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The trajectory of the target probability effect

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Abstract The effect of target probability on detection times is well-established: Even when detection accuracy is high, lower probability targets are detected more slowly than higher probability ones. Although this target probability effect on detection times has been well-studied, one aspect of it has remained largely unexamined: How the effect develops over the span of an experiment. Here, we investigated this issue with two detection experiments that assessed different target probability ratios. Conventional block segment analysis and linear mixed-effects modeling converged on two key findings. First, we found that the magnitude of the target probability effect increases as one progresses through a block of trials. Second, we found, by examining the trajectories of the low- and high-probability targets, that this increase in effect magnitude was driven by the low-probability targets. Specifically, we found that low-probability targets were detected more slowly as a block of trials progressed. Performance to high-probability targets, on the other hand, was largely invariant across the block. The latter finding is of particular interest because it cannot be reconciled with accounts that propose that the target probability effect is driven by the high-probability targets.

Keywords Attention · Target detection · Stimulus probability

Introduction

It has been known for some time that target probability affects detection. In visual search paradigms, low-probability targets are detected less accurately than higher probability counterparts (Rich, Kunar, Van Wert, Hidalgo-Sotelo, Horowitz & Wolfe, 2008; Wolfe, Horowitz, Van Wert, Kenner, Place & Kibbi, 2007). In other paradigms like the go/no-go or simple detection ones, detection accuracy is often close to perfect. Nevertheless, even with such paradigms, there is still a behavioral cost associated with rare targets: They are detected more slowly than frequent ones (Laberge & Tweedy, 1964; Miller & Pachella, 1973). In this study, we were particularly interested in the effect of target probability (TPe) on detection times when accuracy is high. Accordingly, we used the simple detection paradigm exclusively in the present study.

Various accounts of the TPe have proposed that the effect is driven by advantages associated with the high-probability targets. For example, one specific view is that the TPe occurs because higher probability targets enjoy a perceptual advantage over lower probability ones (Biederman & Zachary, 1970; Dykes & Pascal, 1981; Lau & Huang, 2010; Miller & Pachella, 1973; Orenstein, 1970). An alternative proposal is that the TPe is caused by response preparation differences, with observers being more prepared to make responses associated with the high-probability targets because these are more expected and/or occur more frequently (Gehring, Gratton, Coles & Donchin, 1992; Hawkins, Mackay, Holley, Friedin & Cohen, 1973).[1] At this point, we do not attempt to arbitrate between the various views. Rather, we simply highlight the fact that a number of theoretical perspectives point to the high-probability targets as being central to the TPe. This is consistent with the general idea that there is an advantage enjoyed by things that are expected or more frequently experienced.

The TPe is typically computed by comparing the mean response time (RT) associated with low-probability targets with that associated with high-probability ones (i.e., $\mathrm{MeanRT}_{\text{low probability}} - \mathrm{MeanRT}_{\text{high probability}}$). This reliance on single values summarizing performance across the span of an experiment necessarily obscures an important issue:

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[1] This proposal typically assumes a scenario in which low- and high-probability targets are associated with different responses, or when probability is manipulated in a blocked fashion. It is less able to account for situations in which low- and high-probability targets are presented within the same block and share the same response.

How the TPe develops over the course of the experiment. The trajectory of the TPe is a particularly important theoretical issue because, although it can occur without much mental effort (Estes, 1964; Hasher & Zacks, 1984), information about stimulus probability cannot be accrued instantaneously. In other words, information about target probabilities will take time to build up within mental task representations. The implication of this is that the TPe should take time to be fully established and is, therefore, unlikely to be of fixed magnitude throughout the course of an experiment. Accordingly, we might expect that TPe magnitude would increase as an experiment progresses, plausibly reaching a stable level when information about stimulus probabilities has been fully acquired and integrated into mental representations of the task at hand.

Of greater importance, the trajectory of the TPe can be decomposed into the trajectories of the low- and high-probability targets. This would allow for an assessment of the respective contributions of these targets to the overall trajectory of the effect. Additionally, examining the low- and high-probability trajectories would offer insight into the locus of the effect. Taking into consideration the two key theoretical points raised earlier—that the TPe is driven by an advantage enjoyed by high-probability targets and that this advantage takes time to be fully established—we might expect the following pattern when assessing these trajectories: Performance to the high-probability targets improves across the span of the experiment (reaching a stable level at some point), while performance to the low-probability targets remains largely invariant. Evidence for such a pattern would support the general idea that the TPe is driven by the high-probability targets.

Although of clear theoretical importance, the issue of the trajectories of the TPe and its constituent components has been largely ignored by the field. To the best of our knowledge, only one other study has assessed, albeit peripherally, the effect of target probability on RTs over the course of a block of trials (Laberge & Tweedy, 1964).[2] Here, we directly examined this issue with two different target probability ratios and adopting two different analytical methods.

Method

Participants

Forty-four undergraduate students from the National University of Singapore participated in this experiment. All participants had normal or corrected-to-normal vision.

[2] It is worth noting, though, that other studies have examined how the (visual) search for rare targets changes across the span of an experiment (e.g., Menneer et al., 2010; Wolfe et al., 2007).

Stimuli

Letter stimuli were utilized for this study. These were presented in white on a black background. Each letter was presented in 24-point Courier New font, which, when viewed from a distance of 50 cm, subtended approximately 1.4° of visual angle both vertically and horizontally.

In both experiments, all letters of the alphabet were used. For the experimental blocks of both Experiments 1 and 2, the letters “W” and “T” were designated as targets, with high–low probability assignment being counterbalanced across participants. The letters “H” and “G” were used as targets in the practice session that preceded the experiments proper. The remaining 22 letters of the alphabet formed the distractor set. The letters designated as targets were never included in the distractor sets.

Procedure

Experiment 1

Twenty-two participants observed a single 300-trial experimental block, with trials being equally distributed between targets and distractors as a whole. Two letters were designated targets; that is, participants attempted to detect, within the same block, the occurrence of either member of a two-letter target set. Critically, one target letter accounted for 10 % of all trials in the block (low-probability target), while the other accounted for 40 % (high-probability target). All stimuli, whether targets or distractors, were presented for 1,000 ms, followed by a blank frame presented for another 800 ms, and then by the presentation of the next stimulus. The same response (index finger button-press of the “/” key) was made to both targets. Since this was a simple detection task, no response was required for distractors. Trial order was randomized for each participant.

Experiment 2

An additional 22 participants performed this experiment, which was identical to Experiment 1, except that, here, the low- and high-probability targets accounted for 5 % and 45 % of all trials, respectively.

In both experiments, participants were not informed of the target probabilities. To familiarize participants with the paradigm, both experiments began with a short practice session of 10 trials, with targets and distractors occurring equally often.

Both experiments were controlled by a PC running the E-Prime software, with the stimuli being presented on a 24-in. LCD monitor.

Results

To begin with, detection accuracy was near ceiling for both these experiments (Table 1). This was important given our interest in the effect of target probability on RTs when detection accuracy is high. We now turn our attention to the critical RT data.[3]

Experiment 1

For our conventional block segment analysis, the experimental block was partitioned into three contiguous segments, each comprising 100 trials. Global probabilities were maintained in all three segments: Low- and high-probability targets and distractors accounted for 10 %, 40 %, and 50 % of trials in each segment, respectively.

Figure 1 depicts the trajectory of the TPe through the different segments of the experiment. Following general convention, we computed the TPe in the following way: $RT_{low\ probability} - RT_{high\ probability}$. Separate TPes were computed for each of the three segments. A one-way ANOVA conducted on these data revealed a reliable effect of segment, $F(2, 42) = 6.11$, $p = .005$. Post hoc Tukey's tests revealed that, while the magnitude of the TPe was smaller in the first segment than in the second ($p = .009$), there was no difference in TPe magnitude across the second and third ($p = .99$). This indicates that TPe magnitude initially increased before reaching a stable level.

To determine what underpinned the pattern observed in Fig. 1, we independently examined the trajectories of the low- and high-probability targets. Figure 2 depicts the RT data for the different probability targets as a function of block segment. We subjected the data to a 2 (probability: high, low) × 3 (segment: first, second, third) ANOVA. This analysis revealed significant effects of probability, $F(1, 21) = 38.16$, $p < .001$, and segment, $F(2, 42) = 10.43$, $p < .001$. More critically, the probability × segment interaction was also significant, $F(2, 42) = 6.11$, $p = .005$.

Because we were interested in the respective trajectories of the different targets, we performed two separate one-way ANOVAs on the high- and low-probability data. For the low-probability targets, we found a significant effect of segment, $F(2, 42) = 12.46$, $p < .001$. For the high-probability targets, on the other hand, there was no such significant effect, $F(2, 42) = 1.89$, $p = .163$. Post hoc Tukey's tests performed on the low-probability targets revealed that detection of these targets became progressively slower from the first to the second segment ($p = .003$) but remained constant across the second and third ($p = .443$). Taken together, this suggests that, while performance to the high-probability targets remained largely invariant across the block, performance to the low-probability targets worsened gradually before reaching a stable level. Note that this pattern runs contrary to what would be predicted if the high-probability targets were the primary determinants of the TPe (see the Introduction).

One might argue that partitioning the experimental block into three segments is arbitrary and that our results might be an artifact of this decision. To address these concerns, we also subjected our data to linear mixed-effects modeling (see Baayen, Davidson & Bates, 2008). These analyses allow us to examine the effect of trial order in a continuous manner, while generalizing the effect across both participants and items. Using R (R Development Core Team, 2011), we fitted a linear mixed-effects model to our RT data, using the lme4 package (Bates, Maechler & Dai, 2012), with *p*-values for fixed effects computed using the languageR package (Baayen, 2012). The influences of target probability and trial order (both linear and quadratic) and the target probability × trial order (linear and quadratic) interaction were treated as fixed effects, while participants and items were treated as random variables. Critically, our analyses revealed a significant interaction between target probability and both linear ($p < .001$) and quadratic ($p = .006$) trial order. To make our results clearer, we have plotted the interaction in Fig. 3. As can be clearly seen, although there

[3] These data were trimmed to exclude outlier trials (>2.5 *SD*s).

Table 1 Accuracy data for the two experiments

	Experiment 1		Experiment 2	
	10 %	40 %	5 %	45 %
Hits	99.1	99.8	98.8	99.8
FAs	1.4		0.7	

Note. The hit and false alarm (FA) rates are given as percentages

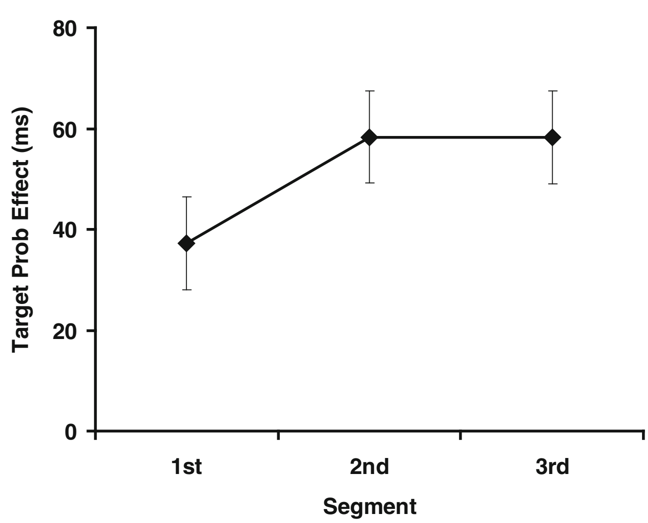

Fig. 1 Target probability effect ($RT_{low\ probability} - RT_{high\ probability}$) as a function of block segment. Error bars indicate 1 *SEM*

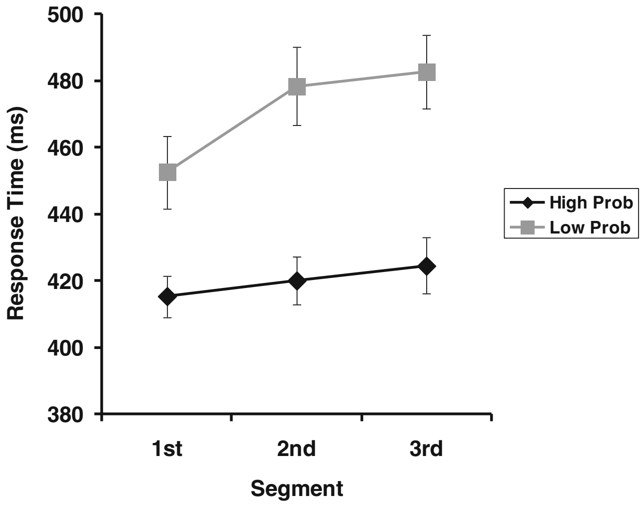

Fig. 2 Mean correct response times to low- and high-probability targets from Experiment 1 as a function of block segment. Error bars indicate 1 *SEM*

was variation in performance to low-probability targets as a function of where one was in the block, there was relatively little change in performance to the high-probability targets. In sum, these results converge nicely with the simpler block segment analyses reported earlier.

Experiment 2

In Experiment 1, changes to the TPe were driven by the low-probability targets. In this second experiment, we tested the generality of this finding by assessing a different low-to-high-probability ratio. In Experiment 1, the ratio was 1:4. Here, we used a low-to-high ratio of 1:9; specifically, in this experiment, low- and high-probability targets accounted for 5 % and 45 % of all trials, respectively.

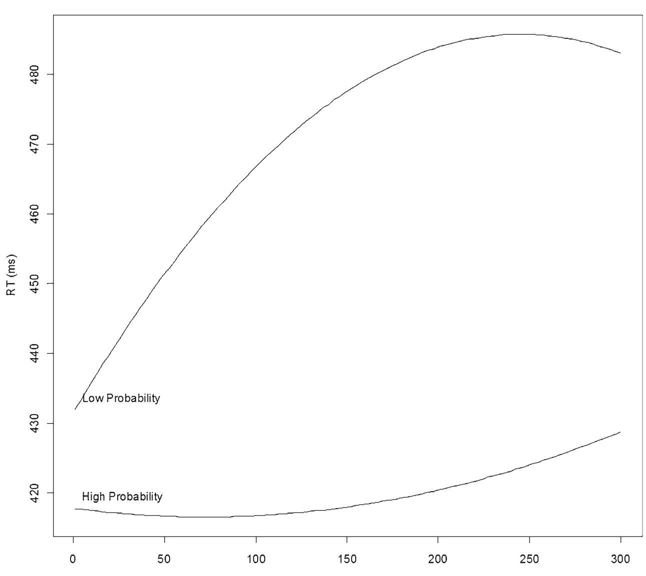

Fig. 3 Partial effect plots for the trial order effect in Experiment 1, as a function of target probability. RT, response time

Figure 4 depicts the trajectories of the low- and high-probability targets in Experiment 2. Consistent with Experiment 1, we found that the main effects of probability, $F(1, 42) = 157.42$, $p < .001$, and segment, $F(4, 168) = 6.71$, $p = .003$, as well as the critical probability × segment interaction, $F(2, 42) = 7.18$, $p = .002$, were significant. Likewise, independent one-way ANOVAs revealed a reliable effect of segment for the low-probability targets, $F(2, 42) = 7.70$, $p = .001$, but not the high, $F < 1$, n.s.. Post hoc tests performed on the low-probability target data revealed that there was a difference between the second and third segments ($p = .016$), but not between the first and second ($p = .185$). A similar picture emerged with mixed effects modeling (Fig. 5). Specifically, the interaction between target probability and linear trial order was significant ($p < .001$).

Although we replicated the general finding that changes to TPe magnitude across a block were driven by the low-probability targets, the specific pattern we observed here is somewhat different from that in Experiment 1 in that we did not observe a clear asymptoting of the low-probability line. What might account for this difference? Here, our low-probability targets were half as likely to occur as in Experiment 1, accounting for only 5 % of trials. We speculate that, when targets are particularly infrequent, as they were here, longer experience may be required for probability information to stabilize within-task representations. The finding that the initial worsening of performance occurred later in this experiment (between the second and third segments) than in Experiment 1 (between the first and second

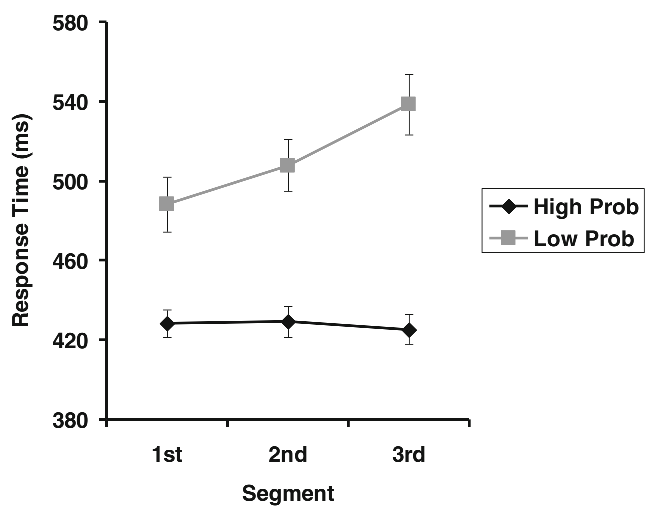

Fig. 4 Mean correct response times to low- and high-probability targets from Experiment 2 as a function of block segment. Error bars indicate 1 *SEM*

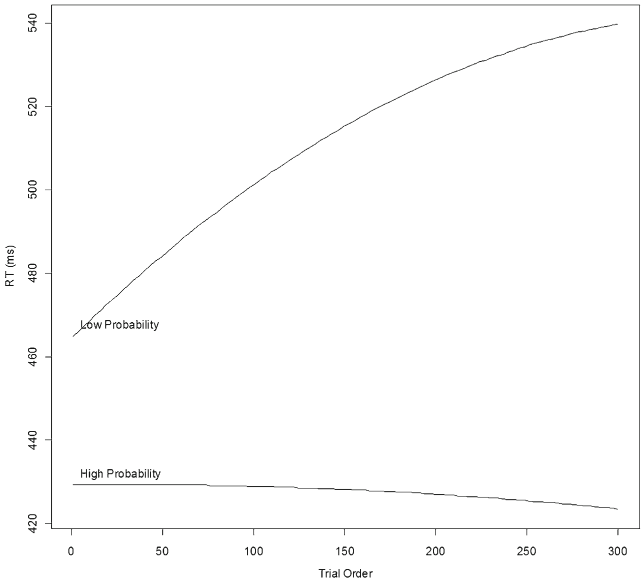

Fig. 5 Partial effect plots for the trial order effect in Experiment 2, as a function of target probability. RT, response time

segments) is consistent with this idea.[4] Plausibly, our 300-trial blocks may not have been long enough for a clear asymptote to be observed. Critically, though, the results of both this experiment and Experiment 1 point to the idea that the TPe is driven by the low-probability targets.

Discussion

Our data speak to several important issues. First, the magnitude of the TPe is not constant across an experiment. Rather, it changes as one gains more experience with the probabilities associated with the different targets. This is unsurprising given that target probability information is necessarily acquired gradually, especially when participants are not informed of the specifics of the probability differences to begin with.

Second, and of greater importance, our data present a genuine challenge to the idea that the TPe is driven by the high-probability targets. Here, we found that it was the low-probability targets that drove the changes in TPe magnitude. Performance to the high-probability targets remained largely constant over the course of a block. Performance to the low-probability targets, on the other hand, became worse as a block wore on. As was noted earlier, various accounts of the TPe are built around the idea that what is expected enjoys an advantage, while that which is unexpected suffers no adverse consequence. Our data dispute this idea by demonstrating that the TPe is caused predominantly by a deleterious effect associated with having to detect less expected task-relevant stimuli. Our findings thus distinguish the TPe from other cognitive phenomena in which performance advantages are associated with more frequently experienced or expected stimuli (Maljkovic & Nakayama, 1994; Summerfield & Egner, 2009).

Our data are consistent with the idea that perceptual templates of both low- and high-probability targets are initially activated to the same level. As one begins to learn that the low-probability targets occur only infrequently or contrary to initial expectation, the default level of activation of templates associated with these targets falls.[5] A consequence of this is that, when low-probability targets appear, greater perceptual evidence is needed in order for threshold to be reached, thus accounting for the increased time required for accurate detection of such targets. Alternatively, our data might also be accounted for by liberal-to-conservative changes to the criterion associated with low-probability targets (Menneer, Donnelly, Godwin & Cave, 2010; Wolfe et al., 2007). Such criterion changes would reasonably result in the requirement for more perceptual evidence to be accumulated before decisions can be made. Distinguishing these two accounts would be a worthy direction for future research.

As was noted earlier, to the best of our knowledge, only one other study has considered how the TPe develops across a block of trials (Laberge & Tweedy, 1964). Partitioning their blocks into 40-trial bins, those authors found, as we did, that performance to the low-probability targets became worse as a block wore on, while performance to the high-probability targets remained largely invariant. Like ours, that study utilized a setup in which different probability targets were presented within the same block; however, it is worth noting that that study was complicated by stimulus–response mapping and stimulus probability switches. Our study, then, can be seen as an in-principle replication of that early work, producing the same pattern of results even when the extraneous elements of that task were removed and when different target probability ratios are observed. Additionally, our use of mixed-effects modeling allowed us to demonstrate that this pattern of results is not an artifact of arbitrary binning strategies.

[4] It is also interesting to note that the initial worsening of performance was produced after experience with a similar number of low-probability target trials in both experiments. In Experiment 1, each segment comprised 10 low-probability target trials. In Experiment 2, each segment contained only 5 low-probability target trials. In other words, the initial worsening of performance occurred after exposure to approximately 10 low-probability target trials in both experiments.

[5] It may be that observers initially expect targets and distractors to be equiprobable (i.e., each accounting for 50 % of all trials). This provides an interesting explanation for why performance to our high-probability targets remains largely invariant across the block. Here, the high-probability targets in Experiments 1 and 2 accounted for 40 % and 45 % of all trials, respectively. Possibly, these values are close enough to 50 % that these targets do not violate initial expectations.

In summary, we examined how the TPe develops within the span of a single experiment. In addition to enlightening on this issue, our data also speak to the issue of the locus of the TPe. Specifically, our data are inconsistent with the view that the TPe is driven by the high-probability targets. Here, we found that changes in the magnitude of the TPe were determined by the low-probability targets.

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