

Statistical Learning of Motor Preparation

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Statistical learning, the process of extracting regularities from the environment, is one of the most fundamental abilities playing an essential role in almost all aspects of human cognition. Previous studies have shown that attentional selection is biased toward locations that are likely to contain a target and away from locations that are likely to contain a distractor. The current study investigated whether participants can also learn to extract that a specific motor response is more likely when the target is presented at specific locations within the visual field. To that end, the additional singleton paradigm was adapted such that when the singleton target was presented at one specific location, one response (e.g., right index finger) was more likely than the other (e.g., right middle finger) and the reverse was true for another location. The results show that participants learned to extract that a particular motor response is more likely when the singleton target (which was unrelated to the response) was presented at a specific location within the visual field. The results also suggest that it is the location of the target and not its shape that is associated with the biased response. This learning cannot be considered as being top-down or conscious as participants showed little, if any, awareness of the response biases present. The results are discussed in terms of the event coding theory. The study increases the scope of statistical learning and shows how individuals adapt automatically, without much awareness, to the regularities present in the environment.

Public Significance Statement

Extracting regularities from the environment is one of the most fundamental human abilities and is often referred to as statistical learning. While this ability to adapt to regularities has been demonstrated in many domains, the current study extends previous findings by showing that humans can also learn to associate that a particular motor response is more likely when a visual target (which is unrelated to the response) is presented at a specific location within the visual field. It demonstrates the impact of statistical learning and the way people adapt automatically, without much awareness, to regularities in the environment.

Keywords: statistical learning, attentional selection, motor response

Extracting regularities from the environment to be able to optimally tune our behavior is one of the most fundamental human abilities and is often referred to as statistical learning. Research has shown that observers easily learn the underlying structure of auditory and/or visual sensors (Frost et al., 2015). It is generally assumed that statistical learning is an implicit process that assimilates the statistical regularities in the input, operating without intent and outside

explicit awareness (e.g., Duncan & Theeuwes, 2020; Fiser & Aslin, 2001; Turk-Browne, 2012; Turk-Browne et al., 2005).

This learning ability to extract regularities from the environment has been demonstrated in many cognitive domains such as language, object recognition, scene and object perception, and conditioning (see Frost et al., 2015 for a review). Several recent studies have shown that statistical learning biases visual selection (Theeuwes

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van Moorselaar contributed equally to writing—original draft and writing—review and editing.

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et al., 2022 for a review). After learning, visual search is optimally adapted to the spatial probabilities of the target (e.g., Geng & Behrmann, 2002, 2005; Huang et al., 2022) of the distractor (Wang & Theeuwes, 2018a) and to the combination of target and distractor probabilities (Gao & Theeuwes, 2020). This implies that if the target appears more often in one location than in other locations, participants learn this structure such that the target is detected faster when it appears at this high-probability location than at low-probability locations (Duncan et al., 2023). Zhang et al. (2022) used the additional singleton paradigm (Theeuwes, 1991, 1992) and varied systematically the probability that the target would be presented in one particular spatial location (probabilities of 30%, 40%, 50%, 60%, 70%, 80%, and 90%). The results showed that attentional biases were optimized to the spatial regularities tracking the experienced probabilities of the locations that were most likely to contain a target. It was concluded that through statistical learning the weights within an assumed visual–spatial priority map are adjusted optimally, resulting in efficient selection priorities. Critically, these findings could not be explained by repetition priming nor by strategic top-down biases (Theeuwes et al., 2022).

One specific design feature of the additional singleton paradigm is that participants need to search for a unique shape singleton and respond to the orientation of the line segment that is placed inside the target element. In this way, there is a clear separation of what participants search for (a unique shape) and what participants respond to (a horizontally or vertically oriented line segment). The target, which can randomly be a red diamond, a red circle, a green diamond, or a red diamond is defined by the fact that it is the unique shape in the current display configuration. Statistical learning studies using this paradigm up till now, have shown robust optimal adjustment to the visual–spatial regularities present in the displays regarding the spatial probabilities (i.e., the frequency of presentation) of both the target and the distractor (Theeuwes et al., 2022). Critically, in all these studies, the adjustment to the regularities present in the display had nothing to do with the frequency of the response that needed to be given as in the typical additional singleton paradigm the line segment placed in the unique shape singleton was always balanced generating equal numbers of right- and left-handed responses. One question that thus has not been answered is whether participants can also learn to adapt to the regularities associated with the frequencies of the responses that need to be given at particular locations. In the current study, we specifically asked the question whether participants can learn that a specific response is more likely needed when the unique shape target is presented at a specific location in the visual field.

It is important to realize that the current study is different from previous studies that have shown that participants can learn that particular stimuli are more likely to appear at particular locations in the visual field (e.g., Geng & Behrmann, 2005; Hoffmann & Kunde, 1999; Shaw & Shaw, 1977). The critical point of the current study is that participants search for a unique shape and when this unique shape happens to be presented at a particular location, the response that needs to be given may be biased. In other words, the target shape, which randomly varies across trials (either a diamond or a circle), is equally likely presented at all locations; the only contingency is that if the target shape is presented at one specific location, one of the responses is more likely than the other one. The question we addressed here is whether participants can learn this.

While this specific question is unique, there is ample evidence that statistical learning plays a crucial role in motor learning. The classic task that is often used in this domain is the serial reaction time paradigm (Nissen & Bullemer, 1987). In this paradigm, a visual stimulus is linked to a distinct and spatially specific motor response. For example, five horizontally presented stimuli presented on a computer screen may be linked to the corresponding five fingers of one of the hands. The participant needs to press the button located under each stimulus as soon as the stimulus lights up. Typically, among a random sequence of stimuli, a sequential sequence is embedded and for those sequences' participants show an improvement of reaction time (RT) relative to the random baseline. These findings have been interpreted as evidence of motor learning of specific temporal-order statistics. Because participants are usually not aware of the repeated sequence, this type of motor learning is considered to be implicit occurring without much, if any, awareness. These results have been replicated many times (e.g., Deroost & Soetens, 2006; Unsworth & Engle, 2005; Willingham et al., 2000). Note, however, that the current study is not so much about sequence motor response learning but about learning that a particular motor response is more likely to follow when a target stimulus is presented at a particular location within the visual field.

The question whether participants learn that specific responses correlate with targets' locations can be related to the idea of event files as discussed in the theory of event coding (TEC; Hommel, 2004; Hommel et al., 2001). Event files are thought to be internal representations of integrated stimulus and response features that are built when humans respond to stimuli and are assumed to be terminated by the response or the effect the response produces (Frings et al., 2023). Importantly, event files can be retrieved when features repeat, and the event file has not decayed yet (see the theory of binding and retrieval in action control [BRAC] for the dynamic management of event files, Frings et al., 2020). In terms of the event-file concept, the presentation of the target singleton at a specific location is coded together with the response as a particular "event." If a feature of this event file (e.g., the location; Singh & Frings, 2020) repeats, then the previous event file, which includes the specific response, will be retrieved (Frings & Rothermund, 2011). Thus, each time the event occurs (i.e., the target singleton is presented at a specific location), the specific response associated with this event is retrieved facilitating responding as the response does not have to be computed but instead, the retrieved event file functions as a shortcut (Henson et al., 2014). It must be noted though that the original formulation of TEC/BRAC does not include a learning mechanism. Yet, a fair assessment of the actual literature regarding this aspect (i.e., the relation between learning and TEC/BRAC) would be that binding and retrieval can form the basis of learning, as for example was shown in Frings et al. (2015) where five repetitions of a particular distractor–response pairing led to longer lasting learning effects. In addition, and particularly important for that matter is the work of Schmidt et al. (2016, 2020). He suggested the same mechanism underlying binding and retrieval as well as contingency learning and that binding and retrieval can be building blocks of contingency learning. Against this background, it seems warranted to argue that binding and retrieval can lead to contingency learning (here in the form of statistical regularities).

The present study investigated whether participants can learn that a specific motor response is more likely needed when the target is presented at a specific location. To that end, across the three experiments, we adapted the additional singleton paradigm such that when the singleton target was presented at a specific location, there was a high

probability that the orientation of the line presented inside the target singleton required a specific response (e.g., 80% right index finger, 20% right middle finger). For the other locations, the required responses were equally likely. Note that the target singleton itself was equally likely to appear at each location, indicating that in this design, there is no biasing of visual attention to any specific location.

It should be noted that each participant always responded with the same particular response to a vertical or horizontal line. Therefore, it is not possible to exclude that the event file contains not only the specific location and features of the response to the target at that location but also the target stimulus itself (i.e., the line with a particular orientation). Previous research showed that both types of bindings exist and contribute to binding effects. For our purpose, we ignore this detail because both bindings go in the same direction, that is, the response–target location binding might just be strengthened by response–target bindings (see e.g., Moeller et al., 2016, for disentangling of this aspect). As a consequence, we cannot exclude the possibility that the source of the effect is (at least in part) perceptual. This in turn would indicate that participants learned to better discriminate one type of line orientation at the target (biased) location. Given the strong influence of location on response bindings (Singh & Frings, 2018), it seems, however, very unlikely that the effect is purely perceptual.

Experiment 1

In Experiment 1, participants performed the additional singleton paradigm by searching for a target singleton. The task involved detecting a diamond among a display of seven circles or a circle among a display of seven diamonds. If the target singleton appeared at one specific location (e.g., top right), there was an 80% probability that the line orientation within the target singleton was vertical, requiring a response with the right middle finger. There was a 20% probability that the line orientation was horizontal, requiring a response with the right index finger. This condition was labeled as the “biased location” condition. For all other locations used to present the target singleton, the required responses were balanced (50%–50%), constituting the “neutral location” condition.

Method

All experiments were approved by the Ethical Review Committee of the Faculty of Behavioral and Movement Sciences of the Vrije Universiteit Amsterdam.

Transparency and Openness

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. The study and analyses were not preregistered. The data, materials, analysis, and article code for the experiment are available on the Open Science Framework (<https://osf.io/ywfydb/>). Data were analyzed using R.

Participants

In the current study, we aimed to investigate the effect of a response bias that was specifically linked to one location. As the size of this effect could not be retrieved based on the previous literature, we used a medium effect size ($f = 0.25$) to conduct a priori power analysis for a repeated measures analysis of variance (ANOVA). Using the G*Power with an α level of .05, power of .80, and a medium effect

size of 0.25, the analysis suggested that a sample size of at least 24 participants was required to detect a significant effect. We anticipated the possibility of participant dropout or incomplete data and thus recruited 34 participants to ensure adequate statistical power.

Thirty-four adults (21 females, $M_{\text{age}} = 25.6$, $SD_{\text{age}} = 4.6$) participated in an online experiment through Prolific, out of which two were excluded as their mean accuracy exceeded $\pm 2.5 SD$ from the overall mean accuracy. All reported having normal or corrected-to-normal (color) vision. Participation took approximately 40 min, and participants earned £5.

Apparatus and Stimuli

Because the experiment took place online, some factors (e.g., lighting and seating conditions) could not be controlled. For replication purposes, item sizes and colors are reported in pixels and RGB values (red/green/blue). The experiment was created in OpenSesame (Mathôt et al., 2012) using OSweb and run using Just Another Tool for Online Studies (Lange et al., 2015).

We employed a version of the additional singleton paradigm (Theeuwes, 1991, 1992) as illustrated in Figure 1. In each display, there was only a single target singleton (there was no color distractor). It consisted of eight shapes (one circle and seven diamonds, or vice versa) presented on an imaginary circle with a radius of 224 pixels. Each shape contained a gray (192/192/192) vertical or horizontal line (41 × 3 pixels). The circles (102 × 102 pixels) and diamonds (115 × 115 pixels) were either in red (255/0/0) or green (0/208/0). The background was dark gray (94/94/94). The fixation dot (20 × 20 pixels) was based on Thaler et al. (2013), to enforce optimal fixation.

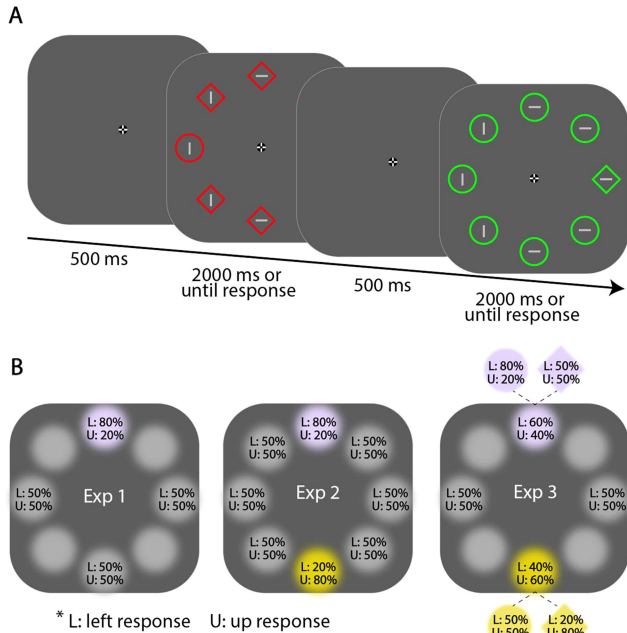
Procedure and Design

Each trial started with a 500 ms fixation display, which was followed by the search display. Participants were instructed to search for the unique shape (i.e., a circle among diamonds or vice versa) and indicate the orientation of the line segment inside (horizontal/vertical) via button press (left or up arrow key) as quickly as possible. These unique shapes could only appear at the four locations along the vertical and horizontal axis or alternatively along the diagonal axis (counterbalanced across participants). Critically, while at three out of these four locations the line inside the target was equally likely to be one of the two possible orientations, at one location, the biased location, one specific orientation (e.g., horizontal) appeared with 80% probability (counterbalanced across participants). The search display was visible until a response was given with a 2,000 ms timeout. Negative feedback, in the form of the letter “X,” was displayed in the center of the screen for a randomly jittered duration of 800–1,000 ms if participants made an incorrect response.

Participants completed 32 practice trials without any regularity, followed by 14 blocks of 80 trials each. A break was included after every block, and the trial order was randomized within blocks. After all trials were completed, three questions were used to assess the participants’ awareness of the regularities. The first question asked whether it was noticed that one of the line orientations occurred more frequently when the target was presented at a specific location. The second question asked the participants to identify the location where in space the imbalance took place. The third question asked the participants to indicate the frequent line orientation at the biased location identified in the second question.

Figure 1

(A) Example Trial Sequence. (B) Illustration of Response Frequency for Three Experiments



Note. Participants were required to search for a unique shape and respond whether the orientation of the line segment inside was horizontal or vertical. Unbeknown to the participants, if the target singleton was presented in one specific location (e.g., on the left side of the display), there was an 80% probability that the orientation of the line inside the target singleton was for example vertical (requiring a response with the right middle finger) and a 20% probability that it was horizontal (requiring a response with the right index finger). This condition was labeled as the “biased location” condition. For all other locations that were used to present the target singleton, the required responses were balanced (50%–50%) constituting the “neutral location” condition. See the online article for the color version of this figure.

Data Analyses

Search times analyses were limited to data of correct trials only. RTs were filtered in a two-step trimming procedure: trials with RTs shorter than 200 ms were excluded, after which data were trimmed on the basis of a cutoff value of 2.5 *SD* from the mean per participant. Exclusion of incorrect responses (7%) and data trimming (3%) resulted in an overall loss of 10% of trials. Remaining RTs were analyzed with repeated measures ANOVAs, followed by planned comparisons with paired *t*-tests using R (R Core Team, 2020). In case of insignificant findings, we also report the Bayes factor in support of the null model. In the case of interactions, this factor represents the model comparisons between models that contain the effect and equivalent models stripped of the effect (BF_{excl}).

Results

To examine whether a specific motor response was prioritized when the target appeared at the biased location, we entered RTs into a repeated-measures ANOVA with within subjects’ factors target location (biased location, neutral location) and response (high-probability

response, low-probability response; where responses at neutral locations were artificially coded as high and low probability based on their status at the biased location). As visualized in Figure 2A, the main effect of response, $F(1, 31) = 25.09$, $p < .001$, $\eta_p^2 = .45$, reflecting overall faster high-probability responses than low-probability responses, was especially prominent at the location that actually contained the response imbalance, which resulted in a reliable interaction, $F(1, 31) = 13.67$, $p < .001$, $\eta_p^2 = .31$. Indeed, planned pairwise comparisons confirmed that low-probability responses were slower than high-probability responses at the biased location, $t(31) = 5.00$, $p < .001$, $d = 0.25$, but not at the neutral locations, $t(31) = 1.32$, $p = .20$, $d = 0.04$, $BF_{01} = 2.40$. Critically, this pattern of results did not change when all trials were excluded where either the target location, or the target response repeated, with the observed difference between high- and low-probability responses still being significant at the biased location, $t(31) = 2.20$, $p = .035$, $d = 0.63$. This finding strongly suggests that the observed effect should not be attributed solely to retrieval of the most recent event, but instead reflects learning across longer time scales.

Mean accuracy analyses mimicked these findings, with the interaction, $F(1, 31) = 8.38$, $p = .007$, $\eta_p^2 = .21$, reflecting more accurate high-probability responses than low-probability responses at the biased locations, $t(31) = 3.91$, $p < .001$, $d = 0.90$, but no difference at the neutral locations, $t(31) = 1.48$, $p = .15$, $d = 0.22$, $BF_{01} = 1.98$, showing that the observed RT effects cannot be attributed to a speed-accuracy tradeoff.

Awareness of the High-Probability Response

Twelve participants reported that they were aware of the regularity during the experiment, but only one of them correctly indicated the location that was biased. The remaining 20 participants reported not being aware of the regularity. After removing participants who reported being aware of the regularity, we found that the difference between high- and low-probability responses remained significant at the biased location, RTs: $t(19) = 3.72$, $p = .001$, $d = 1.26$; accuracy: $t(19) = 2.93$, $p = .009$, $d = 1.19$. This suggests that the observed effect cannot be attributed to participants’ explicit knowledge of the statistical regularity.

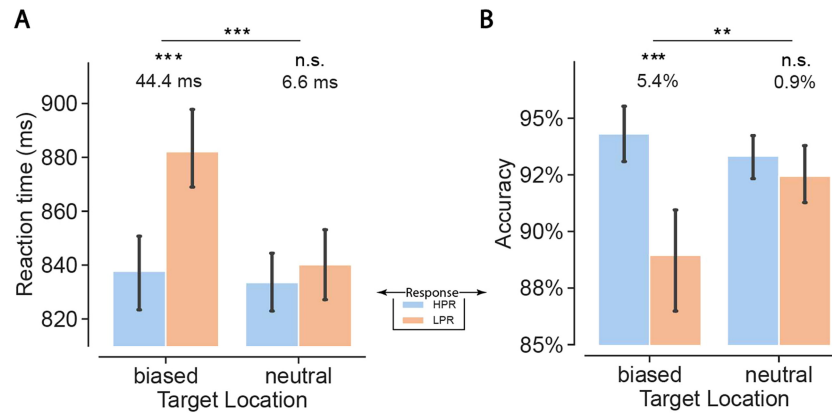
Discussion

The current findings clearly demonstrate that participants can learn to prioritize a given response at a given location. Yet it should also be noted that overall response frequency was not matched across all locations, and therefore it remains unclear whether such learning also occurs when a particular response is no longer overall more probable than the other response option. Experiment 2 was designed to address this issue while replicating the findings of Experiment 1.

Experiment 2

In Experiment 1, the high-probability response had a higher overall frequency than the low-probability response because only one location had a biased response. To balance the overall response frequency, in Experiment 2 two out of eight locations were selected as the biased location, such that response imbalance at one biased location (e.g., 80% probability of horizontal line) could be reversed at the other biased location (e.g., 80% probability of vertical line).

Figure 2
Mean RTs and Accuracy as a Function of Target Response (High-Probability Response, Low-Probability Response) and Target Location (Biased, Neutral) in Experiment 1



Note. All error bars here and in subsequent plots represent 95% within-subject confidence intervals (Morey, 2008). HPR = high-probability response; LPR = low-probability response; RTs = reaction times. See the online article for the color version of this figure.

** $p < .01$. *** $p < .001$.

Method

The methods of Experiment 2 were identical to Experiment 1, except for the following changes. To determine how specific a response bias was tied to a specific location, in the current experiment, the target could be present at any of the eight locations within the display. In this experiment, two of these locations had a response bias. As the number of trials for the critical condition was half of that in Experiment 1, to maintain adequate statistical power, we increased the sample size by approximately 2 times compared to the sample size used in Experiment 1. Sixty-seven adults (29 females, $M_{\text{age}} = 25.8$, $SD_{\text{age}} = 4.75$) participated in an online experiment through Prolific. They all reported having normal or corrected-to-normal (color) vision. Participation took ± 40 min and participants earned £5. Two participants were excluded for their mean accuracy exceeded ± 2.5 SD from the overall mean accuracy, leaving 65 participants for analysis.

Eight locations were equally likely to contain the target and two of these locations were used as the biased locations (opposite to each other and counterbalanced across participants). Critically, at these biased locations, the response regularities were reversed such that the high-probability response at one biased location was the low-probability response at the other biased location, and vice versa. At the end of the experiment, participants' awareness of the response regularity was again assessed via the following questions. First, participants were asked to indicate whether they (a) noticed one location with response bias, (b) noticed two locations with response bias, or (c) did not notice anything. Regardless of their response to the first question, they were then asked to identify the two biased locations with frequent responses.

Results

To examine whether participants remained sensitive to the response imbalance at the biased locations, when the overall probability of each response was matched across search displays, RTs were again analyzed with a repeated-measures ANOVA with within subjects' factors

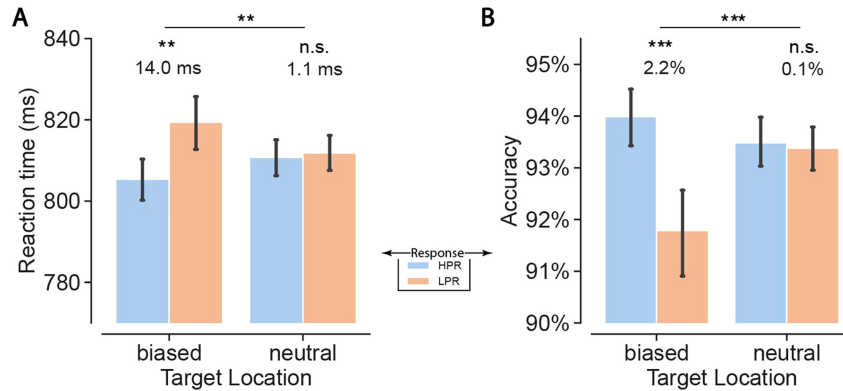
target location (biased location, neutral location) and response (high-probability response, low-probability response). However, as there were now two biased locations, with reversed regularities, responses at half of the neutral locations (selected at random) were artificially labeled as high and low probability based on their status at one of the biased locations, whereas for the other half this was done based on the other biased location. As visualized in Figure 3A and reflected by a reliable interaction, $F(1, 64) = 8.32$, $p = .005$, $\eta_p^2 = .12$, relative to the neutral locations, where responses did not differ, at the biased locations, high-probability responses were faster and low-probability responses were slowed. Indeed, planned pairwise comparisons confirmed that high-probability responses were faster than low-probability responses at the biased locations, $t(64) = 3.17$, $p = .002$, $d = 0.63$, whereas no such difference was present at the neutral locations, $t(64) = 0.45$, $p = .66$, $BF_{01} = 6.68$. As visualized in Table 1, the difference between high- and low-probability responses was evident at both locations, indicating that learning was not restricted to a single location. In line with Experiment 1, the difference at the biased location again could not be explained by retrieval of selection episodes at the preceding trial, as the effect remained significant when all immediate repetitions (i.e., response and/or location) were excluded, $t(64) = 2.54$, $p = .01$, $d = 0.6$.

Similar to Experiment 1, analyses on mean accuracy again mimicked this pattern of results, with reliable interaction, $F(1, 64) = 12.33$, $p < .001$, $\eta_p^2 = .16$, reflecting more accurate responses for high- than low-probability responses at the biased locations, $t(64) = 3.64$, $p < .001$, $d = 0.49$, but not at the neutral locations, $t(64) = 0.34$, $p = .73$, $BF_{01} = 6.96$.

Awareness of the High-Probability Response

Similar to Experiment 1, there was again very little evidence that the observed effects were the result of an explicit strategy. Only one participant out of the five participants who reported being aware of the response regularity at both locations during the experiment correctly identified both locations, and only two correctly identified

Figure 3
Mean RTs and Accuracy as a Function of Target Response (High-Probability Response, Low-Probability Response) and Target Location (Biased, Neutral) in Experiment 2



Note. When the target was presented at the neutral locations, responses were artificially coded as the HPR and LPR in the neutral locations. HPR = high-probability response; LPR = low-probability response; RTs = reaction times. See the online article for the color version of this figure.

** $p < .01$. *** $p < .001$.

one out of the two locations. Moreover, only seven out of the 11 participants who reported being aware of the response regularity at one location correctly identified that location. Consistent with the findings of Experiment 1, the exclusion of participants who reported being aware of the regularity did not change the results as the difference between high- and low-probability responses at the biased location remained highly significant, RTs: $t(48) = 3.97, p < .001, d = 0.90$; accuracy: $t(48) = 2.90, p = .006, d = 0.76$ (see Table 1).

Discussion

In the current experiment, two locations had a biased response ensuring that the overall response frequency across the whole display was balanced. The results show that participants can learn different response biases each associated with a different location. While in Experiment 1, participants were slower to respond when a low-probability response was needed, the current findings indicate that now participants responded faster when the high-probability response was needed relative to when a low-probability response was needed.

Experiment 3

The first two experiments showed that participants can learn specific response biases each associated with specific locations. As is typical for the additional singleton paradigm (Theeuwes, 1991) the target was randomly chosen to be either a diamond between circles or a circle between diamonds. Because the target shape varied randomly from trial to trial, participants learned to associate the location (and not the shape) with a specific response. In Experiment 3, we wanted to determine whether participants can only learn the association between a response and a location or alternatively whether they can also learn the association between a response and the target shape presented at that location. To that end, we ensured that the response bias only occurred when the target was presented at the biased locations and had a specific shape. For example, in case the target was a diamond and was presented at one of the biased locations, it contained a horizontal line 80% of the time and a vertical line 20% of the time, whereas a circle at the location contained a vertical line or a horizontal line with equal probability.

Table 1
RTs for Responses in Different Biased Locations in Experiment 2 and Experiment 3

Response	All participants		"Unaware" participants	
	Biased location (left as HPR)	Biased location (up as HPR)	Biased location (left as HPR)	Biased location (up as HPR)
	<i>M</i> ± <i>SD</i>	<i>M</i> ± <i>SD</i>	<i>M</i> ± <i>SD</i>	<i>M</i> ± <i>SD</i>
Experiment 2				
HPR	800 ± 134	812 ± 135	762 ± 106	777 ± 113
LPR	812 ± 139	831 ± 146	778 ± 117	797 ± 121
Experiment 3				
HPR	757 ± 145	774 ± 145	739 ± 118	760 ± 109
LPR	783 ± 152	778 ± 143	760 ± 121	769 ± 123

Note. Results are averaged for all participants, and for participants who were classified as unaware because they indicated that they did not notice any response imbalance. HPR = high-probability response; LPR = low-probability response; RTs = reaction times.

Method

The methods of Experiment 3 were identical to Experiment 2, except for the following changes. As the goal of Experiment 3 was to test whether observers could also learn to associate a certain response with a specific shape at the biased location, we ensured that the response bias was only presented within the biased shape. As a result, the number of trials for the critical condition (i.e., high-probability response) when the target was a biased shape and at the biased location was halved relative to Experiment 1. To maintain the statistical power, we increased the sample size to roughly 2 times compared to the sample size used in Experiment 1. Sixty-four adults (27 females, $M_{\text{age}} = 24.31$, $SD_{\text{age}} = 4.05$) participated in an online experiment through Prolific. They all reported having a normal or corrected-to-normal (color) vision. Participation took ± 40 min and participants earned £5. One participant was excluded because their mean accuracy exceeded ± 2.5 SD from the overall mean accuracy, leaving 63 participants for analysis.

The target was presented with equal probability at the four selected locations, and at each of these locations, the target could be either a diamond or a circle with equal probability. As in Experiment 2 at two of the four locations (opposite to one another; counterbalanced across participants), one response occurred with a higher probability (i.e., 80%), but critically only when a specific shape appeared at that location. To balance the overall response frequency across displays, at these biased locations, the response regularities were reversed such that the high-probability response at one biased location was the low-probability response at the other biased location, and vice versa. Moreover, both shapes were coupled to a response regularity such that the diamond was coupled to a response regularity at one biased location, and the circle at the other biased location.

Results

To examine whether the spatial learning as observed in Experiments 1 and 2 could be tied to a specific shape at that location, as a first step, following the procedure adopted in Experiment 2, we first analyzed whether the high-probability response was faster than the low-probability response at the biased locations. Replicating Experiments 1 and 2, and visualized in Figure 4A, a significant target location by response interaction, $F(1, 62) = 7.51$, $p = .008$, $\eta_p^2 = .11$, reflected that high-probability responses were faster than low-probability responses at the biased locations, $t(62) = 4.33$, $p < .001$, $d = 0.70$; Table 1 again shows the effect for each individual biased location, whereas no such difference was evident at the neutral locations, $t(62) = 0.35$, $p = .73$, $BF_{01} = 6.83$. As in all previous experiments, this observed difference between high- and low-probability responses at the biased location remained evident, although only trending, after the exclusion of all trials with either a target location and/or a response repetition, $t(62) = 1.78$, $p = .088$, $d = 0.37$. As shown in Figure 4B, analyses on mean accuracy again mimicked this pattern of results, with a reliable interaction, $F(1, 62) = 4.96$, $p = .030$, $\eta_p^2 = .07$, reflecting more accurate responses for high than low-probability responses at the biased locations, $t(62) = 4.27$, $p < .001$, $d = 0.49$, but not at the neutral locations, $t(62) = 1.1$, $p = .27$, $BF_{01} = 4.00$.

Having established that participants again learned to adapt to response-associated regularities at the biased location, we next examined whether this learning was sensitive to the embedded shape regularity. For this purpose, we exclusively analyzed RTs at the biased locations with a repeated-measures ANOVA with within subjects'

factors target shape (biased shape, neutral shape) and response (high-probability response, low-probability response; where responses at neutral shapes were artificially coded as high and low probability based on their status in the biased shape at the matching location). As visualized in Figure 4C, although high-probability responses were again faster than low-probability responses, main effect response: $F(1, 62) = 18.55$, $p < .001$, $\eta_p^2 = .23$, the interaction failed to reach significance, $F(1, 62) = 2.81$, $p = .10$, $\eta_p^2 = .04$, $BF_{\text{excl}} = 6.16$, suggesting that it is the location and not the shape that is associated with a biased response. At the same time, as shown in Figure 4D, it should be noted the same analysis on mean accuracy did yield a reliable interaction, $F(1, 62) = 9.95$, $p = .002$, $\eta_p^2 = .14$, which reflected a difference between high- and low-probability responses in the biased, shapes, $t(62) = 4.38$, $p < .001$, $d = 0.65$, but not in the neutral shapes, $t(62) = 1.52$, $p = .13$, $d = 0.19$, $BF_{01} = 2.51$. While this may suggest that not only the location but also the specific shape was associated with the high-probability response, it should be noted that the Bayes factor only provided anecdotal evidence against the null hypothesis that in neutral shapes accuracy did not differ between high- and low-probability responses. Thus, while we cannot exclude the possibility that shape contributed to the observed learning, we believe it is most likely that learning resulted in a prioritization of the high-probability response at the biased location, which then manifests as faster and more accurate responses at that location when the response matches the high-probability response irrespective of the specific shape that happens to be present.

Awareness of the High-Probability Response

As in the previous experiments, there was again very little evidence that participants had explicit knowledge about the underlying regularities. Six participants reported being aware of the response regularity at both locations during the experiment, correctly identified both locations, and four correctly identified one out of the two locations. Moreover, only seven out of the 13 participants who reported being aware of the response regularity at one location, correctly identified that location. In line with the findings of the previous two experiments, the difference between high- and low-probability responses at the biased location remains significant, RTs: $t(43) = 3.58$, $p < .001$, $d = 0.67$; accuracy: $t(43) = 2.88$, $p = .006$, $d = 0.75$, after removing participants who reported being aware of any regularity (see Table 1).

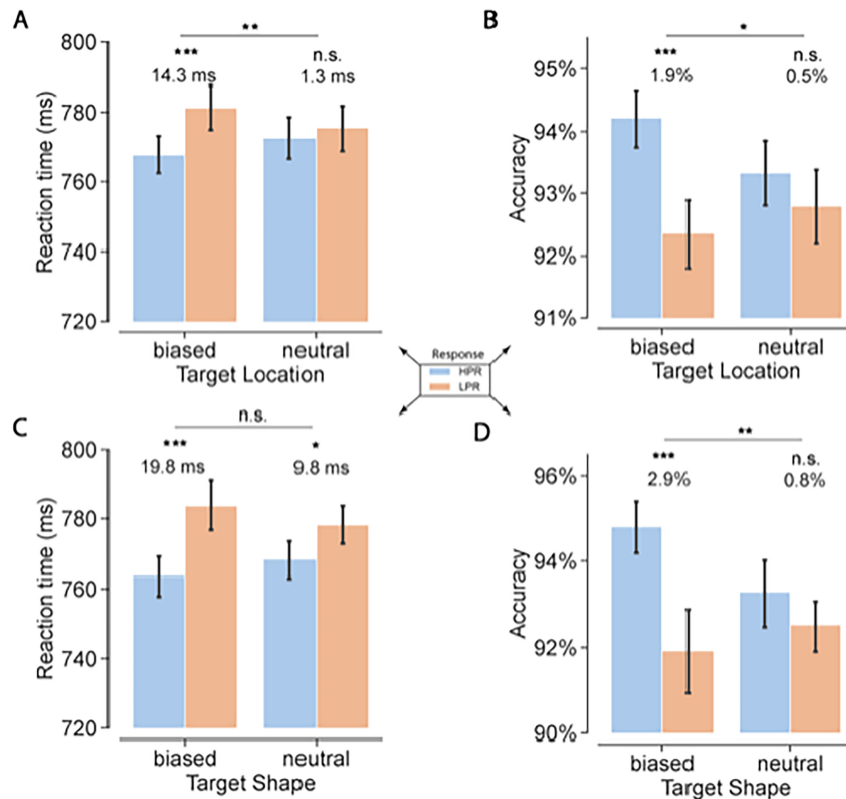
Discussion

The present findings show that it is the location and not the shape that is associated with a biased response. Regardless of the shape presented at the biased locations, participants were biased to respond faster to the high-probability response than to the low-probability response. This finding indicates that the shape of the target is irrelevant to the association of location and response and that it is thus only the location that drives the effect.

General Discussion

The present study shows that participants learn to adapt to response-associated regularities present in the visual field. Specifically, participants can learn specific response biases each associated with a particular location in the visual field. These response biases are foremost location specific and less associated with the specific shape presented at these locations. While the effects suggest that people learn to "expect" that particular motor responses are more likely at particular locations in

Figure 4
 Mean RTs (A) and Accuracy (B) as a Function of Target Response (High-Probability Response, Low-Probability Response) and Target Location (Biased, Neutral) in Experiment 3



Note. When the target was presented at the neutral locations, responses were artificially coded as the HPR and LPR in the neutral locations. Mean RTs (C) and (D) accuracy as a function of target response (HPR, LPR) and target shape (biased, neutral) while the target was presented at the biased locations. HPR = high-probability response; LPR = low-probability response; RTs = reaction times. See the online article for the color version of this figure.
 * $p < .05$. ** $p < .01$. *** $p < .001$.

the visual field, this type of expectation cannot be considered as being top-down or conscious as our findings show that participants have little, if any, awareness of these response biases. The current study is yet another demonstration of the impact of statistical learning and how individuals adapt automatically, without much awareness, to the regularities present in the environment. In the following, we will connect these results to two different prominent theories, namely the event-file theory and predictive coding (Clark, 2013; Friston, 2005).

The current findings can be explained in terms of TEC and BRAC which assume that stimulus and response features are coded into object files or event files (e.g., Frings & Rothermund, 2011; Hommel, 2004; Kahneman & Treisman, 1984). According to these theories, event files are stored in memory and include binary bindings of stimulus and response information in a unitary mental representation (e.g., Moeller et al., 2016). The files are assumed to be automatically retrieved by stimuli that match features of the previous episode. If we apply this reasoning to the current findings, it implies that a shift of attention to a particular location in space (needed to select the target), results in the retrieval of a specific event file that associates this particular location with specific response information. In this sense,

statistical learning represents the formation of particular event files that are associated with particular locations in the visual field.

It should be noted that the results of Experiment 3 are not fully consistent with the idea of hierarchical event files. In this experiment, the biased location–response correlation was only present for a particular shape, that is, at one particular location, one target shape (e.g., the diamond) had a biased response (e.g., 80% vertical, 20% horizontal), while the other target shape (i.e., the circle) presented at that location had an unbiased response (50%–50%). Therefore, a true hierarchical event file should contain a connection between a location, a shape, and a response, and hence only if a specific shape repeats at a specific location, the location and response become associated. While there have been arguments in favor of hierarchical event files (Moeller & Frings, 2021), that include higher-order bindings, there are also arguments suggesting that there can only be simple binary bindings between features (Hommel, 2004; Moeller et al., 2016). According to this reasoning, a particular location is bound to a particular response, and the shape presented at that location is not part of this binding. Note that across all locations shapes and responses are not correlated (they are only correlated for two specific locations) and

therefore there can be no binding between a particular shape and a response irrespective of location. Against the background of this reasoning, our results seem to be consistent with the notion of simple binary feature bindings (e.g., Hommel, 2004).

While the notion that only binary feature bindings are possible is compelling, it should be noted that there are alternative explanations for the absence of an effect of the shape. The current experiment employed the additional singleton task and it is known that the target (which is a diamond between circles or a circle between diamonds) automatically pops out from the background. Indeed, in the original Theeuwes (1991, 1992) version of this task, the number of elements in the display was varied and it was shown that search slopes were basically flat signifying pop-out search. Given that attention is automatically shifted to the local feature discontinuities (i.e., a singleton), the actual target shape that drives this shift of attention is irrelevant. Indeed, attention is captured by a singleton and the shape that constitutes this singleton is irrelevant. Because the shape is irrelevant it may not be coded as being part of the event file as previous studies suggested less likely integration of irrelevant features (Hommel, 1998; Moeller & Frings, 2014; Singh & Frings, 2018; Singh et al., 2018).

Alternatively, there is yet another explanation that still fits with the event-file idea but that may have nothing to do with stimulus feature bindings (and would thus also explain why the shape was not bound). If one assumes that a shift of attention to a particular location in space is like a covert attentional response then one may speculate that what we see here is a form of response–response (R–R) binding (Moeller & Frings, 2019a, 2019b). In R–R bindings, responses are integrated (e.g., R1 is integrated with the following R2) so that if R1 repeats, R2 is retrieved, facilitating R2 responses. Concerning our task here, this would imply that the covert shift of attention to a particular location in space (R1) is associated with a particular manual response (R2) following the attention shift. Thus, repeating an attention shift toward a location retrieves the event file containing this attention shift and the manual response associated with it—which at the biased location can very well explain our result. What is more, this might also explain why the shape was not bound as R–R bindings do not comprise stimulus features (Moeller & Frings, 2019a). Of course, this interpretation hinges on the idea that an attention shift is treated as an action. At least we can say that R–R bindings have not only been observed for two manual responses but also survive effector switches (Moeller & Frings, 2019c). Thus, this interpretation remains a possible explanation still in line with TEC and BRAC but focuses on the response level.

Another account that rather easily accommodates the present results is predictive coding (Clark, 2013; Friston, 2005). Predictive coding refers to a theoretical framework that explains how the brain processes and interprets sensory information. It suggests that the brain generates predictions about incoming sensory inputs based on prior knowledge and expectations, and then compares these predictions with the actual sensory signals. Any discrepancies between the predictions and the actual inputs are used to update the internal models and refine future predictions. The same principle of prediction error minimization has also been used to provide an account of behavior (Adams et al., 2013) in which motor actions are not commands but descending proprioceptive predictions (i.e., while the visual system delivers visual input the motor system delivers proprioceptive input). The correlation of response and location at the high probability location will reduce the prediction error for this condition and accordingly, the performance is good in this instance. More generally, the idea of predictive coding and statistical regularities share many facets, for example, the idea

that inference is used to predict future events (albeit they might differ with respect to awareness; see below). Yet, concerning the comparison to TEC/BRAC, one might argue that while predictive coding focuses on the top-down processing and generation of predictions, binding and retrieval processes are more concerned with the bottom-up integration of sensory information and the retrieval of information. Predictive coding and processes as described by TEC/BRAC are not mutually exclusive and can interact with each other. For example, predictive coding can influence the binding and retrieval processes by biasing attention toward expected features or facilitating the retrieval of relevant information from memory.

Previous findings investigating the effects of statistical regularities on visual search have shown that visual selection is optimally adapted to probabilities of the target (e.g., Geng & Behrmann, 2002, 2005; Zhang et al., 2022) and of the distractor (Wang & Theeuwes, 2018a, 2018b). It was shown that when the target appears more often in one location than in other locations, participants learn this structure such that the target is detected faster when it appears at this high-probability location than at low-probability locations (Geng & Behrmann, 2002, 2005; Huang, et al., 2022). Similarly, if the distractor is presented more often in one location than at other locations, participants suppress this high-probability location such that the impact of the distractor is less (Van Moorselaar & Theeuwes, 2021; Wang & Theeuwes, 2018a, 2018b). These findings were explained by assuming that through statistical learning the weights within a hypothetical visual–spatial priority map are adjusted according to the probabilities of targets and distractors in the visual field (see Theeuwes et al., 2022). In the current experiments, the target was presented equally probable at all locations, and therefore the weights of the spatial priority map of visual selection were not adjusted. Yet, what was adapted are the likely responses on this spatial priority, representing the connection between a location on the spatial priority map with a likely response. The current findings also show that the larger majority of participants were not aware of the regularities present in the visual field. Only a few participants were aware of the location and the associated response bias even though one response was 4 times more likely than the other response. The current findings regarding awareness are similar to most other statistical learning studies that have demonstrated little to no awareness of the regularities (see Duncan & Theeuwes, 2020; see also Theeuwes et al., 2022 for a review). It confirms the notion that human behavior is constantly adjusted to the contingencies that exist in the world without the intention to learn and without much, if any, conscious awareness. The current study shows that this also holds for regularities regarding motor responses.

While these findings are consistent with previous reports on awareness of statistical regularities, it should be noted that the way we measured awareness can be criticized on methodological grounds as inferences about being aware or not are made on the basis of null effects in relatively small samples (see Vadillo et al., 2020).

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