Research Article

# Task-Related Versus Stimulus-Specific Practice

## A Diffusion Model Account

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**Abstract.** When people repeatedly practice the same cognitive task, their response times (RT) invariably decrease. Dutilh, Vandekerckhove, Tuerlinckx, and Wagenmakers (2009) argued that the traditional focus on how mean RT decreases with practice offers limited insight; their diffusion model analysis showed that the effect of practice is multifaceted, involving an increase in rate of information processing, a decrease in response caution, adjusted response bias, and, unexpectedly, a strong decrease in nondecision time. In this study, we aim to further disentangle these effects into stimulus-specific and task-related components. The data of a transfer experiment, in which repeatedly presented sets and new sets of stimuli were alternated, show that the practice effects on both speed of information processing and time needed for peripheral processing are partly task-related and partly stimulus-specific. The effects on response caution and response bias appear to be task-related. This diffusion model decomposition provides a perspective on practice that is more detailed and more informative than the traditional analysis of mean RT.

**Keywords:** response times, practice, diffusion model, classification

When people repeatedly perform the same task, their performance becomes fast, accurate, and relatively effortless. For example, you are able to read this text quickly, virtually without errors, and, hopefully, without investing too much effort. The ease with which you just read the previous sentences is due to your extensive practice with reading in general; however, there is a chance – admittedly remote – that your ease of reading was enhanced because you were familiar with an article that started with the very same two sentences (i.e., Dutilh Vandekerckhove, Tuerlinckx, & Wagenmakers, 2009). This example highlights the distinction between learning that is related to the task (e.g., the skill of reading in general) and learning that is specific to the stimulus (e.g., reading particular sentences). This distinction is the focus of this article.

Research on skill acquisition and practice has a long history of theorizing and experimenting and involves many different skills in many different domains (e.g., Crossman, 1959; Logan, 1992; Pirolli & Anderson, 1985). Researchers in the field of cognitive skill acquisition have focused mainly on the practice-induced speed-up in mean response time (MRT). This speed-up is typically largest at the initial stage of training and diminishes as practice progresses. The functional form of the speed-up has been the topic of a fierce academic debate. The primary candidate to account for the shape of the speed-up is the power function (i.e., the famous "power law of practice," Logan, 1990; Newell & Rosenbloom, 1981, p. 3). This power law speed-up is consistent with several theories of skill acquisition, most notably Logan's instance theory (Logan, 1988, 2002). However, other researchers have argued that evidence in favor of the power law might be an artifact of averaging over many different learning curves, and that the true underlying curve is characterized by an exponential speed-up (Heathcote, Brown, & Mewhort, 2000).

Although some theories take into account the entire distribution of response time (RT), the large majority of experimental studies consider only MRT. In recent work we showed that this selective focus on MRT, a focus that ignores the distributional form of RT and its interdependence with accuracy, offers a deceivingly limited view on the effects of practice (Dutilh et al., 2009). By applying Ratcliff's diffusion model to the data of a 25-block lexical decision task, we were able to decompose the effect of practice into changes in several underlying psychological processes that together determine observed performance. Our main conclusion was that the effect of practice on performance is multifaceted: Not only did practice increase the speed of information processing, as expected, but this increase was accompanied by a decrease in response caution and a decrease in the time needed for nondecisional processes. Since the study did not feature transfer blocks with new stimuli, we were not able to conclude whether the practice effects were caused by an increased familiarity with the stimuli, an increased familiarity with the task, or a combination of both.

In this article, we aim to use the diffusion model again to decompose the effects of practice, but this time we also differentiate task-related from stimulus-specific factors (e.g., Ahissar & Hochstein, 1993; Forbach, Stanners, &


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Hochhaus, 1974; Logan, 1990). In order to do so, we designed an interleaved transfer experiment in which participants responded to alternating blocks of new and repeated stimuli.

The outline of this paper is as follows. We first introduce Ratcliff's diffusion model. Next we summarize the results of our previous study and emphasize the importance of unraveling task-related and stimulus-specific effects of practice. Then we describe our current transfer experiment and discuss its results both descriptively and in terms of diffusion model parameters.

## The Diffusion Model

The diffusion model provides a formal, comprehensive, and detailed account of performance on speeded two-choice tasks (e.g., Ratcliff, 1978; Ratcliff & Tuerlinckx, 2002; Voss, Rothermund, & Voss, 2004; for recent reviews see Ratcliff & McKoon, 2008; Wagenmakers, 2009). The model accounts not just for MRT but captures the entire distribution of correct and error RTs as well as percentage correct. One of the major strengths of the diffusion model is that its main parameters can be interpreted in terms of latent psychological processes that drive performance.

Here we describe the diffusion model as it applies to the lexical decision task, where a participant has to decide quickly whether a presented letter string is a word (e.g., *party*) or a nonword (e.g., *drapa*). The core of the model is the Wiener diffusion process that describes how the relative evidence for one of the two response alternatives accumulates over time. The meandering lines in Figure 1 illustrate the continuous and noisy accumulation of evidence for a word response over a nonword response, when a word is presented. When the amount of diagnostic evidence for one of the response options reaches a predetermined response threshold (i.e., one of the horizontal boundaries in Figure 1), the corresponding response is initiated. The dark line in Figure 1 shows how the noise inherent in the accumulation process can sometimes cause the process to end up at the wrong (i.e., nonword) response boundary.

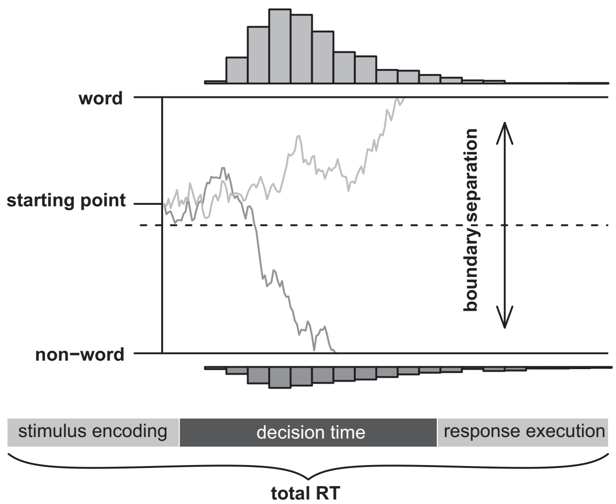


*Figure 1.* The diffusion model as it applies to the lexical decision task. A word stimulus is presented (not shown) and two example sample paths represent the accumulation of evidence which results in one correct response (light line) and one error response (dark line). Repeated application of the diffusion process yields histograms of both correct responses (upper histogram) and incorrect responses (lower histogram). As is evident from the histograms, the correct, upper word boundary is reached more often than the incorrect, lower nonword boundary. The total RT consists of the sum of a decision component, modeled by the noisy accumulation of evidence, and a nondecision component that represents the time needed for processes such as stimulus encoding and response execution.

### The Diffusion Model Parameters

As in Dutilh et al. (2009), the version of the diffusion model that we apply in this article has seven parameters. These are:

1. Mean drift rate ($v$). Drift rate quantifies the deterministic component in the information-accumulation process. This means that when the absolute value of drift rate is high, decisions are fast and accurate; thus, $v$ indexes task difficulty or subject ability.
2. Across-trial variability in drift rate ($\eta$). This parameter reflects the fact that drift rate may fluctuate from one trial to the next, according to a normal distribution with mean $v$ and standard deviation $\eta$. The parameter $\eta$ allows the diffusion model to account for data in which error responses are systematically slower than correct responses (Ratcliff, 1978).
3. Boundary separation ($a$). Boundary separation quantifies response caution and modulates the speed-accuracy trade-off: At the price of an increase in RT, participants can decrease their error rate by widening the boundary separation (e.g., Forstmann et al., 2008).
4. Mean starting point ($z$). Starting point reflects the a priori bias of a participant for one or the other response. This parameter is usually manipulated via payoff or proportion manipulations (Edwards, 1965; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008; but see Diederich & Busemeyer, 2006).
5. Across-trial variability in starting point ($s_z$). This parameter reflects the fact that starting point may fluctuate from one trial to the next, according to a uniform distribution with mean $z$ and range $s_z$. The parameter $s_z$ also allows the diffusion model to account for data in which error responses are systematically faster than correct responses.
6. Mean of the nondecision component of processing ($T_{er}$). This parameter encompasses the time spent on common processes, that is, processes executed irrespective of the decision process. The diffusion model assumes that the observed RT is the sum of the nondecision component and the decision component (Luce, 1986):

$$RT = DT + T_{er}, \tag{1}$$

where $DT$ denotes decision time. Therefore, nondecision time $T_{er}$ does not affect response choice and acts solely to shift the entire RT distribution.

7. Across-trial variability in the nondecision component of processing ($s_t$). This parameter reflects the fact that nondecision time may fluctuate from one trial to the next, according to a uniform distribution with mean $T_{er}$ and range $s_t$. The parameter $s_t$ also allows the model to capture RT distributions that show a relatively shallow rise in the leading edge.

Many experiments attest to the validity and specificity of the parameters of the diffusion model. For instance, Voss et al. (2004), Ratcliff and Rouder (1998), and Wagenmakers et al. (2008) show that accuracy instructions increase boundary separation, easier stimuli have higher drift rates, and unequal reward rates or presentation proportions are associated with changes in starting point. Moreover, simulation studies have shown that the parameters of the diffusion model are well identified (e.g., Ratcliff & Tuerlinckx, 2002; Wagenmakers, Van der Maas, & Molenaar, 2005).

Finally, Ratcliff (2002) has shown that the model fits real data but fails to fit fake but plausible data. These and other studies justify the psychological interpretation of the diffusion model parameters in terms of underlying cognitive processes and concepts.

## A Diffusion Model Account of Practice

In Dutilh et al. (2009), participants completed a 10,000-trial lexical decision task that consisted of 25 blocks administered in five sessions on five consecutive days. Each block consisted of the same set of 200 unique words and 200 unique nonwords. Contrary to the standard interpretation of the practice effect as a unitary phenomenon, a diffusion model decomposition of the data suggested that the practice effect was multifaceted: Not only did practice increase the participants' rate of information processing $v$, but it also caused a decrease in response caution $a$. This combination of effects allowed participants to speed up with practice, while retaining the same level of accuracy. Furthermore, practice also resulted in a change in the a priori preference $z$ for the "word" versus "nonword" response; over the course of the experiment, the slight a priori preference for "word" responses shifted to a slight a priori preference for "nonword" responses. A final and unexpected effect of practice was to decrease the nondecision time $T_{er}$. This nondecision component decreased by about 100 ms over the course of the entire experiment, a decrease that accounted for about 40% of the total practice-induced change in MRT.

## Task-Related Versus Stimulus-Specific Effects

One important question not addressed in Dutilh et al. (2009) is the extent to which the practice-induced changes in the diffusion model parameters are task-related or stimulus-specific. Because the Dutilh et al. (2009) study did not feature any transfer blocks consisting of new stimuli, it is impossible to claim with certainty that, say, the practice-induced decrease in nondecision time $T_{er}$ is exclusively due to an increase in familiarity with the stimuli; instead, an alternative explanation is that the effect on $T_{er}$ is due to an increase in familiarity with the task (i.e., the experimental setup including the button boxes, the computer screen, and the pace at which the trials were presented). This distinction between task-related and stimulus-specific learning is also important in light of existing theories of practice, as we explain below.

Most theories of skill acquisition and learning assume that practice enhances the association between individual stimuli and the appropriate response category (e.g., Logan's instance theory of automatization, Logan, 1988; its successor, the instance theory of attention and memory, Logan, 2002; and Rickard's component power laws model, Rickard, 1999). This assumption maps naturally onto the increase in drift rate that we found with practice (e.g., Logan, 2002, p. 391). For our current study, it is important to note that this stimulus-specific explanation of the practice effect on drift rate implies that it does not transfer to new stimuli.

Furthermore, Logan (1992) suggests that "intercept processes," such as perceptual registration and response execution, might contribute to the practice-induced speed-up in MRT. This suggestion is supported by the practice-induced decrease in $T_{er}$ reported in Dutilh et al. (2009). Although this has not been explicitly stated, Logan's "intercept processes" (i.e., $T_{er}$ in the diffusion model) are most easily conceived of as task-related rather than stimulus-specific. Therefore, we expected the practice effect on $T_{er}$ to transfer to new stimuli without loss.

In order to assess the relative contribution of task-related versus stimulus-specific learning, we conducted a new experiment in which transfer blocks with unique stimuli were presented in alternation with a single block of repeated stimuli.

# Method

## Participants

Eight native speakers of Dutch each participated for course credit on four consecutive days in sessions that took approximately 1 hr.

## Materials

We composed 11 lists of 200 unique words and 200 unique nonwords. The words were selected from the Subtlex database (Brysbaert & New, 2009). The average frequency per million of the 22,000 words was 1.23 ($SD$ = 0.81). Each list consisted of 40 four-letter words (mean frequency = 1.10, $SD$ = 0.83), 80 five-letter words (frequency = 0.99, $SD$ = 0.80), and 80 six-letter words (frequency = 1.54, $SD$ = 0.69). The 22,000 nonwords were created using the WUGGY program (Keuleers & Brysbaert, 2010), which

 

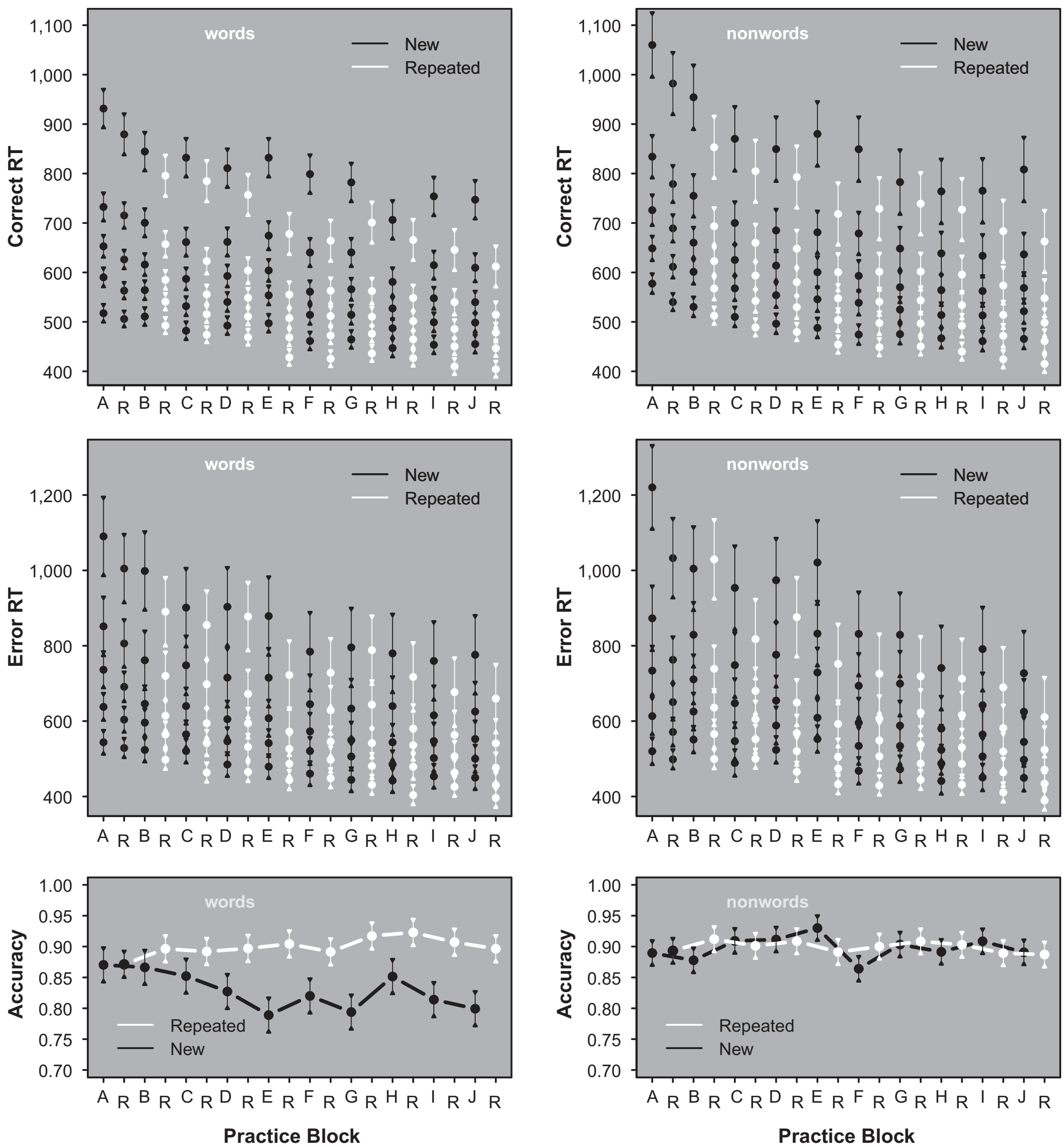


*Figure 2.* Practice-induced changes in RT distributions (separately for word and nonword stimuli, and for correct and error responses).

constructed pronounceable nonwords by replacing one letter in an existing Dutch word, vowel by vowels, consonants by consonants. The words that served as the basis for constructing the nonwords were again selected from the Subtlex database but none of them were also present in the word lists. In similar fashion a set of 15 words and 15 nonwords was created to serve as a practice list.

## Design

In the experimental procedure, we distinguish 10 stimulus lists that are each presented once (labeled A through J) and one stimulus list that is presented repeatedly (labeled R). The trials were presented in blocks, each of which contained one complete stimulus list that was shuffled before presentation. Blocks from stimuli lists R and A through J were presented as follows: A R B R C R D R E R F R G R H R I R J R, thus alternating blocks containing *new* stimuli, presented only once, with blocks containing the repeatedly presented stimulus list.

The blocks were distributed over four sessions. The first session started with the presentation of the practice list and featured four experimental blocks. The next two sessions each featured five blocks and the final session featured six blocks.

## Procedure

Stimuli were presented on a 17-inch CRT screen about 40 cm from the participant, using the Presentation software for Windows (version 10.3). Letters were presented in lowercase font, 6 mm in height, in white on a black background. Responses were registered using a two-button response device attached to the computer's parallel port to achieve maximum timing accuracy. The experimenter was in the same room as the participants for the entire duration of the experiment.

The stimuli remained on the screen until a response was made. Feedback and instruction to participants promoted accurate but fast responding: responses slower than 2,000 ms were followed by the message "TE LANGZAAM" (i.e., "too slow"), and responses faster than 200 ms were followed by the message "TE SNEL" (i.e., "too fast"). Correct responses within the 200–2,000 ms window triggered no feedback at all, whereas error responses were followed by the message "FOUT" (i.e., "incorrect"). The duration of the feedback was 1,200 ms. Each trial started with a blank screen that was presented for 250 ms.

# Results

Preliminary inspection of the data revealed that one participant behaved erratically throughout the experiment, with accuracy oscillating between 83% and 94%, and an anomalous but substantial increase in mean RT with practice. In addition, this participant's mean RT showed a 250 ms shift upwards between the third and fourth session. Therefore, we omit this participant's data here. A plot of the data from this anomalous participant can be found in the online appendix available on the first author's website. This website also contains the raw data of all participants. Below, we first present the descriptive results and next present the results from our diffusion model decomposition.

## Outlier Removal

Before analyzing the data, we determined lower and upper bounds to exclude outlier RTs. Visual inspection revealed that 250 ms and 2,000 ms were reasonable cut-offs for fast and slow outliers, respectively. Out of all 56,000 responses in the entire experiment, only 33 responses were excluded as slow outliers and 20 were excluded as fast outliers.

## Descriptive Results

Figure 2 shows the RT and accuracy data averaged over participants. The left and right columns of panels represent the responses to word stimuli and nonword stimuli, respectively. The upper four panels show for each practice block the RT distribution summarized by the .1, .3, .5, .7, and .9 quantiles, as averaged over participants. The upper two RT panels contain correct RTs, and the lower two RT panels contain error RTs. In each panel, the white symbols show the data of the repeated stimulus list R, whereas the black symbols show the data of the *new* lists that were only presented once. Note that the first *repeated* block is colored black, since at the first presentation, the stimuli in this block were never seen in the experiment before. The 95% confidence intervals are based on the Participant × Practice block interaction error term in a within-subjects ANOVA.[1] As shown in Loftus and Masson (1994), these confidence intervals can be used to infer the statistical significance of a within-subjects effect, in this case, the effect of practice.

As expected, both mean and spread of the RT distributions decrease with practice. In fact, the entire RT distribution – from the leading edge to the tail – decreases with practice, for both words and nonwords, and for correct and error responses. This general effect is present for the repeated blocks and, to a lesser extent, also for the blocks containing new stimuli, from now on referred to as *transfer* blocks.

The bottom left and bottom right panels show the average mean accuracy over participants for words and nonwords, respectively. For word stimuli, practice slightly increases accuracy for the repeated block and slightly decreases accuracy for the transfer blocks. For nonword stimuli, practice has little effect on accuracy.

## Diffusion Model Analyses

In order to obtain insight into the processes that underlie the data patterns described above, we fitted the diffusion model to the data. We chose to fit the model using the chi-square method, one of the methods in the freely available DMAT package in Matlab (Vandekerckhove & Tuerlinckx, 2007, 2008).[2]

As in Dutilh et al. (2009), we did not restrict the parameters over participants or blocks, that is, every Participant × Block cell was treated as an independent condition, in which all seven parameters of the diffusion model were estimated separately. Furthermore, we allowed words and nonwords to have different drift rates $v$ and different variabilities of drift rate $\eta$. Starting point $z_0$ was modeled as a fraction of boundary separation $a$, that is, as relative bias $B$. This method of analysis is consistent with its exploratory nature; as yet, little is known about the functional form by which the diffusion model parameters may change with practice – in fact, little is known about the extent to which the diffusion model parameters change at all.

Figure 3 shows the most important parameters of the diffusion model – drift rate $v$, boundary separation $a$, response

[1] ANOVAs were performed separately for new and repeated blocks, and for word and nonword stimuli.
[2] Our preferred method of analysis – Bayesian parameter estimation – was plagued by numerical problems causing slow sampling and slow convergence.

 

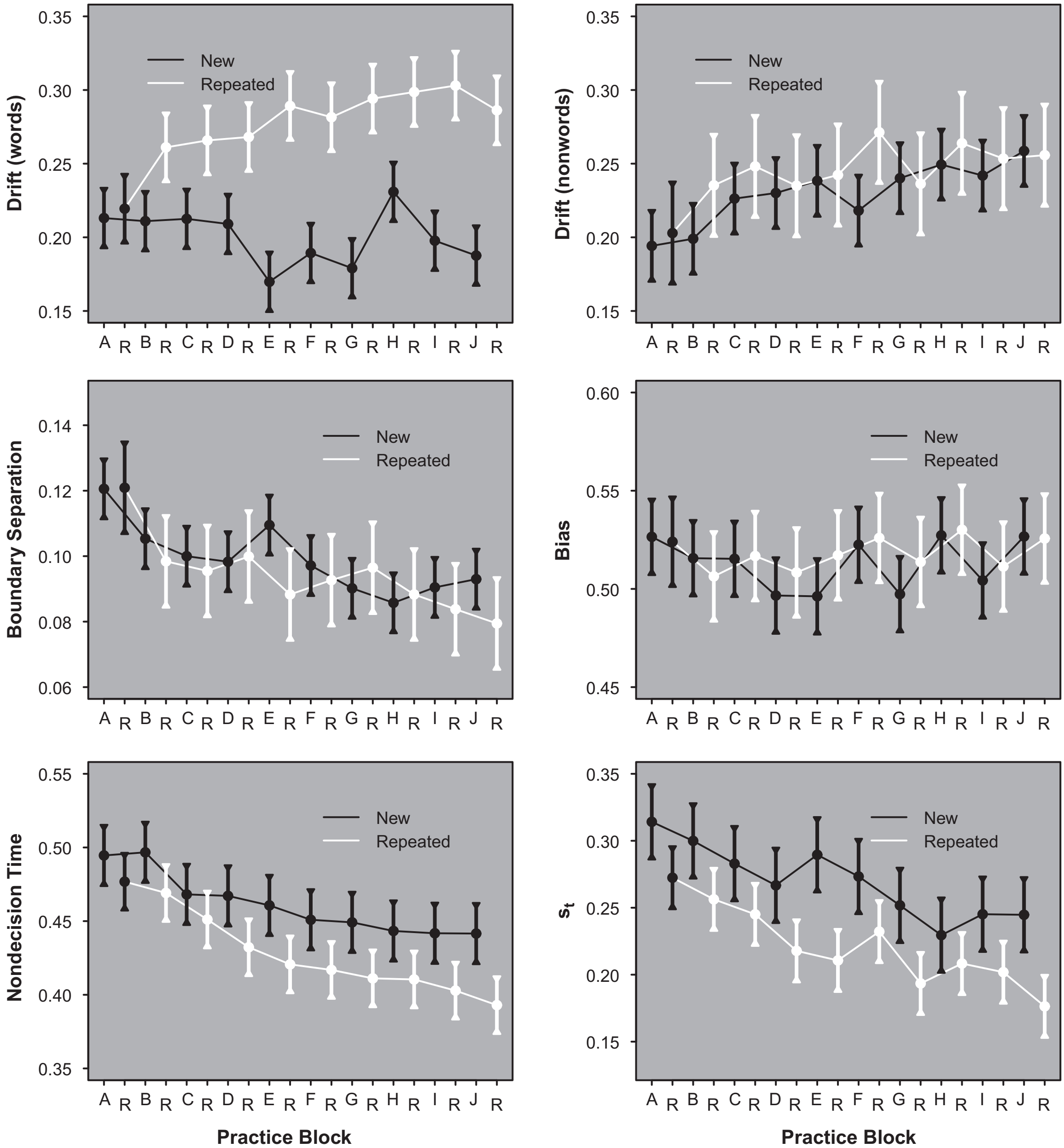


*Figure 3.* Practice-induced changes in the five most important parameters from the diffusion model. All R blocks (white) contain the same stimuli, whereas the A–J blocks (black) are transfer blocks that contain unique stimulus sets. See text for details.

bias $B$, and nondecision time $T_{er}$ along with variability in nondecision time, $s_t$ – as they change with practice. In each panel the black lines represent the parameter estimates for the transfer blocks. The white lines represent the parameter estimates for repeatedly presented blocks. Again, the first *repeated* block is colored black, since this is its first presentation. The parameter estimates are averaged over participants. As in Figure 2, the 95% confidence intervals are based on the within-subjects error term in a repeated measures ANOVA conducted on the new and repeated blocks separately. We discuss the parameters in turn below.

We used Bayesian linear regression to determine statistically whether the diffusion model parameters were affected by practice and whether this practice effect depended on the repeated presentation of stimuli (Gelman & Hill, 2007). Specifically, we conducted regression analyses in which each diffusion model parameter served as criterion. The predictors in these regression analyses were practice block number and a binary variable indicating whether the block contained new or repeated stimuli. The resultant posterior distributions for the regression weights reflect the uncertainty in their estimate and allow one to calculate the probability that a regression weight is larger than 0 (i.e., the mass of the posterior distribution to the right of 0). When this probability for the interaction term was smaller than .95 we excluded that term and interpreted the regression model without the interaction.

### Diffusion Model Inference: Drift Rate

The upper two panels of Figure 3 show the effect of practice on drift rate $v$. The left and right panels show drift rates for word and nonword stimuli, respectively. Drift rate clearly increases for repeatedly presented word stimuli. This increase is strongest over the first five blocks and levels off later in practice. For new word stimuli, however, drift rate appears to be more or less stable. This interaction between practice and repeated presentation is confirmed by a regression weight ($\beta$) of the interaction that is greater than 0, $Pr(\beta > 0) \approx 1$. For nonword stimuli, drift rates appear to increase with practice, no matter whether the stimuli were presented only once or repeatedly (the main practice effect's $\beta$ is greater than 0, $Pr(\beta > 0) \approx 1$). Note, however, that the between-subjects variance is rather large for the repeated nonwords, as expressed by the larger confidence intervals.

### Diffusion Model Inference: Boundary Separation

The middle panel of the left column of Figure 3 shows the practice effect on boundary separation $a$. As in the Dutilh et al. (2009) study, we find that the increase in drift rate described above is accompanied by a clear decrease in response caution that persists over the entire experiment, $Pr(\beta > 0) \approx 1$. The combination of increased drift rate and lowered response caution explains how participants became faster while retaining more or less constant accuracy. Note that the setting of response caution appears independent of the type of stimuli, either new or repeated.

### Diffusion Model Inference: Response Bias

The middle panel of the right column of Figure 3 shows the practice effect on response bias $B$. For repeated and transfer blocks, response bias does not change systematically with practice. On average, participants display a slight a priori preference for the "word" over the "nonword" response.

### Diffusion Model Inference: Nondecision Time

The lower left panel of Figure 3 shows the practice effect on nondecision time $T_{er}$. For both repeated and new stimuli, nondecision time decreases over the entire experiment. Specifically, the average decrease in nondecision time is about 50 ms, which is about 20% of the total practice-induced decrease in RT. Parameter $T_{er}$ decreases more strongly for repeated stimuli than for new stimuli (the interaction's $\beta$ is greater than 0, $Pr(\beta > 0) \approx 1$).

### Diffusion Model Inference: Variability Parameters

The lower right panel of Figure 3 shows how variability in nondecision time $s_t$ decreases with practice. We found that this effect is more pronounced for repeated than for unique stimuli (interaction's $\beta$ is greater than 0, $Pr(\beta > 0) \approx 1$). Figures for the two remaining variability parameters of the diffusion model (i.e., variability in drift rate $\eta$ for words and nonwords and $s_z$) are omitted here but can be found on the first author's website. Variability in drift rate $\eta$, estimated for words and nonwords separately, does not change systematically with practice. Variability in bias ($s_z$) does appear to decrease systematically with practice, $Pr(\beta > 0) = 0.90$.

## Discussion

In this study, we used Ratcliff's diffusion model to disentangle the effects of practice into their task-related and stimulus-specific components, components that were confounded in the design by Dutilh et al. (2009). Here we conducted a transfer experiment in which blocks of new stimuli alternated with blocks of repeatedly studied stimuli. In this transfer experiment, stimulus-specific learning is indicated when performance on repeated stimuli benefits from practice but performance on new stimuli does not. In contrast, task-related learning is indicated when performance on repeated stimuli benefits from practice just as much as performance on new stimuli.

The descriptive results showed that practice benefits performance on both repeatedly presented and new stimuli. With practice, the entire RT distribution shrinks and the leading edge shifts downwards; this occurs for both new and repeated stimuli, but more so for repeated stimuli. Effects on accuracy were small and only present for word stimuli.

In terms of the diffusion model parameters, we found that nonword drift rate benefits from practice independently of the stimuli presented whereas word drift rate benefits for repeated stimuli only. This result suggests that the task of deciding that a letter string is a nonword is a skill that improves with practice. On the other hand, recognizing a letter string as an existing word is a skill that has been developed before the experiment but can still benefit from increased stimulus familiarity. This result implies that the practice-induced increase in drift rate reported in Dutilh et al. (2009) and Ratcliff, Thapar, and McKoon (2006) might be partly stimulus-specific and partly task-related.

Next, we found that response caution decreased with practice at an equal rate for both new and repeated stimuli. This general decrease in response caution in combination with increasing drift rates explains why accuracy remains stable with decreasing RT. It also explains why responses on new word stimuli, for which drift rate remained stable, became less accurate with practice.

Furthermore, nondecision time $T_{er}$ decreased with practice, for both repeated and transfer blocks. This implies that the practice effect on nondecision time is partly task-related, supporting Logan's idea of a speed-up in "intercept processes" such as perceptual registration and response execution. However, the decrease of $T_{er}$ was stronger for repeated stimuli than for uniquely presented stimuli. This suggests that some perceptual processes might benefit from word familiarity. Further study is needed to clarify how this benefit of familiarity can occur without a concomitant increase in accuracy (remember that $T_{er}$ does not affect accuracy).

In sum, the findings reported here replicate those from Dutilh et al. (2009): practice is a multifaceted phenomenon that involves changes in speed of information processing, response caution, and nondecision processing. The experimental design of the current study allowed us to further decompose these effects into task-related and stimulus-specific effects. Our analysis showed that effects on drift rate and nondecision time are partly task-related and partly stimulus-specific, whereas the effects on response caution and response bias are mostly task-related. In general, we conclude that the model-based decomposition of practice brings insights much deeper than those provided by a standard analysis of mean RT.

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