

Practice increases the efficiency of evidence accumulation in perceptual choice

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Abstract

Most models of choice response time base decisions on evidence accumulated over time. A fundamental distinction among these models concerns whether each piece of evidence is equally weighted (“lossless” accumulation) or unequally weighted (“leaky” accumulation). We tested a hypothesis derived from Heathcote and Brown’s (2002) self-exciting expert competitor (SEEXC) model of skill acquisition: that evidence accumulation becomes less leaky with practice. The hypothesis was supported by observation that the effects of prime stimuli increased with practice. We used metacontrast masked primes, which could not be consciously discriminated by most subjects, avoiding methodological problems associated with conscious strategy changes. The form of the “Law of Practice” in our data is also shown to be consistent with the SEEXC model.

With few exceptions (e.g., Falmagne, 1965; Watson, 1979), models of choice response time (RT) assume that decisions are based on the sum of evidence that is accumulated over time (see Luce, 1986, and Smith, 2000, for reviews). These models account for a broad range of phenomena in human and animal behavior and even neural dynamics. A fundamental point of difference concerns the efficiency of accumulation. One large and successful class of models assumes that the accumulation process is lossless. That is, during the decision process, pieces of evidence arriving early are given the same weight as those arriving late, near the end of the decision processing (e.g., Carpenter & Reddi, 2001; Grosjean, Rosenbaum, & Elsinger, 2001; Laming, 1968; Link & Heath, 1975; Ratcliff, 1978, 1981; Ratcliff & Rouder, 1998; Ratcliff, Van Zandt & McKoon, 1999; Roitman & Shadlen, 2002; Stone, 1960; Van Zandt, Colonious & Proctor, 2000; Vickers, 1970). The lossless assumption is attractive because, for a stationary signal, it makes the most efficient use of the available evidence.

In contrast, in an equally large and successful class of models, the effect of each piece of evidence is determined by its order of arrival¹ (e.g., Brown & Heathcote, in press; Busemeyer & Townsend, 1993; Grice, 1972; Killeen, 2001; Lacouture & Marley, 1991, 1995; McClelland, 1979, 1993; Page, 2000; Smith, 1995; Usher & McClelland, 2001; Vickers & Lee, 1998, 2000). Most of these models assume “leaky” accumulation, where previously summed evidence is slowly forgotten. Leakage affects evidence arriving early in the process more than late evidence, as the early evidence has a longer period over which it is subject to leakage. The assumption of leakage in evidence accumulation has many benefits. For example, leakage allows the evidence sum to “track” non-stationary signals. That is, for a leaky accumulator the asymptotic evidence

total depends on the strength of the input signal, so if the input signal changes strength, the overall magnitude of the evidence sum reflects the change. By contrast, lossless accumulation requires a “reset mechanism” to follow non-stationary input signals. Some models also allow positive feedback in evidence accumulation, where early pieces of evidence dominate later pieces, making evidence accumulation fast and relatively resistant to changes in direction (“explosive” evidence accumulation).

We propose that leakage in evidence accumulation decreases with practice at a choice task. This prediction was derived in order to accommodate the exponential form of the “Law of Practice” for individual subjects: the relationship between mean RT and practice, see Heathcote, Brown, and Mewhort, 2000 (but see Newell & Rosenbloom, 1981, for a different view). Page (2000) observed that neural accumulator models of choice RT predict a power law of practice, when it is assumed that practice increases the strength of inputs to the decision process. Heathcote and Brown (2000) pointed out that this prediction does not match individual, unaveraged data (see also Brown & Heathcote, 2003). However, they showed that if practice increases recurrent self-excitation, and so decreases leakage, neural accumulator models can accommodate an approximately exponential law of practice.

Evidence for Leakage

At least three arguments have been used to support the existence of leakage in evidence accumulation processes. Usher and McClelland (2001) argued that leakage in their model accounts for the observation of imperfect choice accuracy in some situations even when decision times are unlimited. However, Busemeyer and Townsend (1993; see also Ratcliff & Smith, in press) show that accuracy in Usher and McClelland’s model

always becomes perfect with sufficient decision time, as in the lossless diffusion models. The second argument for leakage relies on neural plausibility; individually, neurons are extremely leaky integrators, with time constants around 5-10ms (“passive leakage”). This contrasts sharply with lossless integrators, which have an infinite time constant. However, even the leakiest choice models assume much longer time constants than 10ms, leading Wang (2002) to suggest that neural implementation requires recurrent excitatory connections (“self-excitation”). Hence, even though accumulation is leaky in individual neurons, this does not imply that evidence accumulation is necessarily leaky at the network or the behavioural level. The energetic cost of neural self-excitation is high, due to increased overall firing rates. For this reason, we propose that practice increases self-excitation in a very specific manner: affecting behavior only in highly practiced tasks, with little generalization. This limits the energy expenditure to networks supporting behaviorally important skills.

The third argument in favor of leaky integration comes from the “expanded judgment” paradigm (e.g., Busemeyer, 1985; Erlick, 1961; Irwin & Smith, 1957; Irwin, Smith & Mayfield, 1956; Pietsch & Vickers, 1997; Smith & Vickers, 1989; Vickers, 1995; Vickers, Burt, Smith & Brown, 1985; Vickers, Foreman, Nicholls, Innes & Gott, 1989), which attempts to directly examine the dynamics of evidence accumulation by breaking stimuli into temporal series of discrete pieces, each possibly favoring a different response. For example, Pietsch and Vickers’ stimuli were sequences of 30 flashes from a pair of lamps displayed over approximately three seconds. Subjects were asked to decide whether the right or left lamp had been flashed more often. In stimulus sequences with equal numbers of flashes on the right and left, participants had a strong tendency to

respond based on the flashes that predominated at the end of the sequence. This finding is consistent with a leaky accumulation process. Expanded judgment paradigms have yielded support for leaky integration, both with human subjects (e.g., Busemeyer & Townsend, 1993; Viviani, 1979) and animals (e.g., Alsop & Honig, 1991; Killeen, 2001).

The relatively slow presentation rates and long presentation times used by Pietsch and Vickers (1997) – and most other expanded judgment experiments – leave open the possibility that leakage is a characteristic of attention or memory processes rather than the decision process. Usher and McClelland (2001), who studied fast perceptual choices, investigated leakage using an expanded judgment task with a much quicker stimulus rate and shorter overall presentation time; eight “S” and eight “H” characters presented for 16ms each in the critical trials of their Experiment 3. They found strong individual differences, with two subjects’ choices being strongly positively correlated with the type of the last few characters, two negatively correlated, and two indifferent, consistent with leaky, explosive and lossless integration respectively. Pietsch and Vickers also found strong individual differences in leakage (see also Vickers, 1995).

We report data from an experiment using fast perceptual choice – orientation discrimination – in a priming paradigm that provides an empirical assessment of information accumulation dynamics. Previous expanded judgment tasks were less than ideal for testing models of perceptual choice RT because the stimuli required an appreciable time to present, at best 256ms (Usher & McClelland, 2001). Choice responses can be made in less than 256ms, so decision processing can take less than 256ms when motor production time is taken into account. This raises the possibility that subjects can reach a decision without observing the entire stimulus, and so the effect of

some parts of the stimulus sequence may be decreased independently of leakage in evidence accumulation. Usher and McClelland minimized this problem by using randomized sequences of varying length, and examining results only from the shortest sequences. Our interference/facilitation priming paradigm has the advantage that all changes in the information content of stimulus display sequences occurred well before subjects were able to respond (90ms).

The priming paradigm employed below relies on metacontrast masking, with procedural details similar to Klotz and Neumann's (1999) Experiment 3. In metacontrast paradigms (e.g., Bridgeman, 1971, 2001; Didner & Sperling, 1980; Francis, 2000, 2003; Kahneman, 1968; Klotz & Wolff, 1995; Lachter & Durgin, 1999; Milner & Goodale, 1995; Schmidt, 2002; Vorberg, Mattler, Heinecke, Schmidt, & Schwarzbach, 2003), subjects make simple shape discriminations quickly, for example between a filled circle and an annulus. Metacontrast masking can occur when the outer contours of a prime shape are coincident with the inner contours of the target shape. With a carefully chosen delay between prime and target display (stimulus onset asynchrony: SOA), subjects cannot reliably discriminate between prime displays. However, metacontrast primes can still induce changes in RT and error rates, even without conscious detection. Such results have been used to argue for a dissociation between conscious and subliminal perceptual systems (e.g., Klotz & Neumann, 1999).

Appropriate use of metacontrast masks enables the presentation of prime displays that subjects are unable to consciously detect, thus ruling out alternative explanations of the predicted effects of practice based on consciously mediated strategies. Three previous studies have examined the effects of practice on metacontrast masking: Ventura (1980),

Hogben and Di Lollo (1984, see also Francis, 2003) and Vorberg et al. (2003). The first two investigations found that practice increased the efficacy of metacontrast prime stimuli: participants were better able to ignore the information content of the masking stimulus with practice. This effect is in accordance with our hypothesis.

Vorberg et al. (2003) investigated the effect of extensive practice (five experimental sessions) on metacontrast masked priming. They interpreted their results using a leaky accumulator model of choice response time, similar to those discussed above (e.g., Smith, 1995; Usher & McClelland, 2001). Vorberg et al. reported that practice had no effect on RT in their task, apparently contradicting our hypothesis that practice reduces leakage. However, there was a very strong effect of practice on error rates in Vorberg et al.'s experiment: the effectiveness of prime stimuli in producing error responses increased with practice, exactly as our hypothesis predicts. This increase can be seen in supplementary material not included in Vorberg et al.'s printed article (their Table 1 available from www.pnas.org). For longer stimulus onset asynchronies, the increase in prime effectiveness with practice was very strong. At a SOA of 56msec there was a 3% “priming effect” on error rates in the first practice session, but a 10% effect in the last session. For a SOA of 70msec (most similar to our stimuli) the priming effect increased from 8% to 18% with practice, and for a SOA of 84msec the priming effect increased from 17% to 28%.

Although each of these three previous studies produced results consistent with our hypothesis that practice increases the importance of early-arriving information, by decreasing leakage, they were designed with different aims in mind and so are not ideal for testing our hypotheses. In particular, participants were (sometimes) required to

identify the prime stimulus and to ignore the following stimulus. This makes the results open to alternative explanations based on conscious strategies; since participants were aware of the existence of prime stimuli, and even trained to detect them, it is possible that their response strategies – rather than leakage – changed with practice. In our experiment, participants were not required to respond based on the properties of the prime stimulus and were unaware of its existence until after the practice phase was complete.

Method

Participants

Subjects were eight undergraduate students at the University of Newcastle, Australia, with normal or corrected to normal vision. Subjects attended two one-hour experimental sessions on consecutive days. Responses were collected using a serial mouse, with the trackball removed. This method of response collection results in timing errors smaller than ± 6 ms (Beringer, 1992). Response collection routines, and other experimental software, can be obtained from the authors. The vertical retrace frequency of the video monitor was 67Hz, corresponding to a refresh period of 15ms.

Stimuli

The stimuli were square and diamond shapes (see Figure 1) presented on a computer screen in a dimly lit room, using black on a white background to minimize problems associated with phosphor decay and changes in overall screen luminance. The target stimuli each covered the same amount of screen area to within three pixels per thousand. Target stimuli had side lengths of 25mm, corresponding to approximately 2.2° retinal eccentricity, given a viewing distance of approximately 60cm. Stimuli were presented in pairs, side-by-side, such that the distance between extreme left and right

points of the pair was 68mm (5.9°). The prime stimuli were smaller than the target stimuli by a factor of $\sqrt{2}$ so that the outer contours of the prime stimuli co-incided with the inner contours of both target stimuli. The vertical height of each prime-target stimulus pair was adjusted by a random uniform displacement from screen center in the range [-11mm,+11mm]. Left and right stimuli were adjusted independently, allowing for a maximum height difference of 22mm, or approximately 90% of target side length. Prime and target stimuli were always presented in the same vertical locations, to preserve the metacontrast phenomenon.

Procedure

Each trial consisted of the sequence represented graphically in Figure 2. A blank white screen was displayed for 100ms after which a (black) dot appeared in the centre of the screen accompanied by four dots forming the corners of a square with side length 80mm. Over the next 720ms the four outer dots moved towards the centre dot, then merged with it and disappeared. This animated fixation display helped draw subjects' focus to the screen center (where the dots converged). A random delay (uniform between 150-750msec) was then enforced, to reduce premature stimulus sampling or anticipation (see, e.g., Grosjean et al., 2001). After the delay, a pair of prime images was displayed for two screen refreshes (30ms). The prime pair could consist of any combination of diamond or square prime stimuli. A blank white screen was displayed for a further three refresh cycles, so that the inter-stimulus interval (ISI) was 45ms. Following this, the target pair was displayed for six refresh cycles (90ms). The target pair always consisted of one square stimulus and one diamond stimulus. After the 90ms had passed, a blank

white screen replaced the target pair. This screen remained until a response was recorded from either mouse button, or 2500ms passed.

The task for half of the subjects was to push the left button if the square stimulus appeared on the left of the screen, and the right button if it appeared on the right. The other half of the subjects performed the same task with respect to the diamond stimulus. All response times were measured from the onset of the target stimulus. If a correct response was made, the trial sequence began again. If an incorrect response was made, feedback was given in the form of a 500Hz tone, for 500ms. If no response was recorded within 2500ms, the same feedback tone was given, and subjects were instructed to take a break if they required one, and then to press a button when ready to continue the experiment.

Trials were presented in blocks of 64. Within each block, half of the trials were neutral (i.e., the prime pair contained two identical stimuli), with the remaining half divided into 16 “congruent” trials and 16 “incongruent” trials. The prime pairs for congruent (incongruent) trials were in corresponding (opposite) positions to the target pairs. Target location was balanced across all conditions. After each block, subjects were instructed to rest as long as they pleased; a minimum rest time of 20s was enforced. During the block rest time, subjects were told how many errors they made in the previous block, and were also given a score: $10/(\text{mean RT in seconds})$. Scores included an exponentially decreasing weighted sum of previous block scores, to reduce noise and help subjects observe overall trends ($\text{score} = 0.7 \times \text{raw score} + 0.3 \times \text{previous score}$), except for the first block.

In their first session subjects were given instructions followed by 20 blocks of practice trials. On the following day, subjects were given a further 20 blocks of practice trials, followed by a prime discrimination task. Before the prime discrimination task, subjects were informed about the sequence of events comprising each trial, including the presence and type of the prime stimuli. They were also shown slow-motion examples of complete stimulus sequences. Following the examples, two blocks of trials were given that were identical to the practice blocks, except that no feedback was provided, and the subjects' task changed; subjects were instructed to push the left response button if the square (or diamond, for half of the subjects) appeared on the left of the screen *in the prime pair* and vice versa. This is the same prime discrimination task described by Klotz and Neumann (1999) in their Footnote 4. Subjects were explicitly told that there was no correlation between positions in the prime and target pairs.

Results

Prime Discrimination Task

Across subjects, 1.3% of responses in the prime discrimination task were removed because they were faster than 180ms. Table 1 also shows the percentages of “right” responses to neutral, left and right prime trials, for individual subjects and grouped across all subjects. The grouped frequencies were significantly different from those expected by chance ($\chi^2(2)=10.8, p<.01$). Separate χ^2 -squared tests for each subject revealed that only subject 6 was able to detect the location of the target in the prime display reliably ($\chi^2(2)=28.8, p<.01$). Subject 6's data were also responsible for driving the significant χ^2 for the grouped data: with the data from subject 6 removed, the grouped data were no

longer significantly different from that expected by chance ($\chi^2(2)=2.3, p>.05$). It is possible that subject 6's ability to detect target location in the prime display may confound further analyses, and so statistical tests are reported both with and without those data. A one-way repeated-measures ANOVA on the effect of prime location on response frequency was also non-significant (all subjects: $F(2,14)=2.13, p>.05, MSE=0.019$).

Practice Task

Data from the first practice block were excluded from further analysis. Error rates in this initial practice block – especially in the first few trials – were much larger than in the rest of the experiment, possibly reflecting a response-learning phase. For instance, the mean error rates across subjects for the first block were 12.5% for the neutral condition, 8.6% for the congruent condition and 26.6% for the incongruent condition. These rates were much larger than for the rest of the first experimental session (5.3%, 3.3% and 18.4% respectively). Across all subjects, 0.59% of remaining RTs were removed because they were faster than 180ms, and 0.03% were removed because they were slower than 1500ms. The data from subjects 6 and 7 had many more anticipatory responses removed (1.4% and 1.8% respectively) than the rest of the subjects. The effects of excluding data from these two subjects are noted where appropriate below.

Table 2 shows the mean RT separately for each participant in the first and second practice sessions, for neutral, congruent and incongruent trials. We analyzed our data in terms of “priming effects”: differences between incongruent and neutral conditions define “interference effects”; differences between neutral and congruent conditions define “facilitation effects”. The use of RT differences rather than RT avoids confounds due to changes in overall performance level with practice. Practice typically decreases RT,

regardless of changes in priming effects. Thus, it may be possible that RTs associated with neutral, congruent and incongruent conditions all decrease with practice, even though priming effects increase (i.e., congruent RTs decrease faster than neutral RTs, and incongruent RTs decrease slower).

The mean interference and facilitation effects on RT in Table 2 were in the expected directions (neutral trials were slower than congruent trials, and faster than incongruent trials). We calculated a 2x3 repeated-measures ANOVA, with practice session and trial type (neutral, congruent and incongruent) as factors. There was a significant main effect of practice session, indicating that practice improved overall performance ($F(1,7)=8.6, p<.05, \text{MSE}=551$, without subjects 6 and 7, $F(1,5)=5.3, p=.06, \text{MSE}=605$). There was also a significant main effect of priming condition ($F(2,14)=66.7, p<.001, \text{MSE}=271$, without subjects 6 and 7, $F(2,12)=61.8, p<.001, \text{MSE}=253$). The interaction between priming condition and session was significant ($F(2,14)=5.3, p<.05, \text{MSE}=5.6$, without subjects 6 and 7, $F(2,12)=7.4, p<.01, \text{MSE}=1.8$), reflecting larger facilitation and interference effects in the second session than in the first.

Previous research (e.g., Pietsch & Vickers, 1997; Usher & McClelland, 2001) identified large individual differences in leakage estimates, so we calculated a binomial test to assess between-subject reliability. From Table 2, we calculated interference and facilitation effects for each participant separately for each practice session. Fourteen of the sixteen facilitation and interference effects increased from the first to the second session. The probability of observing fourteen or more increases under a null hypothesis of equally likely increases and decreases is $p=.0021$. With the data from subjects 6 and 7 removed, eleven of the twelve remaining effects increased ($p=.0032$). Our hypotheses

about the effects of practice on information integration actually entail an even more rigorous prediction: that *both* interference and facilitation effects increase separately. We tested this hypothesis with separate binomial tests for interference and facilitation effects. Seven of the eight interference effect sizes increased between sessions, and so did seven of the eight facilitation effect sizes (both $p=0.035$). With subjects 6 and 7 omitted, all remaining six effect sizes increased between sessions for both facilitation and interference (both $p=.016$).

Table 3 shows the error rates for each participant separately for different priming conditions and practice sessions. Once again, the facilitation and interference effects were in the expected direction. A 2x3 ANOVA on error rates showed a significant main effect of priming stimulus condition ($F(2,14)=19.5, p<.001, MSE=0.0063$, without subjects 6 and 7: $F(2,10)=10.1, p<.01, MSE=0.0069$). Error rates were on average stable across sessions (non-significant main effect of practice session: $F(1,7)<1, MSE=0.00074$, without subjects 6 and 7, $F(1,7)<1, MSE=0.00039$). Although overall the interaction between session and priming condition was not significant ($F(2,14)=1.76, p>.05, MSE=0.00038$), with the data of subjects 6 and 7 omitted it was highly significant ($F(2,10)=9.8, p<.01, MSE=0.00013$), with larger interference and facilitation effects after practice. We again calculated a binomial test using interference and facilitation effects calculated from Table 3. Of the 16 interference and facilitation effects, 14 increased between sessions ($p=.0021$). When subjects 6 and 7's data were removed, all 12 of the remaining effects increased ($p=.00024$). When facilitation and interference were considered separately, all eight interference effect sizes increased from the first to second session ($p=.0039$). Of the eight facilitation effect size pairs, only six increased between

sessions ($p=.15$). When the data from subjects 6 and 7 were omitted, all six remaining interference effects increased ($p=.016$) and five out of six facilitation effects increased ($p=.10$).

Discussion

The results of binomial tests on error rates and mean RTs supported the hypothesis that increased practice leads to increased facilitation and interference effects for congruent and incongruent primes respectively. The results of ANOVA tests on RTs provided similar support, as did the ANOVA for error rates when the potentially suspect data from participants 6 and 7 were excluded. These results together suggest that practice increases interference and facilitation effects from prime stimuli, even when those stimuli are not detected. The observed decrease in mean RT between sessions makes these results even stronger. Typically, an overall decrease in RT would be expected to reduce differences between conditions, but interference and facilitation effects increased in the second session. The overall decrease in RT is also consistent with the hypothesised decrease in leakage, which speeds the decision process. Further, our results cannot be explained by speed-accuracy tradeoff (SAT); overall error rates were stable across sessions, but we observed increased priming effect sizes in *both* RT and error rate.

Our results pose an interesting question: why does practice apparently strengthen the facilitation and interference effects of prime displays, but not the ability to consciously detect those same primes? Supporting the current data, Klotz and Neumann (1999, Experiment 3) concluded that extra practice did not improve performance in their prime discrimination task. However, contrary to our results, Klotz and Neumann also concluded that extra practice had no effect on the magnitude of the facilitation and

interference effects for RT or error rates (reported in their Table 1). Vorberg et al. (2003) found results consistent with ours – practice increased differences in error rates between congruent and incongruent conditions. A possible reason for different results in Klotz and Neumann’s experiment is that they used less practice than the current design or Vorberg et al.’s design (1280 trials vs. 2560 here, even more in Vorberg et al.). This explanation suggests that practice increases self-excitation slowly, consistent with the notion that self-excitation is energetically expensive, and thus reserved only for specific tasks that are performed often.

Generality of Results

The results of our experiment support the hypothesis that practice at a perceptual choice task reduces leakiness in an information accumulation process. However, with only eight participants and just one experimental paradigm, the reader may wonder about the generality of this result. We carried out three other experiments of similar design (see Brown, 2002, for full details). Each of these three experiments supported our hypothesis. The third experiment was very similar to the one reported here, but without variable stimulus foreperiods and independent random vertical positioning of the stimuli. Random foreperiods were used to ameliorate possible effects due to changes in premature stimulus sampling (e.g., Laming, 1968). With fixed onset times, it is possible that increased prime effect sizes with practice could occur because participants learned to temporally focus their attention on the prime. However, the same pattern of results was obtained in both experiments, suggesting that changes in premature stimulus sampling were not an important factor. Further evidence that premature stimulus sampling did not have large effects on our data is provided by a comparison of correct and error RT. RTs

associated with error responses were marginally longer than RTs associated with correct responses for all eight subjects in the current experiment: the mean difference across participants (for responses from the neutral priming condition) was 5.0msec. Premature stimulus sampling is associated with mean error RTs that are *shorter* than mean correct RTs (Luce, 1986).

Our two other experiments used a relative line length judgment task. Two lines were presented on screen and participants responded to the taller one – differences were well above threshold. Prime stimuli could be neutral (two lines of equal height), congruent (similar to target display) or incongruent (mirror image of target display). These two experiments also showed increasing effects of prime stimuli with practice. The prime stimuli were more easily visible in the line length experiments, allowing for possible confounding explanations based on conscious strategies. The consistency of results across the line length and metacontrast experiments suggests that the priming effect is not mediated by conscious strategies.

Our results provide support for the novel hypothesis that priming effects increase with practice, and thereby support the hypothesis that evidence accumulation becomes less leaky with practice. However, our experiments do not rule out all other alternative explanations for increased priming effects with practice. For example, Smith, Ratcliff and Wolfgang (submitted) suggest that decisions about briefly presented stimuli are based on a representation, obtained by integrating the input over a time window, which is maintained at a stable level in a visual short term memory (VSTM). The variable stimulus onset timing we used helps to rule out the possibility that increased priming effects were due to learning to better align the beginning of the window with the prime

onset. However, the increased priming effects might still be due to decreased leakage in the VSTM integration process itself. Our model, in contrast, locates the change of leakage in the decision process. It is also possible to explain our results without reference to changes in leakage anywhere in the decision process. One such explanationⁱⁱ holds that practice improves the quality of the memorial representation of the prime stimulus. Thus, with greater practice, the memory trace for the prime exerts greater influence on decisions made about the target. In this theory, the memory for the prime improves in quality, but not in strength, so primes remain subliminal even after practice.

It is difficult to imagine that such theories could be differentiated from our hypothesis of decrease information leakage through experiments of the kind reported here. Indeed, change in leakiness of the information integration process could be viewed as an approximation to changes in memory quality: improved memory quality implies that information from earlier in the decision process is retained for longer, which is exactly the hypothesis instantiated by reduced leakage. In the next section we provide further evidence, based on neutral trial RTs from the present experiment and the other experiments reported in Brown (2002), which is consistent with changes in leakage with practice.

The Self-Exciting Expert Competitor Model

Heathcote and Brown (2000) proposed that, in order for decision models of the type proposed by Page (2000) and Usher and McClelland (2001) to accommodate an exponential Law of Practice, practice might increase recurrent self-excitation, decreasing effective leakage. Heathcote and Brown showed that, for a leaky accumulator, the input must increase at a faster than quadratic rate with practice trials in order to approximate an

exponential law of practice. Page proposed that the input to the decision process is the maximum activation produced by a set of instances, each laid down by a practice trial. As practice trials (N) increase so does the maximum, but at a rate slower than linear in practice trials. Hence, Page's model cannot accommodate an exponential form of the law of practice. Indeed, any model which attributes practice effects solely to an unbounded change in input seems implausible, especially when the input increases at greater than the square of the number of practice trials, as not many trials would be required before the input became extremely large. This was the motivation for Heathcote and Brown's suggestion that practice decreases RT by decreasing leakage rather than increasing the input.

Heathcote and Brown (2002) developed the details of this approach, which they called the Self-Exciting Expert Competitor (SEEXC) model. They demonstrated, analytically for a single leaky integrator unit and by simulation for a two-unit leaky competitive integrator, that a learning rule which produces a bounded change in weights (ϵ) on a self-excitatory (recurrent) connections ($\frac{d\epsilon}{dN} = \lambda(k - \epsilon)$, where λ is a learning rate parameter and k is passive leakage) could capture an important property of practice data, a *relative learning rate* (RLR) which is asymptotically greater than zero as N increases.

Heathcote et al. (2000) first suggested RLR as a way discriminating the shapes of similar functions such as the power and exponentialⁱⁱⁱ. RLR quantifies the rate of change of the practice function as a proportion of the distance from asymptotic RT (A), formally: $RLR = -\frac{dRT}{dN} / (RT - A)$. For an exponential function ($A + Be^{-\alpha N}$, where B is a scale parameter), RLR is a constant equal to the rate parameter of the exponential function (α). For a power function ($A + BN^{-\beta}$, where β is a rate parameter), RLR decreases

hyperbolically to zero with practice. Heathcote et al. examined 7910 practice series from 475 subjects in 24 experiments using a broad range of skill acquisition paradigms, and found that the exponential function provided a significantly better fit than the power function in every experiment.

Heathcote et al. (2000) also showed that, even more consistently but with a lesser absolute improvement, the four parameter APEX function ($A + Be^{-\alpha N} N^{-\beta}$) provided a better fit than the “general” power function ($A + B(N + E)^{-\beta}$), which adds a fourth parameter (E) to the power function allowing for practice prior to experimental measurement. Critically, the APEX and general power functions differ in the asymptotic behaviour of their RLRs; both decrease initially, but the RLR of the general power decreases to zero whereas the RLR of the APEX function asymptotically equals the rate of its exponential component. Hence, it appears that any viable practice function must have an RLR that remains greater than zero. In some data sets the APEX function fit significantly better than the simpler exponential function, suggesting that a decrease in initial RLR might also be a desirable property for a practice function, at least in some paradigms.

Heathcote et al. (2000) did not provide a theoretical motivation for the APEX function; it was used as a convenience for comparing power and exponential functions. However, Heathcote and Brown (2002) showed that a four parameter function with properties very similar to the APEX function can be derived as an approximation to the practice function produced by the SEEXC model:

$$RT(N) = A + B \left(\frac{(1 - c)e^{-\lambda N}}{1 - ce^{-\lambda N}} \right)$$

Like the APEX function, the SEEXC practice function has an asymptotic RLR greater than zero (λ) that decreases initially with practice. Unlike the APEX function, which shares with the power function an infinite RLR when $N-E=0$, the RLR of the SEEXC function is bounded: $\lambda/(1-c) \geq RLR > \lambda$. Clearly, as c approaches zero the RLR of the SEEXC practice function approaches a constant, just like the exponential, and as c increases it can accommodate the cases where Heathcote et al. (2000) found the APEX function provided a clearly better fit than the exponential function.

In order to further test the SEEXC model, we fit the SEEXC practice function to data from the present experiment, and from the three similar experiments described in Brown (2002). We fit block mean RT for neutral-prime data, using only correct responses and excluding the first practice block. The use of block mean RTs is appropriate for least squares fitting of practice curve data (Brown & Heathcote, 2003). Full details for those experiments and the curve fitting methods used are available in Brown. Neutral trial data were used as they provided the greatest number of observations and corresponded to the assumption of input stationarity used in deriving the SEEXC practice function. For comparison we also fit power and exponential practice functions, as used by Heathcote et al. (2000). As illustrated in Table 4, we replicated Heathcote et al.'s finding that the exponential function provides a clearly better fit than the power function. The SEEXC practice function provided a better fit than either the power or exponential functions. Figure 3 shows data from one subject as an illustrative example: the SEEXC function fits better than the exponential function because it is better able to capture early rapid learning. Heathcote et al. also fit two other four-parameter practice functions, the generalised power function and the APEX function. Our SEEXC function

fit as well as either of those, and is to be preferred because it is based on a psychological model, rather than used as a fitting convenience. As with our earlier results showing that leakage decreases with practice, these results support the SEEXC model as an account of the development of skill in perceptual choice.

Conclusions

The prediction tested here, that practice reduces leakage in evidence accumulation, was formulated on the basis of a theory of skill acquisitions, SEEXC, and considerations quite separate from previous results related to evidence leakage. As such, its confirmation represents a strong endorsement of the SEEXC theory, with further support provided by successfully describing some of the subtler aspects of the Law of Practice. More broadly, the idea that practice reduces leakage in information accumulation is consistent with other effects of practice such as automaticity. Under our formulation, highly practiced responses are fast because evidence accumulates more quickly when leakage is offset by increased self-excitation. Highly practiced responses also require less total input to achieve the response threshold, so they can be triggered by only a brief input, and once triggered are hard to inhibit. Highly practiced responses, such as reading, are also resistant to interference effects from less practiced responses, such as naming the color in which a word is printed in the Stroop paradigm (McLeod, 1991). Changes in self-excitation naturally predict these effects. Because color naming is less practiced, evidence about printed color accumulates slowly, and when it eventually impacts on the reading process it has little influence because the reading response is already largely determined by early arriving direct evidence from the reading process. Reading, in

contrast, has a larger interfering effect on color naming because slowly accumulating direct evidence from ink color is more easily modulated by indirect effects from reading.

Our finding that practice reduces leakage may also reconcile apparently contradictory evidence supporting lossless and leaky evidence accumulation. For example, Usher and McClelland (2001) and Pietsch and Vickers' (1997) results supporting the presence of leakage in information accumulation used only 500-600 trials. In contrast, Ratcliff and Smith (in press) and Smith et al. (in press) found evidence against leakage using data from three highly practiced tasks involving thousands of trials. Large numbers of trials were required to obtain stable fits of sequential-sampling models to individual subject's data. Their fits favored lossless integration because the leakage parameter for an OU diffusion model was estimated as not significantly different from zero in most cases. The large difference in the number of trials may explain the opposite findings, although it may also be due to the nature of the OU model. In any case, our results indicate that the effects of practice should be taken into account when considering these issues. More generally, our finding that leakage changes systematically with practice supports leaky accumulation models, such as Usher and McClelland's and the OU diffusion model, which allow different values of leakage, and reject lossless accumulation models such as the Weiner diffusion.

The present findings also suggest a role for self-excitation within Usher and McClelland's (2001) model. Usher and McClelland did not examine the role of self-excitation, choosing instead to treat it as a constant effectively absorbed into the estimate of passive leakage. Brown and Heathcote (in press) examined a deterministic form of Usher and McClelland's model, both with and without a self-excitation parameter. When

estimates of self-excitation were allowed to vary, it played a role separately identifiable from passive leakage in trials where response speed was emphasized. Wang (2002) also suggested that self-excitation is necessary at the neural level in order to obtain sufficiently long time constants to model the relatively slow accumulation process seen in perceptual decision making. Wang hypothesized that self-excitation was mediated by NMDA receptors, suggesting a testable physiological locus for the self-excitation learning effects proposed here.

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Footnotes

ⁱ Most of these models actually assume that the effect of each piece depends on the sum, or on a set of sums, at the time of arrival, rather than directly on the actual order or time of arrival. However, in the paradigms we discuss these two factors are correlated, so for simplicity we talk about arrival time effects.

ⁱⁱ We are thank Philip Smith for suggesting this explanation.

ⁱⁱⁱ Luce (1986) and Wickens (1998) used hazard rate, which has the same formal definition as RLR, to discriminate RT distribution functions and forgetting curves respectively.

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Thanks to Doug Mewhort for suggestions as to possible confounds in our tests of the leakage and practice hypothesis, and to David Rosenbaum, Phil Smith and Greg Francis for helpful reviews.

Table Captions

Table 1. Percentages of *right* responses to neutral, left and right prime stimuli, by subject. χ^2 values marked with an asterisk are significant at the $p=.05$ level.

Table 2. Mean RT (ms) for correct responses to target stimuli for each subject, by experimental session and priming condition.

Table 3. Error rates (percent) for target stimuli for each subject by experimental session and priming condition.

Table 4. Mean R^2 across subjects for practice function fits. Experiments 1-3 refer to numbering used in Brown (2002).

Figure Captions

Figure 1. The target stimuli were diamond (left) and square (right) shapes with identical inner contours.

Figure 2. Time course of events in a typical trial. The trial pictured is a neutral trial (prime stimulus favors neither response). Stimuli were black-on-white.

Figure 3. Sample practice curves. Data (circles) are block average RTs from Subject 7 for neutral-prime trials, excluding the first block. Dashed line represents best fitting exponential function: $y=261+101e^{-0.071x}$, where y is block mean RT (in msec) and x is practice block number. The solid line shows the best-fitting practice curve derived from the SEEXC model, with parameters $A=261\text{ms}$, $B=146\text{ms}$, $c=0.72\text{ms}$, $\lambda=0.050$ (see text for equation).

Table 1

	Prime Target Location			χ^2
	Neutral	Left	Right	
Subject 1	48.4	46.9	46.9	0.03
Subject 2	35.9	28.1	46.9	2.45
Subject 3	46.0	44.0	38.7	0.42
Subject 4	58.1	54.8	71.9	2.30
Subject 5	47.6	34.4	56.3	3.15
Subject 6	51.6	9.4	75.0	28.80*
Subject 7	51.6	40.6	65.6	4.04
Subject 8	41.3	59.4	31.3	5.37
Grouped Data	47.6	39.5	54.1	10.8*

Table 2

Subject Number	Session 1			Session 2		
	Neutral	Congruent	Incongruent	Neutral	Congruent	Incongruent
1	288.6	258.1	320.7	297.8	264.6	332.0
2	296.0	257.1	323.1	268.4	229.2	296.4
3	320.8	263.3	375.5	285.4	225.8	345.2
4	351.9	322.4	387.3	325.7	294.0	364.8
5	276.8	256.2	308.2	280.2	259.4	312.4
6	266.5	222.1	290.5	250.3	218.0	290.8
7	311.2	300.6	330.6	273.4	256.3	295.1
8	300.3	265.7	329.8	257.8	228.0	295.2
MEAN	301.5	268.2	333.2	279.9	246.9	316.5

Table 3

Subject Number	Session 1			Session 2		
	Neutral	Congruent	Incongruent	Neutral	Congruent	Incongruent
1	3.9	3.3	13.5	2.2	0.6	12.5
2	6.6	2.3	34.9	8.8	0.9	39.1
3	2.0	1.0	12.8	1.4	0.0	14.7
4	1.8	3.0	5.6	2.3	1.6	8.4
5	2.0	2.3	8.6	1.3	1.3	8.4
6	8.1	2.0	34.5	5.3	0.9	24.7
7	12.5	9.2	25.7	14.1	6.6	27.5
8	5.9	3.3	11.8	8.0	1.6	19.7
MEAN	5.3	3.3	18.4	5.4	1.7	19.4

Table 4

	Function				
	Power	Exponential	General Power	APEX	SEEXC
Experiment 1	.302	.321	.322	.332	.328
Experiment 2	.266	.295	.302	.308	.308
Experiment 3	.395	.445	.465	.472	.471
Current Experiment	.282	.322	.315	.323	.323

Figure 1

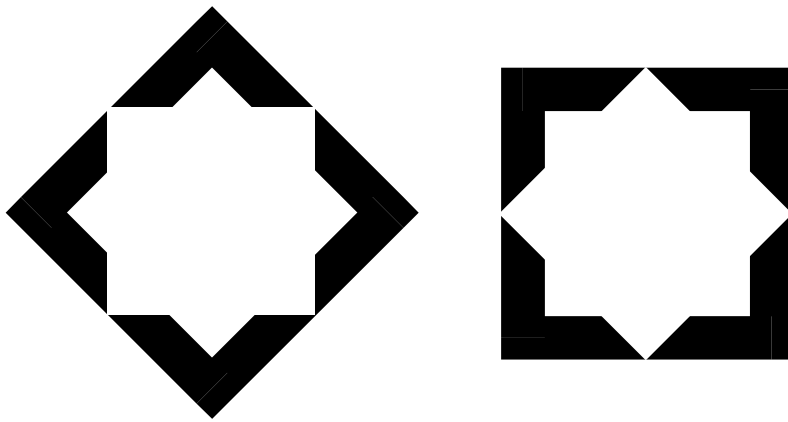


Figure 2

