 1, where intermixed easy trials did include an easy HPQ. Based on these findings, we suggest that the lack of generalization of difficult HPQ is not due to competition with easy HPQ. However, it remains unclear why the presence of easy search trials with an even target distribution in Experiment 3 interfered with the learning of difficult HPQ. We speculate that the ‘even’ distribution of targets in easy search in Experiment 3 might disrupt the probability learning of difficult search by increasing the variability of signal to noise ratio (SNR) signals (0% vs. 50% probability; Hong et al., 2022 and Jungé et al., 2007). In other

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words, participants might develop a stronger sense of "randomness" from the easy search, potentially weakening the statistical learning of difficult search. However, this is a speculative hypothesis that requires further investigation.

It is possible that the learning effect of difficult HPQ is fragile and rapidly extinguishes with time, potentially leading to weaker generalizability in Experiment 1's testing phase. Additionally, learning to prioritize difficult HPQ in Experiment 3's training phase might require more time to develop and, therefore, occur later point. To investigate this, we analyzed the learning effect in Experiment 1's testing phase and the generalization effect in Experiment 3's training phase across five blocks to determine whether there is any temporal discounting of generalization and late emergence of learning, respectively. However, we observed neither a decrease in generalization in Experiment 1's testing phase nor an increase in learning in Experiment 3's training phase. Furthermore, when comparing the search RT for difficult HPQ with LPQ in the first block of Experiment 1's testing and the last block of Experiment 3's training, the RTs did not differ significantly. These results suggest that, at least, the learning of difficult HPQ is not easily generalized, and learning of difficult HPQ does not easily emerge when difficult search trials are intermixed with easy search trials with an even target probability. It is worth noting that this analysis is exploratory, so we should be cautious with our interpretation due to potentially low power. It is worth noting that this analysis is exploratory, so we should be cautious with our interpretation due to potentially low power.

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Overall, these three experiments suggest that prior experiences with easy search more strongly influences the current search than prior experience with difficult search, when the two levels of difficulty are intermixed.

An important question remains. Why do these two searches show different intensity of learning and generalization? While further research will be needed to provide a definitive answer, we offer a speculative account, which holds that difficult search induces weaker reinforcement learning (or search habit) than easy search when they are randomly intermixed. Jiang and colleagues (Jiang, 2018; Jiang & Sisk, 2019; Jiang, Swallow, et al., 2014; Jiang, Won, et al., 2014; Salovich et al., 2018; for review, Jiang, 2018) proposed that in a search trial, successful target detection reinforces the preceding sequence of attentional shifts, increasing the likelihood that they will be deployed again during future search attempts. However, easy search is typically comprised of fewer and faster attentional shifts until the target is found than difficult search (Williams & Pollatsek, 2007; Zelinsky & Sheinberg, 1997). Thus, there is likely to be greater correlation across trials among sequences of attentional shifts in easy search than difficult search, which could facilitate the development of a search habit. This suggests that the learning of difficult search, while robust in isolation, could be relatively fragile when intermixed with other search conditions (even when they lack high probable locations).

We note that asymmetric generalizability depending on task difficulty has also been found in the perceptual learning literature (reverse hierarchy theory; Ahissar & Hochstein, 1997, 2004). Unlike the current form of learning investigated, perceptual learning is characterized as improvements in a specific perceptual task (e.g., finding a slightly tilted vertical line among vertical lines) after long intensive training and sensitive

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to the specific stimulus (e.g., vertical line; for review; Gibson, 1969). Ahissar and Hochstein (1997, 2004) found after training in an easy perceptual task, participants generalized their learning to a different stimulus (e.g., horizontal line) whereas after training in a difficult perceptual task, the learning remained highly stimulus specific (e.g., only vertical line). Despite the differences between perceptual learning and the present form of implicit learning, it is notable that both forms of learning exhibit similar results—namely, asymmetric generalizability depending on the context of intermixing easy and difficult search trials. Further work will be needed to determine whether a similar mechanism may underlie these similar findings.

A recent study demonstrated a noteworthy slope effect in probability cueing, revealing a shallow slope for the HPQ in contrast to the LPQ. This finding strongly suggests a significant influence of probability on attentional allocation (Golan & Lamy, 2023). Unfortunately, the present studies yielded mixed results concerning the slope effect. We hypothesized that the inconsistency of the slope effect in our study might be attributed to the smaller sample size and, more importantly, the distribution of high quadrants in the search displays. Our study featured two HPQs and two LPQs, deviating from the one HPQ and three LPQs arrangement in Golan & Lamy (2023). This difference, coupled with the potential impact of larger high-probable areas and more search items, might account for the attenuated slope effect observed in our findings. Subsequent studies are necessary to empirically investigate these speculations.

Also, although shorter RTs for the target in the HPQ likely indicate attentional guidance toward probable locations, as suggested by previous eye-tracking studies (Jiang, Won, & Swallow, 2014; Jones & Kaschak, 2012; Walthew & Gilchrist, 2006), it remains

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challenging to definitively exclude the alternative explanation that covert attention might initially shift to the LPQs and then rapidly reject items in those locations, resulting in shorter RTs. Further studies are necessary for more comprehensive investigations.

In conclusion, this study examined how past search experiences interact with each other and which search experience influences the current search behavior using search difficulty. We found that when easy search experiences and difficult search experiences are mixed, the former show dominant learning over the latter and also are generalizable to the current search.

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