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Assessing the Speed−Accuracy Trade-Off Effect on the Capacity of Information Processing

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The ability to trade accuracy for speed is fundamental to human decision making. The speed–accuracy trade-off (SAT) effect has received decades of study, and is well understood in relatively simple decisions: collecting more evidence before making a decision allows one to be more accurate but also slower. The SAT in more complex paradigms has been given less attention, largely due to limits in the models and statistics that can be applied to such tasks. Here, we have conducted the first analysis of the SAT in multiple signal processing, using recently developed technologies for measuring capacity that take into account both response time and choice probability. We show that the primary influence of caution in our redundant-target experiments is on the threshold amount of evidence required to trigger a response. However, in a departure from the usual SAT effect, we found that participants strategically ignored redundant information when they were forced to respond quickly, but only when the additional stimulus was reliably redundant. Interestingly, because the capacity of the system was severely limited on redundant-target trials, ignoring additional targets meant that processing was more efficient when making fast decisions than when making slow and accurate decisions, where participants' limited resources had to be divided between the 2 stimuli.

Keywords: speed–accuracy trade-off, capacity, linear ballistic accumulator model, decision making

The speed–accuracy trade-off (SAT) is one of the oldest and most pervasive effects in human perception and performance (Forstmann et al., 2008; Garret, 1922; Hick, 1952; Ollman, 1966; Pachella, 1974; Ratcliff & Rouder, 1998; Schouten & Bekker, 1967; Wickelgren, 1977; Woodworth, 1899). Slower responses tend to be more accurate than faster responses. Further, people seem capable of making the choice to forgo responding accurately in order to make quicker decisions. As such, differences in one variable cannot be interpreted without ensuring that the other is not also changing. For example, when accuracy appears to improve, we must also ensure that participants did not simply slow down.

In the laboratory, we have studied the SAT by having participants make decisions with an emphasis on making either fast or accurate responses. This manipulation of response caution in simple decision tasks has a long history, and is well understood (e.g., Brown & Heathcote, 2005, 2008; Forstmann et al., 2008; Forstmann et al., 2010; Forstmann et al., 2011; Ollman, 1966; Ratcliff, Thapar, & McKoon, 2004; Ratcliff & Rouder, 1998; Wickelgren, 1977). All good models of decision making account for the SAT effect, and though they differ on many key assumptions, most share an evidence accumulation framework (e.g., Brown & Heathcote, 2008; Ratcliff, 1978; Usher & McClelland, 2001).

According to evidence-accumulation models, information is repeatedly sampled from a stimulus and used as evidence for one of the alternative responses. When there is enough evidence for one particular response, a choice is made and the time taken to accumulate evidence is the decision time. In such models, it is commonly assumed that changes in caution are due only to changes in the amount of evidence required to make a decision (Brown & Heathcote, 2008; Forstmann et al., 2008; Ratcliff & Rouder, 1998; Ratcliff & Smith, 2004; Voss, Rothermund, & Voss, 2004). In other words, the SAT is a result of changes in how much evidence is required before a decision is made, but is not influenced by the rate at which evidence is accumulated or the quality of the evidence being accumulated.

Though much is known about the SAT effect in simple tasks (e.g., detection or discrimination of a single item, lexical decision tasks, recognition memory), the influence of caution on performance in more complex tasks has proved more challenging, particularly from a modeling or statistical perspective. We have focused on complex tasks in which multiple inputs must be processed (e.g., multiple item detection, discrimination). We were

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interested in how the processing of multiple signals is influenced by the SAT. Such an analysis has historically been impossible, but we have taken advantage of two recently developed techniques for assessing the processing capacity that permit the explicit study of caution (Eidels, Donkin, Brown, & Heathcote, 2010; Townsend & Altieri, 2012). Thus, we have provided the first principled investigation into the influence of the SAT on the capacity for human multiple-item processing.

Capacity

Humans possess an impressive means of processing multiple sensory inputs. The ability to deal with multiple sources of information can be thought of in terms of the workload capacity of that processing system. In this context, workload refers to the number of to-be-processed sources, and workload capacity reflects the change in the speed of information processing of individual sources as a result of a change in workload. Workload capacity is often assessed using the redundant-target paradigm. For example, in a redundant-target detection task, participants are presented with either zero, one, or two targets, and asked to respond to the presence of at least one target. Consequently, whenever there are two targets present, the second target is redundant.

Workload capacity is measured by comparing performance with two (redundant) targets relative to a single target. Limited capacity implies that the presence of the second, redundant signal slows down the processing of both stimuli together. Unlimited capacity occurs when the presence of additional signals results in no change in processing efficiency. Finally, super capacity refers to an increase in processing efficiency when stimuli are presented together rather than alone.

It is now well understood that comparing mean reaction time (RT) between single- and redundant-target conditions is not sufficient to understand capacity. The problem is that even when individual targets are processed at the same rate, the mean RT for two targets may still be faster than for one target due to statistical facilitation (Egeth & Dagenbach, 1991; Miller, 1982; Townsend & Nozawa, 1995). To overcome this issue, Townsend and colleagues (Townsend & Nozawa, 1995; Townsend & Wenger, 2004) developed the capacity coefficient, which compares the entire distribution of correct RTs in single- and redundant-target conditions. The capacity coefficient uses the RTs in the single-target conditions to produce predictions for what should happen on redundant-target trials, under the assumption that the second target had no influence on the processing of the first target (i.e., an unlimited-capacity, independent parallel [UCIP], race model). The observed RT distributions in the redundant-target condition are compared with the predictions of the baseline UCIP model to determine whether the additional targets help or hurt performance (i.e., are better or worse than unlimited capacity, respectively).

Although the capacity coefficient is a powerful diagnostic tool, one disadvantage is that it assumes responses are always correct. This is rarely an issue in detection tasks, where the presence of a target is enough to elicit a response and so accuracy is typically at ceiling for above-threshold target contrasts. However, if one is forced to sacrifice accuracy to respond quickly (i.e., when there is a SAT), then the capacity coefficient is no longer an appropriate tool for measuring capacity. For this reason, there has been no study of the influence of the SAT on how multiple signals are processed.

Two recent major advances in methodology have made it possible to now measure capacity when performance is not at ceiling. Eidels et al.'s (2010) parametric capacity measure and Townsend and Altieri's (2012) nonparametric capacity assessment function both give a measure of capacity that takes into account accuracy and RT. With these new tools, which we now briefly introduce, we can investigate the influence of the SAT on workload capacity.

Linear Ballistic Accumulator−Based Capacity

Recall that Townsend and Nozawa's (1995) capacity coefficient derives its form from the predictions of an UCIP race model. Though the original capacity coefficient does not assume a particular parametric form, Eidels et al. (2010) showed that it was possible to extract a capacity measure using a particular model—the linear ballistic accumulator (LBA) model (Brown & Heathcote, 2008). The LBA is an evidence-accumulation model designed to account for accuracy and RT distributions in simple, two-choice tasks. Eidels et al. (2010) extended the LBA model to account for accuracy and RT in the more complex, redundant-target experiment. A capacity measure is calculated by using a parameterization of the model specifically chosen to assess the impact of adding additional targets on processing speed. As such, the model uses both accuracy and RT to determine whether additional signals help or hinder processing, and is therefore capable of determining the influence of the SAT effect on workload capacity.

Assessment Function

Townsend and Altieri (2012) provided an update to the capacity coefficient by incorporating choice probabilities and incorrect RT distributions along with the correct RT distributions. Their new assessment function, $A(t)$, also uses the UCIP race model as a baseline model with which to compare observed data, but now considers both the speed and the accuracy of observed responses. The $A(t)$ functions are more nuanced than the standard capacity coefficient, but this additional complexity brings more information about how redundant signals are processed, as well as an ability to take into account the influence of the SAT.

Our aim was to use the parametric (LBA-based) and nonparametric (assessment function) measures of workload capacity to investigate the influence of the SAT on multiple signal processing. We present the results of two redundant-target experiments in which we asked participants to make discrimination decisions with an emphasis on either being accurate or responding quickly. Based on the many previous results demonstrating the influence of the SAT in simple tasks, we expected that our manipulation of response caution would only affect the amount of evidence required to respond, but not the rate at which items were processed (i.e., we did not expect the capacity of the processing system to be influenced by speed or accuracy emphasis).

Experiment 1

Our original aim was to manipulate caution in a redundant-target detection task, as detection is the standard redundant-target task that is used to assess capacity (Townsend & Altieri, 2012).

However, pilot testing revealed a number of issues with manipulating response emphasis in a detection task. The major problem is that detection is easy, and so responses tend to be both fast and almost perfect. It is therefore difficult for participants to respond more quickly and make errors, as required under speed emphasis. A second issue arises due to the nature of the detection task, in which a target is either present or absent. The format of trials is generally such that a fixation cross begins a trial, followed by a short pause, and then the target either appears or remains absent. During pilot testing, we found that error responses occurred as a result of misjudging when the target would appear. That is, errors were so fast that they usually preempted the presentation of the target.

Although it may be possible to adapt the design of the detection task to make it more amenable to a response caution manipulation, we instead decided to use a discrimination version of the redundant-target task. In our discrimination task, participants were asked to classify targets as either light or dark (depending on the proportion of black and white pixels). On single-target trials, we presented just one target to be classified, while in redundant-target trials we presented the same target in two on-screen locations. As in the detection version of the redundant-target task, a measure of workload capacity comes from the difference in RT and accuracy between redundant- and single-target trials.

Method

Participants. Eight participants each completed three identical experimental sessions. Participants were recruited using noticeboards posted around the University of New South Wales, and were reimbursed $15 for each session. Our plan was to test eight participants, but one participant did not return after completing just one session, and so a ninth individual was recruited to ensure we had eight full data sets.

Stimuli and design. Each target was a 30 × 30 pixel square containing a random arrangement of white and black pixels. Targets were either light, containing 45% black pixels, or dark, containing 55% black pixels. Targets were presented on a 24-in. monitor with resolution 1680 × 1050. A target could be presented in one of two locations—upper and lower. In the upper location, the center of the target was 17 pixels above the center of the screen, and in the lower location, the center of the target was 17 pixels below the center of the screen. The distance between the two targets when both targets were present was 4 pixels. We also used a circle with a 7-pixel diameter presented in the center of the screen as a fixation point.

The experiment was a 2 × 3 × 2 (Emphasis [accuracy, speed] × Location [upper, lower, or both] × Brightness [light, dark]) within-subjects design. At the start of each block of trials, participants were told whether they should be as accurate as possible, or if they should respond as quickly as possible, without resorting to guessing. Either a single target was presented in either of the upper or lower locations, or two targets were presented simultaneously in both locations. The target (or targets) was either light or dark (depending on whether the proportion of black pixels was 45% or 55%, respectively). If two targets were presented, then they were identical. Participants were told explicitly that when two targets were presented that they would be the same.

Procedure. Each trial began with a fixation cross presented for 500 ms. Either one target or two targets were then presented until a response was made. Participants were instructed to press the "F" key on the keyboard if the target (or targets) was light, and to press the "J" key if the target (or targets) was dark. An on-screen reminder of the button mappings was displayed at the bottom of the screen on every trial. The feedback participants received depended on the emphasis condition for that block. In accuracy-emphasis blocks, participants received feedback on the accuracy of their response. If correct, then the word CORRECT was displayed in the center of the screen for 500 ms. If incorrect, the word INCORRECT was shown for 1,500 ms. In speed-emphasis blocks, participants received feedback on both the accuracy and the speed of their response. If the RT was faster than 500 ms, the phrase GOOD TIME was displayed in the center of the screen for 500 ms. If the RT was slower than 500 ms, the phrase TOO SLOW was shown for 1,500 ms. In addition to the feedback on RT, participants were told whether their responses were Correct or Incorrect underneath the RT feedback. The screen then remained blank for 500 ms, and the next trial began. At the end of each block of trials, participants were given their percent correct and mean RT for that block.

Participants completed four blocks of 180 trials. In each block, half of the targets were light and half were dark. For each target type, one third of trials were presented in the upper location, one third were presented in the lower location, and one third were presented in both locations. The order of trials within a block were randomized. The response-emphasis condition alternated from speed to accuracy from block to block, continuing across sessions. The emphasis in the first block of trials was such that half of the participants began with speed emphasis and half with accuracy emphasis. During the first session only, participants first completed two practice blocks of 90 trials, one with accuracy emphasis and another with speed emphasis (always in that order). Practice trials were identical to standard trials, but were removed from analysis.

Results

We first excluded all trials on which RT was greater than 3 s or was less than 280 ms. The lower cutoff of 280 ms was chosen because it marked the point at which all participants' responses were at chance performance. For each participant, and for each emphasis condition, any trial for which RT was greater than 2.5 *SD* above the mean was excluded. Overall, 5.2% of the data was removed based on this censoring.

Summary measures. The mean proportion of correct responses for dark and light stimuli were almost identical ($P_{dark} = 0.85$ and $P_{light} = 0.86$, $p = 0.79$), as was mean RT ($RT_{dark} = 619$ ms and $RT_{light} = 599$ ms, $p = 0.20$), and so, in what follows, we collapsed over light and dark stimulus conditions. We submitted proportion correct responses and mean RT for correct responses to a 2 × 2 (Emphasis [speed or accuracy] × Targets [redundant or single]) within-subjects analysis of variance (ANOVA). The emphasis manipulation had the expected effect on proportion correct, with a higher proportion of correct responses under accuracy emphasis ($P_{accuracy} = 0.93$) than under speed emphasis ($P_{speed} = 0.78$), $F(1, 7) = 41$, $p < .001$. The mean RT for correct responses was also faster under speed emphasis ($RT_{speed} = 462$ ms) than under accuracy emphasis ($RT_{accuracy}$ = 752 ms), $F(1, 7) = 22.48$, $p = .002$.

The main effect of targets failed to reach significance for either dependent variable, but this was because the difference between redundant-target and single-target conditions depended on whether speed or accuracy was emphasized, that is, the interaction was significant for proportion correct, $F(1, 7) = 6.4$, $p = .04$, and for mean correct RT, $F(1, 7) = 18.3$, $p = .004$. Under accuracy emphasis, responses were 28 ms slower and 1.5% less accurate when there were two targets ($P_{redundant} = 0.92$ and $RT_{redundant}$ = 771 ms) than when there was just one target ($P_{single} = 0.93$ and RT_{single} = 743 ms). However, when speed was emphasized, responses were 8 ms faster and 2% more accurate when there were two targets ($P_{redundant} = 0.79$ and $RT_{redundant}$ = 465 ms) than when there was one target ($P_{single} = 0.78$ and RT_{single} = 460 ms). As mentioned earlier, these results tell us relatively little about the capacity of the processing system, and so we turn to our parametric and nonparametric measures of capacity for further analysis.

LBA-based capacity. We first briefly outline the standard LBA, and then describe its extension to the redundant-target task. We then show how the parameters of the model can be used to assess the influence of redundant targets.

Consider first an LBA model for the classification of a single target as either light or dark (i.e., having less or more black pixels). Each response, light or dark, receives its own accumulator, and these accumulators are assumed to be independent of one another. The starting evidence in accumulator i begins at a random value between 0 and A. Evidence then accumulates linearly and without noise at a rate drawn from a normal distribution with mean v_i and *SD* s. The mean accumulation rate, v_i, for the correct response will be larger than for the incorrect response. For example, if a target has more black than white pixels, then there should be more evidence for the dark response, and hence v_{dark} should be larger than v_{light}. One of the two responses is made when the evidence for the corresponding accumulator reaches threshold b. The decision time is equal to the time taken for evidence to first reach threshold, and the predicted RT is decision time plus the time taken for nondecision aspects of RT (such as the motor response or stimulus encoding), t_0.

In the LBA model for the redundant-target paradigm, we assumed that when two targets were presented, they would be processed in four independent, parallel accumulators—one accumulator for each response, for each target. The LBA-based capacity measure, hereafter referred to as v_{cap}, was calculated by taking the difference between the accumulation rate for the correct response when two targets were present (the same accumulation rate was used for each of the two targets) and the accumulation rate for the correct response when just one target was present ($v_{cap} = v_{rt} - \mathbf{v}_{st}$, where v_{st} is the rate for the single-target conditions and v_{rt} is the accumulation rate for each target in redundant-target conditions). If the accumulation rate for two targets is the same as the rate for just one target (i.e., $v_{rt} = v_{st}$ or $v_{cap} = 0$), then capacity is said to be unlimited, reflecting the fact that there is no change in the rate of processing across the double- and single-target conditions. When evidence accumulation rate is slower when there are two targets compared with when there is just one target, then capacity is said to be limited ($v_{rt} < v_{st}$ or $v_{cap} < 0$). Finally, if accumulation rate is faster when there are two targets, then we have super capacity ($v_{rt} > v_{st}$ or $v_{cap} > 0$). Eidels et al. (2010) showed that v_{cap} was largely consistent with the nonparametric estimates of capacity using the standard capacity coefficient. One goal of the present article was to examine how v_{cap} corresponds to Townsend and Altieri's (2012) assessment function.

As mentioned earlier, we collapsed over light and dark responses and stimuli, and therefore talk about only correct and incorrect responses. We fit a model that held the majority of parameters constant across correct and incorrect responses, single- and redundant-target displays, and response-emphasis conditions. The parameters held constant were (a) the maximum of the between-trial start-point distribution, A, (b) the *SD* of the between-trial drift rate distribution, s, and (c) the nondecision time parameter, t_0. We allowed only accumulation rate parameters to vary across single- and redundant-target conditions. We estimated a mean accumulation rate in the correct accumulator separately for single-target displays, v_{st}, and redundant-target displays, v_{rt}. The mean accumulation rate for the incorrect response was fixed at $1 - v_{st}$ and $1 - v_{rt}$, as a means of solving the scaling property of RT models (see Donkin, Brown, & Heathcote, 2009, for more information).

We varied the remaining parameters in two different model parameterizations, which assumed different effects of the response-emphasis conditions. The first parameterization assumed that only response threshold, b, varied across speed- and accuracy-emphasis conditions. This *selective influence* model is consistent with the standard effect of response caution in two-choice tasks in that only response thresholds are influenced. This first model had seven free parameters: A, t_0, s, v_{st}, v_{rt}, b_{acc}, and b_{spd}. The second parameterization allowed both response thresholds and the accumulation rate parameters to vary with response emphasis. This second model allowed for the possibility that caution influences both response thresholds and capacity. The second model had an additional two parameters, for a total of nine free parameters: A, t_0, s, b_{acc}, b_{spd}, $v_{st_{acc}}$, $v_{rt_{acc}}$, $v_{st_{spd}}$, and $v_{rt_{spd}}$.

The two models were fit to each of the eight individual participant's full RT distributions for correct and incorrect responses, in each of the single- and redundant-target conditions under both speed and accuracy emphasis using maximum likelihood estimation. Brown and Heathcote (2008) have provided equations for the probability density, $f(t \mid \Theta)$, and cumulative density, $F(t \mid \Theta)$, of an LBA accumulator with parameters Θ. When there is just one target present, the likelihood that the correct accumulator C has reached threshold by time t before the incorrect accumulator I has reached threshold by the same time is:

$$f_C(t|\Theta_C)[1 - F_I(t|\Theta_I)] \tag{1}$$

When there are two targets present, the likelihood that the correct response is given by time t can happen when the accumulator associated with the correct response for either target A or target B is the first to reach threshold. Therefore, the likelihood of a correct response at time t is:

$$\begin{aligned} f_{C_A}(t|\Theta_{C_A})[1 - F_{C_B}(t|\Theta_{C_B})] \cdot [1 - F_{I_A}(t|\Theta_{I_A})] \cdot [1 - F_{I_B}(t|\Theta_{I_B})] \\ + f_{C_B}(t|\Theta_{C_B})[1 - F_{C_A}(t|\Theta_{C_A})] \cdot [1 - F_{I_A}(t|\Theta_{I_A})] \\ \cdot [1 - F_{I_B}(t|\Theta_{I_B})] \end{aligned} \tag{2}$$

The likelihood of incorrect responses can be obtained by simply switching all of the C and I subscripts. Best-fitting parameters were found using a combination of SIMPLEX and particle swarm optimization.

We assessed model parsimony using the Bayesian information criterion (BIC). The value of BIC decreases as the quality of the fit of a model to data, l, increases. However, BIC becomes larger as the number of free parameters, k, in the model increases. More formally, $\text{BIC} = k \log N - 2l$. The model with the smallest BIC value is said to provide the most parsimonious account of the data.

We found the more complex parameterization of the LBA model, which allowed both accumulation rate and response thresholds to vary as a function of the response-emphasis manipulation, had the smallest BIC for all eight participants. The difference in BIC between the two models across individuals ranged from 7.56−73.48 points. These BIC values can be turned into BIC weights (Wagenmakers & Farrell, 2004). Once transformed, the smallest probability for the accumulation rate *and* response-threshold model, relative to the response-threshold-only model, was 0.98. As such, we will now focus our discussion on the model in which accumulation rate and response threshold both change across emphasis conditions.

The best-fitting parameters for each individual are reported in Table 1. As expected, response thresholds were larger, $t(7) = 5.7$, $p < .001$, under accuracy emphasis ($b = 0.48$) than under speed emphasis ($b = 0.29$). Figure 1 contains the accumulation rates for redundant-target trials and single-target trials under both accuracy and speed emphasis. Rates for redundant-target trials were smaller than for single-target trials (i.e., $v_{cap} < 0$), suggesting that capacity was limited in this task, $F(1, 7) = 42$, $p < .001$. Further, accumulation rates were higher under accuracy emphasis than under speed emphasis, $F(1, 7) = 37$, $p < .001$. Also, the difference between redundant- and single-target accumulation rates was larger under accuracy emphasis than under speed emphasis, suggesting that capacity was more limited under accuracy emphasis, $F(1, 7) = 52$, $p < .001$.[1]

Assessment function. Townsend and Altieri (2012) derived their assessment function to account for behavior in detection tasks, with particular decision rules (e.g., respond when at least one target is present). Our experiment used a different decision rule, and thus required us to derive our own assessment function for Experiment 1. In our experiment, participants were instructed to indicate whether the target (or targets) was light or dark, but were told that whenever two targets were presented, the brightness of each target would be identical (hence, if one target was light, then the other would necessarily also be light). Therefore, the baseline model used to derive the assessment function assumed that participants responded as soon as one of the targets was finished being processed (cf. the LBA model above).

Our assessment function takes the same form as Townsend and Altieri's (2012) $A(t)$, in that it partitions RTs into four categories: (a) the probability that a correct response is made by time t, (b) the probability that an incorrect response is made by time t, (c) the probability that a correct response will be made but has not happened by time t, and (d) the probability that an incorrect response will be made but has not happened by time t. Following Townsend and Altieri (2012), we called these circumstances, respectively, (a) correct and fast, (b) incorrect and fast, (c) correct and slow, and (d) incorrect and slow. The influence of additional targets was measured for each of these four types of responses by comparing performance on redundant-targets trials with that predicted based on the UCIP race model.

The equations for calculating $A(t)$ in Experiment 1 are given in Table 2. The full details of the derivation of these equations are given in Appendix A, but the following two examples may help readers understand how we derived the assessment functions. A correct and fast response on a redundant-target trial occurred in our Experiment 1 when a participant correctly identified a stimulus in channel A before channel B has finished processing or when the stimulus in channel B is correctly identified before channel A finished processing (the first equation in Table 2). On the other hand, an incorrect and slow response occurred when the stimulus in channel A was incorrectly identified before channel B finished being processed, or when the stimulus in channel B was incorrectly processed before channel A finished (the final equation in Table 2). It is important to note that although their calculations differed, the interpretation of our alternative capacity measure was the same as that for the standard $A(t)$.

This interpretation is more nuanced than the standard capacity coefficient. Those familiar with the standard capacity coefficient of Townsend and Nozawa (1995) will recall that values greater, equal, and less than 1 simply implied super, unlimited, or limited capacity, respectively. However, when interpreting the $A(t)$ function, one has to consider the type of response being made. For example, the interpretation of $A(t)$ for correct and fast responses bears the closest resemblance to the standard capacity coefficient. When $A(t) = 1$ for correct and fast responses, this implies that the observed responses made before time t were as probable as expected by the UCIP race model (i.e., as if the addition of the second, redundant target had no influence on the processing of the first target). A correct and fast $A(t) > 1$ means that participants made more correct responses by time t than was expected, and thus were exhibiting a form of super capacity. Similarly, correct and fast $A(t) < 1$ implies that fewer correct responses were made by time t than expected by the UCIP model (i.e., capacity was limited).

The interpretation differs for the other types of responses. For example, for the incorrect and slow responses, $A(t) > 1$ would mean that more incorrect responses were made after time t than was expected in the UCIP model, which implies a type of limited capacity. Finally, one must also consider the time t under consideration. For example, a limited capacity system might yield $A(t) > 1$ for correct and slow responses for a larger t, because correct responses were much slower than was expected.

We calculated the four different types of $A(t)$ separately for speed- and accuracy-emphasis conditions. The upper panel of Figure 2 shows the four different types of capacity for the speed-emphasis condition. The bottom panel of Figure 2 shows the four capacities for the accuracy-emphasis condition.

[1] There are many different means of calculating capacity from linear ballistic accumulator parameters, such as $(v_{rt} - v_{st})/s$ or v_{rt} / v_{st}. We reach the same conclusions (e.g., that capacity is more limited under accuracy emphasis) regardless of the specific measure of capacity that is used. However, as with all interactions where the underlying scale of the dependent variable cannot be known, the results should be interpreted with caution (though we do assume that accumulation rates lie on a linear scale).

Table 1
Best-Fitting Parameter Estimates for Each Individual Participant in Experiment 1

	Participant							
Parameter	1	2	3	4	5	6	7	8
s	0.23	0.35	0.38	0.38	0.57	0.40	0.55	0.28
A	0.14	0.13	0.19	0.28	0.17	0.10	0.52	0.11
t_0	0.17	0.24	0.27	0.23	0.27	0.24	0.30	0.24
b_{acc}	0.35	0.49	0.41	0.61	0.54	0.29	0.82	0.30
b_{spd}	0.28	0.22	0.22	0.42	0.28	0.18	0.52	0.23
$v_{st_{acc}}$	0.73	1.02	0.88	1.05	1.28	0.79	1.01	0.87
$v_{rt_{acc}}$	0.67	0.74	0.70	0.88	1.08	0.62	0.80	0.77
$v_{st_{spd}}$	0.64	0.81	0.73	0.85	0.96	0.67	0.79	0.69
$v_{rt_{spd}}$	0.60	0.64	0.66	0.73	0.86	0.61	0.68	0.67

Comparison of all four panels in Figure 2 reveals a number of differences between the $A(t)$ functions under speed- and accuracy-emphasis conditions. The assessment functions within each panel can be readily summarized as follows:

(1) For correct and fast responses, $A(t)$ appears more limited under accuracy emphasis than speed emphasis. Under accuracy emphasis, $A(t)$ lies consistently below 1, suggesting that responses were slower and less frequent than expected. Mirroring the results using the LBA-based capacity measure, the $A(t)$ functions under speed emphasis appear much closer to unlimited capacity. In particular, one can see that, in the speed condition, the $A(t)$ functions rise relatively quickly back to a value closer to unity. However, under accuracy emphasis, one sees that $A(t)$ not only fails to reach the same height as the speed emphasis $A(t)$ function, but also takes much longer to reach asymptote.

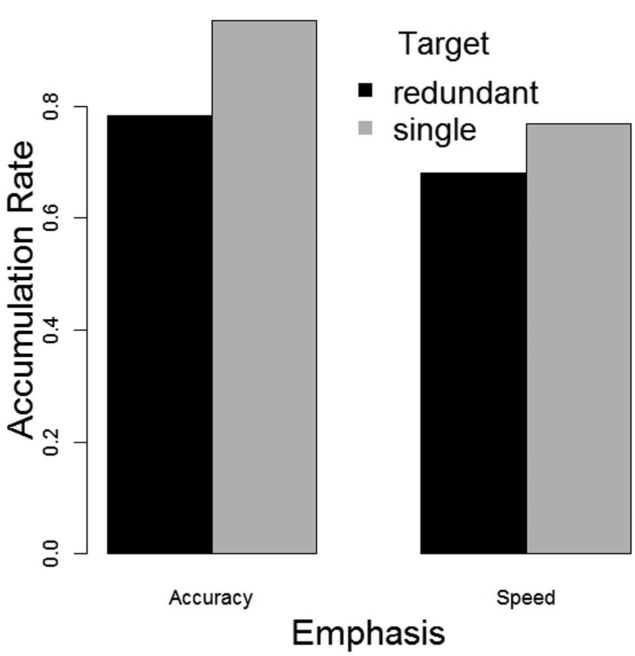

Figure 1. Accumulation rates for redundant- and single-target trials under accuracy- and speed-emphasis conditions. Rates suggest that capacity is limited, and more so under accuracy emphasis.

(2) For correct and slow responses, $A(t)$ is greater than 1, indicating that correct and slow responses were more probable and slower than expected. One can also see that almost all $A(t)$ functions under speed emphasis begin above unity, while those under accuracy emphasis tend to begin at a value below unity. As will soon be shown, such a pattern suggests that responses under accuracy emphasis are more limited in capacity than under speed emphasis.

(3) Looking at incorrect and fast responses, one can see that incorrect responses made by time t under speed emphasis were less probable than expected, which is characteristic of a system with higher capacity. On the other hand, the $A(t)$ functions under accuracy emphasis were closer to 1, consistent with the interpretation that capacity is more limited in the accuracy condition.

(4) For the incorrect and slow responses, the $A(t)$ measure is greater than 1, indicating faster than expected and more incorrect and slow responses compared with the unlimited capacity parallel baseline model. It is worth noting that the $A(t)$ functions under speed emphasis start at values below unity, while those under accuracy emphasis tend to start above 1, another trend that is expected if capacity is more limited under accuracy emphasis (see Figure 3).

To sum up, the $A(t)$ measure indicates that the process used in our discrimination task was less efficient than the baseline model in the sense that correct and fast responses were less probable but incorrect responses or correct but slow responses were more probable. Further, this limited capacity processing is more extreme under the accuracy-emphasis than in the speed-emphasis condition.

As is probably clear by now, the interpretation of $A(t)$ functions is nontrivial. To help our interpretation of the results in Figure 2, we generated data from an LBA model of limited capacity ($v_{cap} <$

Table 2
Numerators for the Discrimination Capacity Assessment Function in Experiment 1

Correct and fast	$-\log[P\{T_{A_C} < T_{A_I}\}\int_0^t [1 - F_B(t')]f_{A\vert C}(t')\,dt' + P\{T_{B_C} < T_{B_I}\}\int_0^t [1 - F_A(t')]f_{B\vert C}(t')\,dt']$
Incorrect and fast	$-\log[P\{T_{A_I} < T_{A_C}\}\int_0^t [1 - F_B(t')]f_{A\vert I}(t')\,dt' + P\{T_{B_I} < T_{B_C}\}\int_0^t [1 - F_A(t')]f_{B\vert I}(t')\,dt']$
Correct and slow	$-\log[P\{T_{A_C} < T_{A_I}\}\int_t^\infty [1 - F_B(t')]f_{A\vert C}(t')\,dt' + P\{T_{B_C} < T_{B_I}\}\int_t^\infty [1 - F_A(t')]f_{B\vert C}(t')\,dt']$
Incorrect and slow	$-\log[P\{T_{A_I} < T_{A_C}\}\int_t^\infty [1 - F_B(t')]f_{A\vert I}(t')\,dt' + P\{T_{B_I} < T_{B_C}\}\int_t^\infty [1 - F_A(t')]f_{B\vert I}(t')\,dt']$

Note. The denominators are presented in Appendix A. Note that $P\{T_{A_C} < T_{A_I}\}$ is the probability that the correct response is made in channel A (over an incorrect response), $F_B(t')$ is the probability that either a correct or incorrect response was made in channel B by time t', and $f_{A|C}(t')$ the probability that the correct response in channel A will be made at time t'.

0) and super capacity ($v_{cap} > 0$).[2] We then calculated $A(t)$ for the simulated data sets, as per Experiment 1. Figure 3 plots the resultant assessment functions. We can now compare the results in Figure 2 with the difference between the solid lines, generated from a limited capacity system, and the dotted lines, generated from a system with super capacity. It is immediately clear from a comparison of all four panels of Figure 2 and Figure 3 that our participants look more like the solid, limited capacity lines than the dotted, super capacity lines.

Our interpretation of the empirical $A(t)$ functions was that capacity looked more limited under accuracy than speed emphasis. However, given our limited experience with the $A(t)$ function, it seems possible that we might expect the qualitative difference between speed- and accuracy-emphasis conditions even if only response thresholds vary (i.e., if capacity is unaffected). To test this possibility, we also simulated data sets in which response threshold was either small (to reflect speed emphasis) or large (accuracy emphasis). Note that drift rates did not differ across speed- and accuracy-emphasis conditions, and so the simulated data were equivalent to the selective influence model tested earlier.[3] Therefore, the light gray (speed-emphasis) and dark gray (accuracy-emphasis) lines correspond to $A(t)$ functions we would expect to see if the caution manipulation had a selective influence on response thresholds. The figure largely confirms that our interpretation of the assessment functions in Figure 2 was appropriate. In particular, we see that the simulated assessment functions tend to shift to the right (and up or down, depending on whether the responses were incorrect or correct, respectively), but show no change in the qualitative form of the function. This is unlike the change in shape we observed in the empirical $A(t)$ functions that we attributed to more limited capacity when responding accurately.

Finally, Townsend and Altieri (2012) described a method for calculating the assessment functions conditionalizing on accuracy, so that only the speed of responses is used to measure capacity. Because accuracy in the redundant- and single-target conditions did not differ greatly, the conditional assessment functions contain relatively little additional information beyond that in Figure 2. Nonetheless, we report the conditional assessment functions for both Experiments 1 and 2 in Appendix B.

Discussion

Manipulating the amount of caution required when responding had the standard effect on behavior—compared with accuracy-emphasis—responses were faster and less accurate when responding quickly was emphasized. The LBA-based analysis of the data revealed that changes in caution were in part due to adjustment of the amount of evidence required to make decisions. Consistent with the standard explanation of the SAT, participants show more caution by increasing the threshold amount of evidence needed to make a response (Ratcliff & Rouder, 1998).

In contrast to typical results, we also observed that the manipulation of caution in our redundant-target experiment also influenced the rate at which evidence accumulated. Responding more quickly led to an overall decrease in accumulation rates. However, the decrease was larger in single-target trials than in redundant-target trials. This pattern caused processing under speed pressure to become more unlimited-like in capacity. That is, though processing was less efficient (accumulation rates were lower), there was less of a cost of having a redundant target present (single- and redundant-target rates were almost identical).

One possible cause of the differential effect of response caution on capacity is that when under speed emphasis, participants may have not always attended to both of the redundant stimuli. By contrast, when accuracy was emphasized, participants may have attempted to extract information from both targets. Due to the limited workload capacity of the processing system, accumulation rates for individual targets were lowered when both items had to be processed. On the other hand, when speed was emphasized, participants may have, in their rush to respond quickly, only attended to one of the two targets. Because attention was directed at just one of the targets, processing was degraded less by the presence of the second target when speed was emphasized (i.e., the true limited capacity of the processing system had less of an effect on performance, because participants simply ignored one of the two stimuli).

Experiment 2

Processing just a single target when attempting to respond quickly was a perfectly reliable strategy in our first experiment because whenever there were two targets, they were both always of the same type (light or dark). In fact, as participants were explicitly

[2] The simulated data sets used to generate Figure 3 were based on 60,000 simulated trials. The following parameters were constant across limited and super capacity data sets: $A = 0.3$, $t_0 = 0.25$, and $s = 0.25$, and the accumulation rate for single-target trials, v_{st}, was set at 0.75. In the limited capacity data set, the accumulation rate for redundant-target trials was $v_{rt} = 0.6$. In the super capacity data set, v_{rt} was set at 0.9.

[3] In the speed-emphasis condition, the threshold was set to $b = 0.35$; and in the accuracy-emphasis condition, the threshold was set to $b = 0.5$.

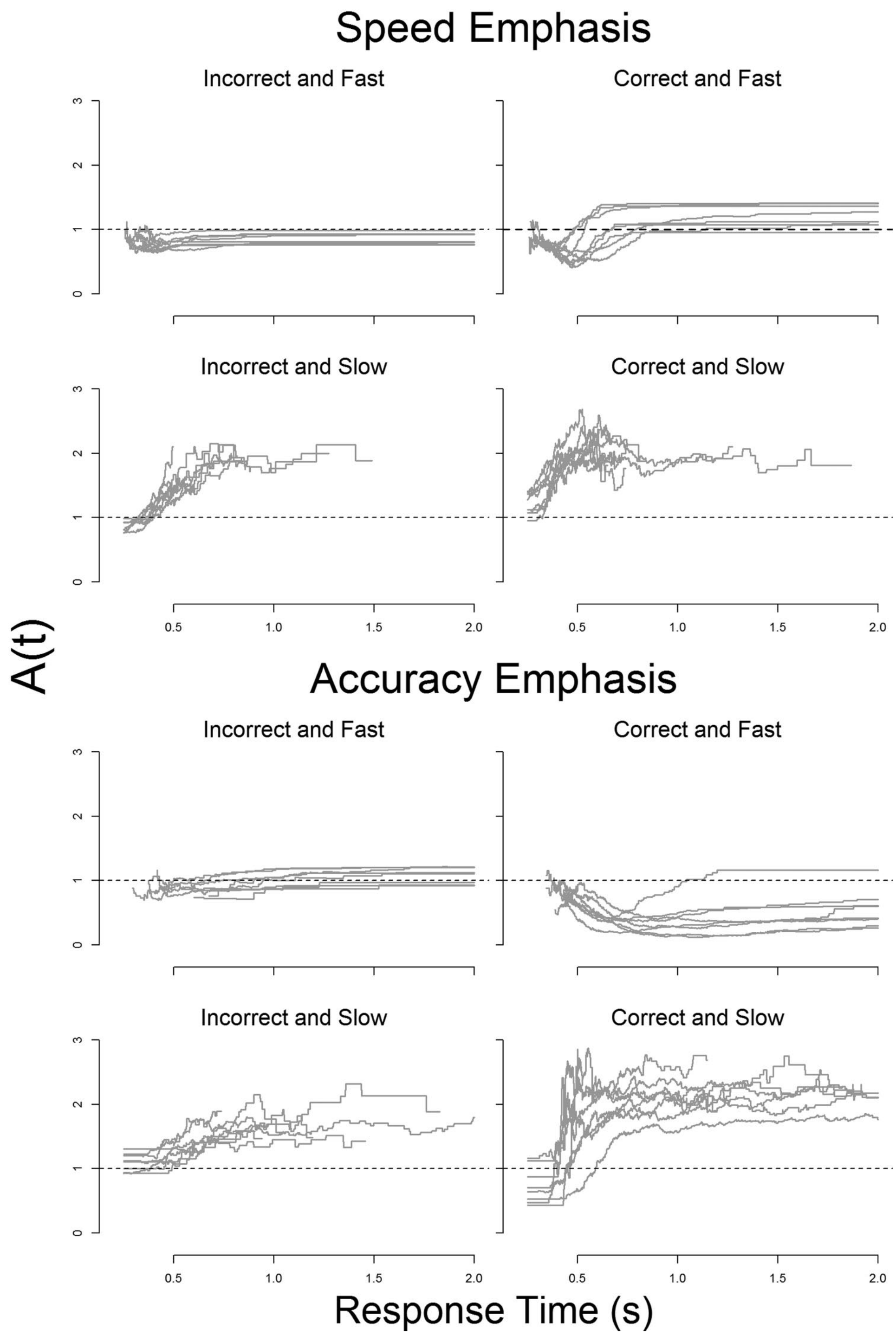

Figure 2. Assessment functions for incorrect and fast, correct and fast, incorrect and slow, and correct and slow responses under speed- and accuracy-emphasis conditions (top and bottom set of plots, respectively) in Experiment 1.

told, the two targets were always identical. In this second experiment, we included trials that broke this contingency. Our second experiment was almost identical to the first experiment, except that we sometimes presented displays containing one light and one dark target. So that participants could respond on these trials, we told them to respond by pressing one button if there was at least one "light" target present, and to only press the other button when there were no light targets present. If participants focused on just

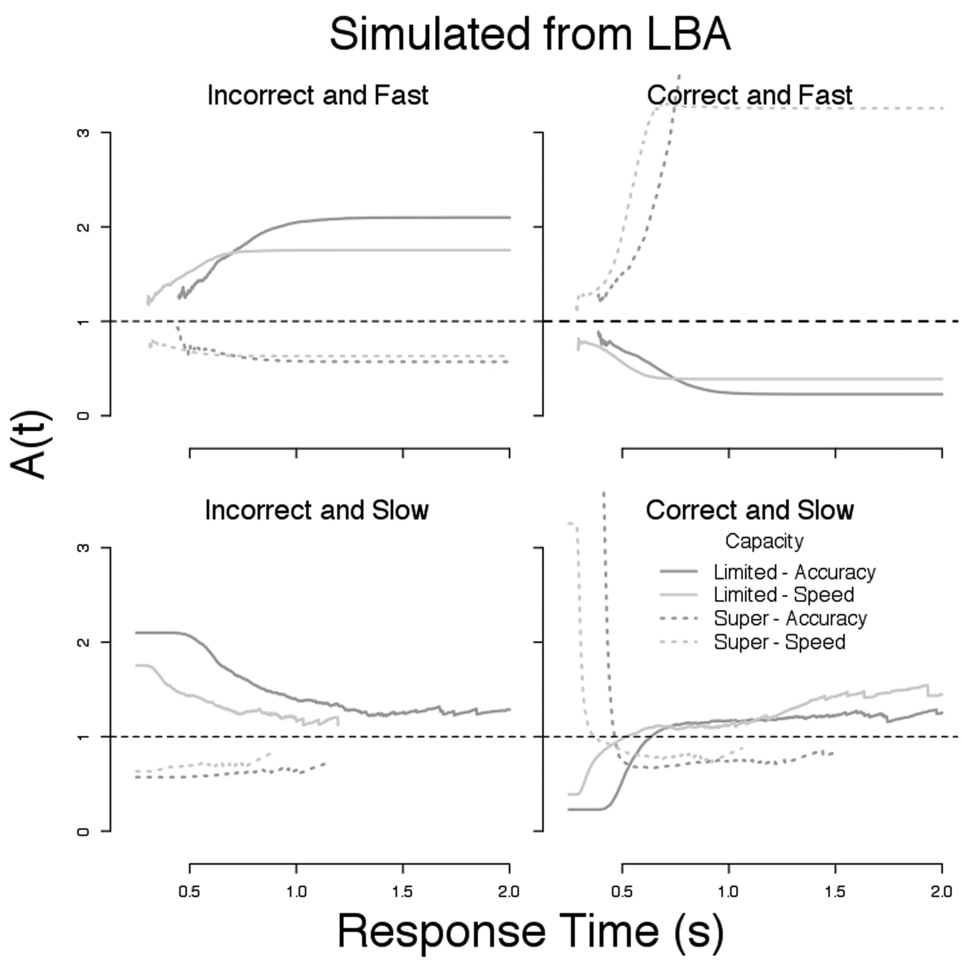

Figure 3. Assessment functions for incorrect and fast, correct and fast, incorrect and slow, and correct and slow responses from two versions of the redundant-target linear ballistic accumulator (LBA) model—with limited and super capacities (thick and dotted lines, respectively).

one target when under speed emphasis, then they would be at chance on displays containing one light and one dark target. An upshot of this new design was that the decision rule in Experiment 2 was the same as in Townsend and Altieri (2012), and so we could use their assessment function.

Method

Eight participants, recruited and reimbursed in the same way as in Experiment 1, completed four sessions in Experiment 2. The stimuli were identical to those in Experiment 1. The design was also identical to that in Experiment 1, except that we now included ”catch” trials, in which two items of different brightness were presented. During this session, participants completed four blocks of 200 trials. In each block, there were 100 single-target trials, half light and half dark, and 100 trials on which two items were presented. Of these, 50 trials were the redundant-target trials, half with two light stimuli and half with two dark stimuli. The new catch trials made up the remaining 50 trials, half with the light stimulus in the upper location (and the dark stimulus in the lower location) and half with the dark stimulus in the upper location.

The instructions were updated to take account of these new trials. Participants were told that they were to press the “F” key if there was ever a light stimulus present on screen, and to press “J” whenever there were no light stimuli present. This response mapping meant that “F” was the correct response on 62.5% of trials (two light stimuli, one light and one dark stimulus, and a single light stimulus.), and the “J” key was correct for 37.5% of trials (a single dark stimulus or two dark stimuli).

Results

The same criteria for censoring of trials was used for the data in Experiment 2. Overall, 3.9% of the data was removed.

Summary measures. We first focused on the single- and redundant-target conditions in which light stimuli were used, because the response instructions given to participants meant that only these conditions were used to calculate capacity. We submitted the proportion of correct responses and mean RT for correct responses to a 2 × 2 (Emphasis [speed or accuracy] × Targets [single or redundant]) within-subjects ANOVA. The emphasis condition again had the expected effect on both proportion correct ($P_{accuracy}$ = 0.95 vs. P_{speed} = 0.90), $F(1, 7) = 89$, $p < .001$, and on mean RT ($RT_{accuracy}$ = 573 ms vs. RT_{speed} = 413 ms), $F(1, 7) = 17$, $p = .004$. However, unlike Experiment 1, we do not observe an interaction between the emphasis and location factors on accuracy or RT (p = .23 and p = .14, respectively). An extra target had no effect on the proportion of correct responses (p = .15), but did lead to an increase in mean RT ($RT_{redundant}$ = 503 ms vs. RT_{single} = 483 ms), $F(1, 7) = 10$, $p = .016$.

Though much less important for the calculation of capacity, we also examined the effect of emphasis and target redundancy for dark stimuli. Being asked to respond more carefully also improved performance for dark stimuli (proportion correct: $P_{accuracy}$ = 0.86 vs. P_{speed} = 0.70), $F(1, 7) = 31.2$, $p < .001$; (mean RT: $RT_{accuracy}$ = 645 ms vs. RT_{speed} = 467 ms), $F(1, 7) = 20.3$, p = .003). The presence of an extra dark stimulus led to an increase in accuracy ($P_{redundant}$ = 0.80 vs. P_{single}= 0.76), $F(1, 7) = 13.9$, p = .007, but had no effect on mean RT (p = .71). Interactions were not significant for dark stimuli (ps > .36).

Finally, we considered the performance on our so-called catch trials. Recall, the idea behind the catch trials was that if capacity was more limited under accuracy emphasis in Experiment 1 because participants were not processing both items when under speed emphasis, and participants in Experiment 2 did the same, then we might see chance performance on catch trials under speed emphasis. Performance on catch trials was certainly not at chance under accuracy ($P_{accuracy}$ = 0.95) or speed (P_{speed} = 0.85) emphasis, but performance was worse under speed-emphasis conditions. To ascertain whether this performance decrement was simply due to a SAT, or also because attention is sometimes given to just one of the two stimuli, we compared the decrement for catch trials to the one observed with two redundant light stimuli. Proportion correct responses and mean correct RT were submitted to a 2 × 2 (Trial Type [catch or redundant light] × Emphasis [speed or accuracy]) within-subjects ANOVAs. The Emphasis × Trial Type interaction was significant, $F(1, 7) = 17.4$, p = .03, suggesting that the decrease in accuracy due to a change in response emphasis was smaller for redundant light stimuli ($P_{accuracy}$ = 0.95 and P_{speed} = 0.90) than for the catch trials. The interaction was not significant for mean RT (p = .13). These results suggest that participants in Experiment 2 may have sometimes adopted the strategy we found in Experiment 1, attending to just one stimulus when forced to respond quickly. However, this behavior must not have been used on every trial, because there was only a 5% drop in accuracy.

LBA-based capacity. We again applied a version of the Eidels et al. (2010) redundant-target LBA model. We had to change some aspects of the model to incorporate the changes in design used in Experiment 2. The basic model structure remained the same—single-target trials require just two accumulators, while redundant-target trials require a race between four accumulators. However, the decision rule used meant that the likelihood functions that yield "F" and "J" responses must be updated. Recall that an "F" response should be given whenever a single light stimulus is detected before dark stimuli are detected in both locations. As such, we could no longer collapse over light and dark responses, and the likelihood of an "F" response on a redundant-target trial is:

$$[f_{L_A}(t)(1 - F_{D_B}(t)) + f_{L_B}(t)(1 - F_{D_A}(t))] \cdot [1 - (F_{D_A}(t))(F_{D_B}(t))] \quad (3)$$

where L and D refer to light and dark response accumulators, respectively. Similarly, the likelihood of a "J" response on redundant-target trials occurs whenever both dark accumulators reach threshold before either of the light accumulators.

$$[f_{D_A}(t)(F_{D_B}(t)) + f_{L_B}(t)(F_{D_A}(t))] \cdot [1 - F_{L_A}(t)] \cdot [1 - F_{L_B}(t)] \quad (4)$$

We again fit two different versions of the model to our data, one that assumed a selective influence of emphasis on response thresholds, and another that assumed both accumulation rates and response thresholds varied with emphasis instruction. Both models assumed that A, t_0, and s were constant across all conditions, and that there were different response thresholds for light and dark accumulators b_L and b_D. Both models also assumed separate accumulation rates for the correct responses for light and dark stimuli, and for single- and redundant-target displays, v_{st_L}, v_{st_D}, v_{rt_L}, and v_{rt_D}. Again, incorrect response accumulators were set at 1 minus the respective correct accumulator.

The model that assumed a selective influence of response threshold estimated separate threshold parameters for speed-emphasis and accuracy-emphasis conditions, requiring two additional parameters to make up the full set of thresholds: $b_{L_{spd}}$, $b_{L_{acc}}$, $b_{D_{spd}}$, and $b_{D_{acc}}$. The model that assumed both response thresholds and accumulation rates change also estimated separate accumulation rate parameters for speed- and accuracy-emphasis conditions, requiring an additional four parameters to yield: $v_{st_{Lacc}}$, $v_{st_{Lspd}}$, $v_{rt_{Lacc}}$, $v_{rt_{Lspd}}$, $v_{st_{Dacc}}$, $v_{st_{Dspd}}$, $v_{rt_{Dacc}}$, $v_{rt_{Dspd}}$.

For six of eight participants, the selective influence model provided the most parsimonious account of the data according to BIC. That is, unlike Experiment 1, most participants in Experiment 2 appeared to only adjust their response thresholds when asked to be more or less cautious. Table 3 shows the best-fitting parameters for each individual under the response-threshold-only model. Each participants' four-response thresholds were analyzed in a 2 × 2 (Stimulus [light or dark] × Emphasis [speed or accuracy]) within-subjects ANOVA. The interaction between emphasis and stimulus was significant, suggesting that the increase in response thresholds from speed to accuracy emphasis was larger for dark stimuli ($b_{D_{spd}}$ = 0.23 vs. $b_{D_{acc}}$ = 0.32) than for light stimuli ($b_{L_{spd}}$ = 0.20 vs. $b_{L_{acc}}$ = 0.26). The accumulation rate for correct responses to light stimuli in single- and redundant-target conditions again revealed that capacity in this discrimination task was limited ($v_{rt_L} = 0.51 < v_{st_L} = 0.74$, $v_{cap} = -0.23$), $t(7) = 20.8$, $p < .001$. Interestingly, accumulation rates for correct responses to dark stimuli were higher when there were two stimuli rather than one ($v_{rt_D} = 0.89 > v_{st_D} = 0.72$, $v_{cap} = 0.17$), $t(7) = 10.2$, $p < .001$. This super capacity is likely because a correct dark response requires that both items be processed correctly (i.e., the decision rule is an exhaustive one). That is, both accumulators for a dark response must reach threshold before either of the incorrect light accumulators. Because people were able to identify two dark stimuli quite well, the model must estimate that the processing of two dark stimuli was more efficient than the processing of a single dark stimulus.

The change in accumulation rate parameters in the more complex model across emphasis conditions was consistent with the observed preference using BIC for the response-threshold model.

Table 3
Best-Fitting Parameter Estimates for Each Individual Participant in Experiment 2

	Participant							
Parameter	1	2	3	4	5	6	7	8
s	0.27	0.24	0.26	0.31	0.24	0.25	0.24	0.19
A	0.18	0.06	0.06	0.06	0.02	0.05	0.01	0.07
t_0	0.25	0.23	0.21	0.23	0.26	0.23	0.28	0.21
$b_{L_{spd}}$	0.20	0.16	0.24	0.19	0.15	0.20	0.21	0.25
$b_{L_{acc}}$	0.26	0.20	0.33	0.25	0.16	0.22	0.37	0.34
$b_{D_{spd}}$	0.20	0.18	0.25	0.22	0.20	0.25	0.23	0.31
$b_{D_{acc}}$	0.29	0.22	0.35	0.31	0.23	0.30	0.43	0.41
v_{st_L}	0.76	0.73	0.80	0.76	0.71	0.72	0.80	0.68
v_{rt_L}	0.53	0.51	0.55	0.53	0.41	0.48	0.58	0.48
v_{st_D}	0.77	0.71	0.60	0.74	0.73	0.79	0.78	0.68
v_{rt_D}	0.89	0.87	0.80	1.00	0.89	0.89	0.95	0.82

We observed no difference between accumulation rates for single- ($v_{st_{Lacc}} = 0.74$ vs. $v_{st_{Lspd}} = 0.73$, $p = 0.77$) and redundant-target ($v_{rt_{Lacc}} = 0.50$ vs. $v_{rt_{Lspd}} = 0.50$, $p = .83$) conditions. Further, for the two participants who were better fit by the model that assumed accumulation rates were influenced by emphasis, the pattern of accumulation rates were not consistent—both participants showed an unusual pattern, wherein accumulation rates were higher for single light stimuli under speed emphasis than accuracy emphasis. One participant showed no effect of emphasis condition on redundant light stimuli, while the other showed higher accumulation rates for redundant light stimuli under accuracy emphasis. For these participants, the difference between accuracy- and speed-emphasis conditions was much larger for dark stimuli than light stimuli, and so perhaps the selection of the more complicated model for these two participants was driven by the dark stimuli, and not the light stimuli.

Assessment function. In Experiment 2, we were able to use the $A(t)$ functions derived by Townsend and Altieri (2012). Rather than restate all of their equations, we point the reader to their Table 1 (more specifically, Equations I-IV in the Table). Despite the different formulation, the idea behind the assessment functions is identical to that used to derive the equations used in our Experiment 1. Responses are partitioned into the four types of responses outlined earlier (correct and fast, incorrect and fast, etc.). The key difference is that the decision rule in Experiment 2 is that participants should respond "light" if any item in the display is light, and "dark" only if there are no light items present. As such, a correct and fast response on a redundant-target trial (i.e., when there were two light stimuli present) would happen in one of five different ways: (a) the light stimulus in channel A is correctly identified by time t while the light stimulus in channel B is incorrectly identified as dark, (b) the light stimulus in channel B is correct by time t while the decision to light stimulus A is incorrect, (c) the decision to light stimulus A is correct and made by time t while a correct decision would have been made to light stimulus B after time t, (d) the decision to light stimulus B is correct and made by time t while the correct decision to light stimulus A would be made after time t, and (e) when the decisions to both light stimuli, A and B, are correct and made by time t. The same logic can be used to develop assessment functions for incorrect and fast, correct and slow, and incorrect and slow responses (see Townsend & Altieri's (2012) Table 1).

Figure 4 contains the assessment functions for each of the types of responses under speed emphasis (rows 1 and 2) and under accuracy emphasis (rows 3 and 4). First, we note that the $A(t)$ functions in Experiment 2 appear similar to those from Experiment 1 (see Figure 2). More specifically, there is a qualitative correspondence between the speed-emphasis and accuracy-emphasis conditions, which can be summarized as follows:

(1) As in Experiment 1, for both speed and accuracy conditions, the correct and fast $A(t)$ measure is less than 1, indicating limited capacity or correct responses occurring slower and less frequently than expected. However, unlike Experiment 1, we saw little difference in the qualitative shape of the $A(t)$ function between speed- and accuracy-emphasis conditions.

(2) The assessment function for incorrect and fast responses is greater than 1, indicating that fast, incorrect responses were more probable in the observed data than predicted under the baseline model.

(3) Correct and slow response $A(t)$ functions are greater than 1 in both conditions, indicating that slow, correct responses were slower and more likely to occur in the observed data than under the baseline model. Also note again that both functions have the same shape under speed and accuracy emphasis, unlike in Experiment 1.

(4) Finally, the assessment functions for incorrect and slow responses were approximately equal to or less than 1 for most observers in both the speed- and accuracy-emphasis conditions. Compared with the baseline model, the probability of an incorrect and slow response was about the same or perhaps slightly less than what was expected. This exception likely reflects a trade-off with accuracy in Experiment 2; that is, on the whole, accuracy was higher overall in both conditions than in Experiment 1. Consequently, once error responses were parceled out into fast and slow quadrants, there were likely to be fewer overall slow errors. Notwithstanding this difference to Experiment 1, capacity considered across all four processing categories was consistent with a limited capacity process. The overall effect of shifting from accuracy to speed emphasis was to shift the assessment function earlier in time without changing its qualitative character.

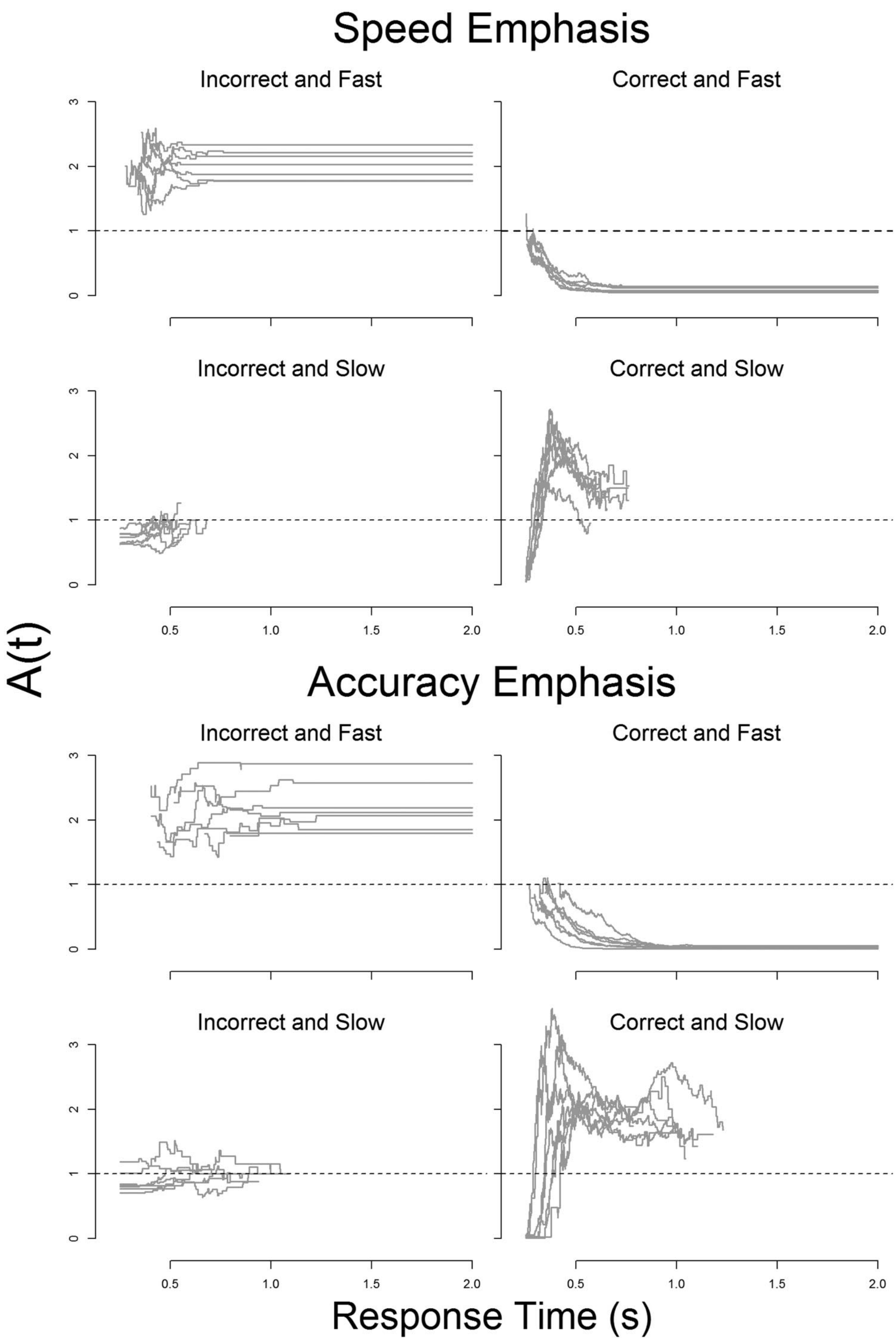

Figure 4. Assessment functions for incorrect and fast, correct and fast, incorrect and slow, and correct and slow responses under speed- and accuracy-emphasis conditions (top and bottom set of plots, respectively) in Experiment 2.

In addition to the conditional assessment functions reported in Appendix B, we also carried out one further analysis related to the impact of having distracting information on processing. The design of Experiment 2 was such that there were trials in which light stimuli were presented alone, and also in the presence of a distracting, dark stimulus. Appendix C reports an analysis of the impact of the distractor item on the processing of the light stimulus, but the results are consistent with those in Figures 2; the presence of an additional stimulus degraded performance, suggesting that workload capacity is limited, but there appears to be relatively little difference between capacity under speed- and accuracy-emphasis conditions.

Discussion

In Experiment 2, we again observed that the increased caution when instructed to respond accurately led to an increase in the proportion of correct responses and in mean RT. However, unlike Experiment 1, we found that more caution led participants to simply collect more evidence before making a decision, while their capacity remained unchanged. This result was found using both the nonparametric assessment function, and the parametric LBA capacity measure. That is, in Experiment 2, participants appeared to trade speed for accuracy in the usual way.

Unlike participants in Experiment 1, those in Experiment 2 showed no further reduction in capacity when being more cautious. We take this result to suggest that participants did indeed ignore one of the two stimuli when being less cautious in Experiment 1. Further, because participants were not at chance during the catch trials, wherein both light and dark stimuli were presented, participants in Experiment 2 appear to have attended to both stimuli before making a decision. It seems likely that the instructions we provided in Experiment 2, and the existence of the catch trials, forced participants to process both stimuli before making a response. Interestingly, participants in Experiment 2 were now more consistent with what is usually observed when caution is manipulated in simple-choice RT tasks—a selective influence of caution on the amount of evidence required to make a decision.

General Discussion

We have presented the first examination of the SAT effect in the context of multiple signal processing, using newly developed measures of workload capacity that can accommodate both accuracy and RT. We found that responding more accurately had a large effect on the pattern of correct and error RT distributions. For instance, responding with an emphasis on fast responses resulted in incorrect responses that were faster than correct responses; by contrast, an emphasis on accuracy resulted in incorrect responses that were slower than correct responses (Ratcliff & Rouder, 1998). This pattern of results has proven challenging for models of choice RT that do not include mechanisms to allow for between-trial variability in drift rates or starting point (Smith & Ratcliff, 2004). Models that can handle this pattern, such as the LBA model, handle the effect of caution by proposing that when making fast responses, observers require less evidence than when making cautious responses.

Our experiments suggest that the primary influence of the SAT required by the decision maker is not on the capacity of a processing system, but on the amount of evidence required to make a choice. The selective influence of caution on response thresholds is in line with the vast majority of results in two-choice tasks (e.g., Brown & Heathcote, 2005; Forstmann et al., 2008; Forstmann et al., 2010; Forstmann et al., 2011; Ratcliff & Smith, 2004). In our second experiment, the assessment function was barely changed at all between the speed- and accuracy-emphasis conditions.

Interestingly, we found that participants were capable of strategically ignoring redundant information when forced to process information quickly. As such, our results suggest that when participants trade accuracy for speed in more complex tasks, they may not simply collect less evidence before making a response, but may also look for strategies that reduce the load of their processing system. In Experiment 1, participants responding quickly would ignore redundant information, which lifted the burden off of their limited-capacity processing architecture. However, we found that participants were only willing to ignore the redundant information when they could be certain that it was indeed redundant. In Experiment 2, when we broke the contingency that pairs of stimuli were always identical, we found that participants almost always processed both stimuli regardless of how much caution was required.

In Experiment 1, the rate of evidence accumulation was faster when participants were being more cautious for both single and redundant trials. This is an unusual pattern, because caution is usually found to have a selective influence on response thresholds and not accumulation rates. However, our result is not unprecedented. For example, Heathcote and Love (2012) and Vandekerckhove, Tuerlinckx, and Lee (2008) found that accumulation rate parameters varied across caution conditions in fits to empirical data. Rae, Heathcote, Donkin, and Brown (in press) also found model-free evidence using a signal-to-respond task to support the notion that participants accumulate evidence at a more efficient rate when attempting to be more accurate. However, the effect of caution on accumulation rate was not present in Experiment 2. The difference between performance in speed- and accuracy-emphasis conditions was much smaller in Experiment 2, presumably because participants could no longer ignore half of the stimuli on redundant-target trials. We suspect that participants in Experiment 1 were so motivated to respond quickly under speed emphasis that they not only ignored redundant information, but also extracted degraded evidence from stimuli. In Experiment 2, participants could not ignore the redundant information, and therefore could not respond as quickly as they might have liked to, and so appeared to have extracted information from stimuli at the same rate as when they were making accurate decisions.

One might wonder whether we have a preference for either the nonparametric or parametric capacity measures given that both have their advantages and disadvantages. The $A(t)$ measure has the benefit of giving a continuous measure of capacity, whereas v_{cap} is a single number that summarizes the overall capacity. Under certain assumptions, the nonparametric measure is also capable of revealing differences in processing architecture (i.e., limited capacity when processing is not parallel). On the other hand, the LBA-based model we presented here enforces a parallel processing architecture. Though it is possible to arrange LBA accumulators in such a way that they do not have a parallel architecture (e.g., Donkin & Shiffrin, 2011, constructed a serial LBA model; see also Fific, Little, & Nosofsky, 2010 and Little, Nosofsky, Donkin, & Denton, 2013, who develop serial and parallel architecture models using other sequential sampling assumptions), such alternatives generally lose the computational advantage that the LBA model offers. On the other hand, v_{cap} allows for more targeted assessment of "noncapacity" aspects of decision making that are related to psychologically valid mechanisms, such as the effect of caution on response thresholds that we observed here. The $A(t)$ measure is also more open to interpretation—we did observe subtle differences between $A(t)$ in the speed- and accuracy-emphasis conditions, and we must rely on our interpretation that these differences are indeed small, and on the combination of evidence from multiple sources. Nonetheless, we believe that using both measures in concert can provide converging and complementary information about the underlying processing system.

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(*Appendix follows*)

Appendix A

Derivation of the Assessment Function for Experiment 1

We describe the assessment function for our alternative decision rule in the same manner that Townsend and Altieri (2012) developed their assessment function, by breaking up the likelihood of responses into the following categories: correct and fast, incorrect and fast, correct and slow, and incorrect and slow. The definitions of these terms are identical to those outlined in the main text. For example, a correct and fast response refers to the likelihood that a response is correct and has finished at or before time t. In each case, the response is determined by whichever process finishes first.

To calculate the assessment function for correct and fast, we consider how a response can be made when a target is presented in both locations A and B. A correct and fast response occurs when either the target in location A is correctly classified OR the target in location B is correctly classified at or before time t. Therefore, the likelihood of a correct and fast response is the sum of the following likelihoods: Either target A is correctly classified at or before time t (correct and fast) while target B is not classified by time t (and, therefore, could be either correct or incorrect—and therefore either correct and slow or incorrect and slow), target B is correct and fast while target A is correct and slow or incorrect and slow, or both target A and target B are correct and fast. These likelihoods can be expressed using the following equation:

$$\begin{aligned} P\{\text{Correct and Fast}\} &= P\{A \text{ Correct is First and at or before } t\} \\ &\quad + P\{B \text{ Correct is First and at or before } t\} \\ &= P\{T_{A_C} < T_{A_I}, T_{A_C} < T_{B_C}, T_{A_C} < T_{B_I}, T_{A_C} \le t\} \\ &\quad + P\{T_{B_C} < T_{B_I}, T_{B_C} < T_{A_C}, T_{B_C} < T_{A_I}, T_{B_C} \le t\}. \end{aligned}$$

To get a function that can be estimated from observable data, we first condition the first term on the probability of A correct and second term on the probability of B correct.

$$\begin{aligned} &= P\{T_{A_C} < T_{A_I}\} P\{T_{A_C} < T_{B_C}, T_{A_C} < T_{B_I}, T_{A_C} \le t | T_{A_C} < T_{A_I}\} \\ &\quad + P\{T_{B_C} < T_{B_I}\} P\{T_{B_C} < T_{A_C}, T_{B_C} < T_{A_I}, T_{B_C} \le t | T_{B_C} < T_{B_I}\}. \end{aligned}$$

Because the completion time for A is the faster of A_C and A_I, we can replace $T_{B_C} < T_{A_C}$, $T_{B_C} < T_{A_I}$ with $T_{B_C} < T_A$ and likewise for B in the second term. Next, assuming the densities for the completion time of A_C conditioned on $A_C < A_I$ and for the completion time of B_C conditioned on $B_C < B_I$ exist, which we denote $f_{A|C}(t)$ and $f_{B|C}(t)$, respectively,

$$\begin{aligned} &= P\{T_{A_C} < T_{A_I}\} \int_0^t P\{t' < T_B | T_{A_C} < T_{A_I}\} f_{A|C}(t')\, dt' \\ &\quad + P\{T_{B_C} < T_{B_I}\} \int_0^t P\{t' < T_A | T_{B_C} < T_{B_I}\} f_{B|C}(t')\, dt'. \end{aligned}$$

If we assume unlimited capacity, independent, parallel processing, then the completion times of T_A and T_B are independent, so we can drop the conditioning,

$$\begin{aligned} &= P\{T_{A_C} < T_{A_I}\} \int_0^t P\{t' < T_B\} f_{A|C}(t')\, dt' \\ &\quad + P\{T_{B_C} < T_{B_I}\} \int_0^t P\{t' < T_A\} f_{B|C}(t')\, dt'. \end{aligned}$$

Using $F_A(t) = P\{T_A \le t\}$ and $F_B(t) = P\{T_B \le t\}$ for the cumulative distribution functions of A and B, we now can write the correct and fast discrimination assessment function as,

$$A_{CF}^{OR}(t) = \frac{\log[P\{T_{A_C} < T_{A_I}\} \int_0^t [1 - F_B(t')] f_{A|C}(t')\, dt' + P\{T_{B_C} < T_{B_I}\} \int_0^t [1 - F_A(t')] f_{B|C}(t')\, dt']}{\log[P\{T_{AB_C} < T_{AB_I}\} F_{AB|C}(t)]}.$$

$P\{T_{A_C} < T_{A_I}\}$ can be estimated with the hit rate when only A was presented, $P\{T_{B_C} < T_{B_I}\}$ can be estimated with the hit rate with only B presented, and $P\{T_{AB_C} < T_{AB_I}\}$ can be estimated with the hit rate when both A and B were presented. $F_A(t)$, $F_B(t)$, and $F_{AB}(t)$ can be estimated using the empirical cumulative distribution function: the number of response times in the condition that were

(*Appendices continue*)

less than or equal to t divided by the total number of responses in that condition. To estimate $\int_0^t [1 - F_B(t')] f_{A|C}(t')\,dt'$, sum the value of $1 - \hat{F}_B(t')$ at each time that there was a correct response to A alone faster than t.

The same logic that was used to derive the correct and fast assessment function can also be used to derive the other assessment functions. The correct and slow assessment function is quite similar to the correct and fast, with the only difference in the bounds of the integral. This comes from requiring that the model is correct, so either A_C or B_C must finish first as above, but slow, so T_{A_C} and T_{B_C} are slower than t,

$$\begin{aligned}
P\{\text{Correct and Slow}\} &= P\{A \text{ Correct is First and after } t\} \\
&\quad + P\{B \text{ Correct is First and after } t\} \\
&= P\{T_{A_C} < T_{A_I}, T_{A_C} < T_{B_C}, T_{A_C} < T_{B_I}, T_{A_C} > t\} \\
&\quad + P\{T_{B_C} < T_{B_I}, T_{B_C} < T_{A_C}, T_{B_C} < T_{A_I}, T_{B_C} > t\} \\
&= P\{T_{A_C} < T_{A_I}\} \int_t^\infty P\{t' < T_B\} f_{A|C}(t')\,dt' \\
&\quad + P\{T_{B_C} < T_{B_I}\} \int_t^\infty P\{t' < T_A\} f_{B|C}(t')\,dt'.
\end{aligned}$$

Hence,

$$A_{CS}^{OR}(t) = \frac{\log[P\{T_{A_C} < T_{A_I}\} \int_t^\infty [1 - F_B(t')] f_{A|C}(t')\,dt' + P\{T_{B_C} < T_{B_I}\} \int_t^\infty [1 - F_A(t')] f_{B|C}(t')\,dt']}{\log[P\{T_{AB_C} < T_{AB_I}\}[1 - F_{AB|C}(t)]]}.$$

The incorrect assessment functions are given by swapping the correct and incorrect subscripts in the correct assessment functions. For, example the correct and fast completion time was determined by either A_C or B_C. To be incorrect, then either A_I or B_I must finish first and, to be fast, that process must have finished at or before t,

$$\begin{aligned}
P\{\text{Incorrect and Fast}\} &= P\{A \text{ Incorrect is First and at or before } t\} \\
&\quad + P\{B \text{ Incorrect is First and at or before } t\} \\
&= P\{T_{A_I} < T_{A_C}, T_{A_I} < T_{B_C}, T_{A_I} < T_{B_I}, T_{A_I} \le t\} \\
&\quad + P\{T_{B_I} < T_{B_C}, T_{B_I} < T_{A_C}, T_{B_I} < T_{A_I}, T_{I_C} \le t\} \\
&= P\{T_{A_I} < T_{A_C}\} \int_0^t P\{t' < T_B\} f_{A|I}(t')\,dt' \\
&\quad + P\{T_{B_I} < T_{B_C}\} \int_0^t P\{t' < T_A\} f_{B|I}(t')\,dt'.
\end{aligned}$$

Therefore, the incorrect and fast assessment function is given by,

$$A_{IF}^{OR}(t) = \frac{\log\Big[P\{T_{A_I} < T_{A_C}\} \int_0^t \big[1 - F_B(t')\big] f_{A|I}(t')\,dt' + P\{T_{B_I} < T_{B_C}\} \int_0^t \big[1 - F_A(t')\big] f_{B|I}(t')\,dt'\Big]}{\log\Big[P\{T_{AB_I} < T_{AB_C}\} F_{AB|I}(t)\Big]}.$$

Finally, combining the change from fast to slow and from correct to incorrect, we arrive at the final assessment function for incorrect and slow,

$$A_{IS}^{OR}(t) = \frac{\log\Big[P\{T_{A_I} < T_{A_C}\} \int_t^\infty \big[1 - F_B(t')\big] f_{A|I}(t')\,dt' + P\{T_{B_I} < T_{B_C}\} \int_t^\infty \big[1 - F_A(t')\big] f_{B|I}(t')\,dt'\Big]}{\log\Big[P\{T_{AB_I} < T_{AB_C}\} F_{AB|I}(t)\Big]}.$$

(*Appendices continue*)

Appendix B

Conditional Assessment Functions

One additional benefit of using the $A(t)$ measures is that we can look at the effect of response emphasis on $A(t)$, conditioned on the accuracy of responses. Townsend and Altieri (2012) have outlined how it is possible to decompose the $A(t)$ measure, which takes into account both the speed and accuracy of responses, into a measure of capacity that takes into account just one of the two variables. By conditionalizing on the accuracy of responses, we can seek further evidence for whether capacity is indeed stable across speed- and accuracy-emphasis conditions.

We direct readers to Townsend and Altieri (2012) for full details on how to conditionalize the $A(t)$ measure on accuracy or speed, but the basic idea is to divide out of each expression for $A(t)$, the probability that the particular response is made. So, for example, the conditionalized $A(t)$ for incorrect and fast responses in Experiment 1 is

$$A_{IF}^{OR}(t) = \frac{\log\left[\frac{\int_0^t P_A\left(T_{A_I} = t' < T_{A_C}\right)dt'}{P_A(C)} \cdot \frac{\int_0^t P_B\left(T_{B_I} = t' < T_{B_C}\right)dt'}{P_B(C)}\right]}{\log\left[\frac{\int_0^t P_{AB}\left(T_{AB_I} = t' < T_{AB_C}\right)dt'}{P_{AB}(C)}\right]} \tag{5}$$

The calculation of the conditionalized $A(t)$ for Experiment 2 takes the same approach, and we direct readers to Townsend and Altieri (2012) for a description of how it is calculated in the context of their assessment functions.

Figures B1 and B2 show the assessment functions conditionalized on accuracy for speed- and accuracy-emphasis conditions for Experiments 1 and 2, respectively. With the influence of accuracy removed, if response thresholds are all that differ between speed and accuracy conditions, we might expect the effect of changing emphasis on capacity to have reduced, leaving an even smaller difference between speed- and accuracy-emphasis conditions. For Experiment 2, we see that the assessment functions have become almost identical. On the other hand, for Experiment 1, we still see systematic and qualitative differences between the shapes of the assessment functions (consistent with the interpretation of different capacities under different emphasis conditions).

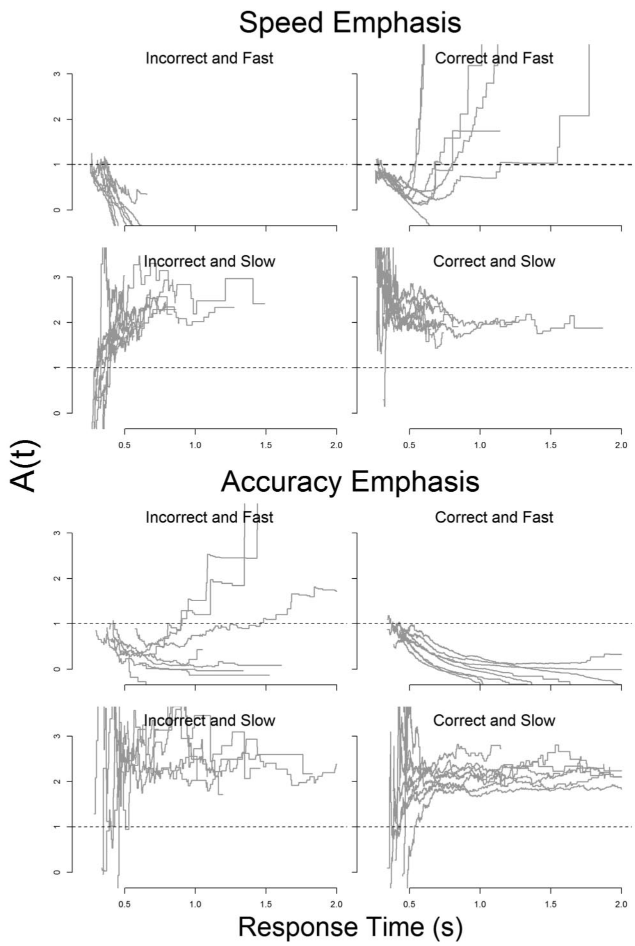

Figure B1. Conditional assessment functions for incorrect and fast, correct and fast, incorrect and slow, and correct and slow responses under speed- and accuracy-emphasis conditions (top and bottom set of plots, respectively) in Experiment 1.

(*Appendices continue*)

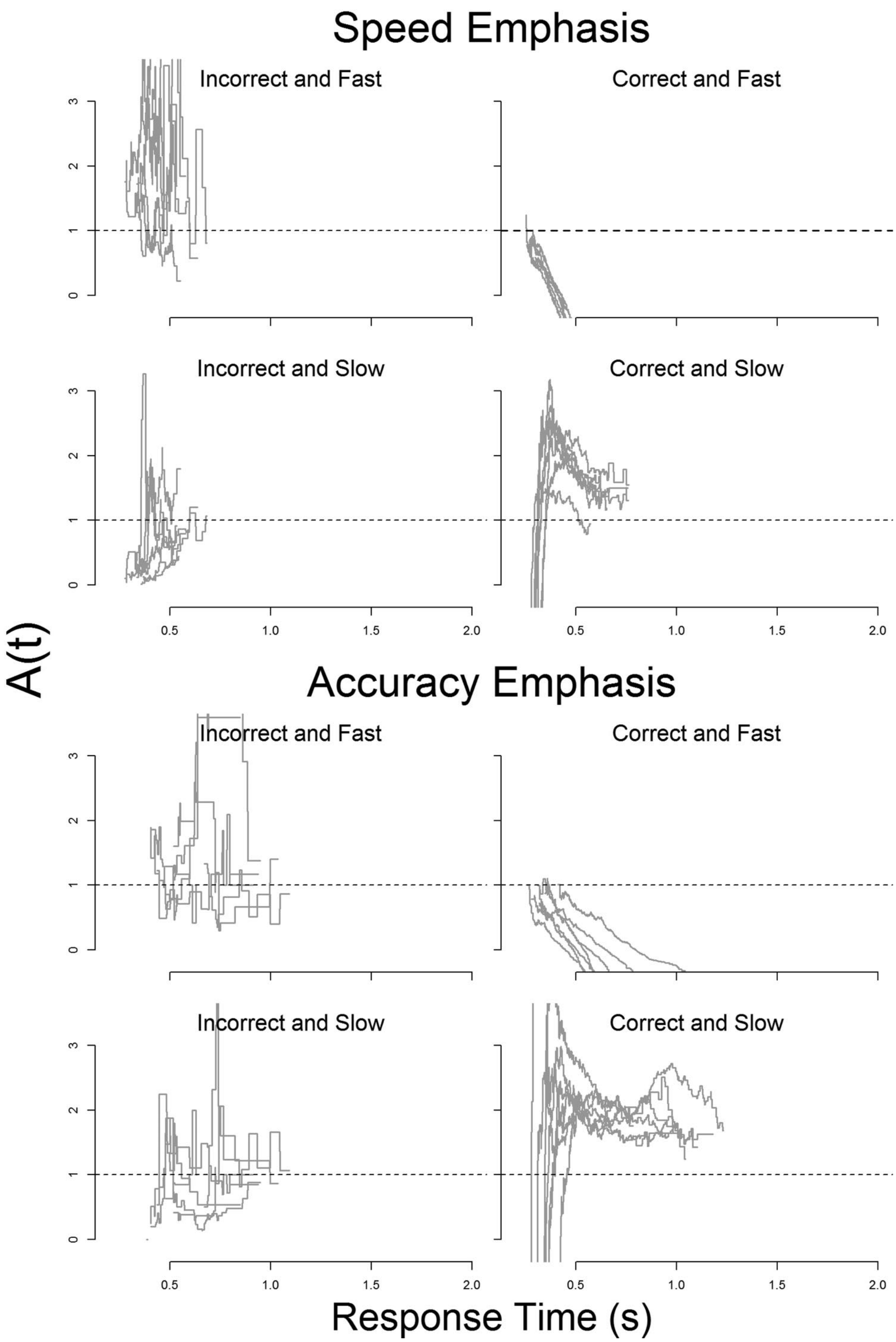

Figure B2. Conditional assessment functions for incorrect and fast, correct and fast, incorrect and slow, and correct and slow responses under speed- and accuracy-emphasis conditions (top and bottom set of plots, respectively) in Experiment 2.

(*Appendices continue*)

Appendix C

The Effect of Distractors in Experiment 2

The design of Experiment 2 permits the analysis of the effect of distracting information on processing capacity. Light stimuli are presented both alone, and in the presence of a distracting dark stimulus. We can ask what influence the distracting dark stimulus has on the processing of the light stimulus by using the following equation:

$$\frac{\log(1 - F(t|\textit{correct and light item alone}))}{\log(1 - F(t|\textit{correct and light item with dark item}))} \tag{5}$$

Figure C1 plots this measure for both speed- and accuracy-emphasis conditions. We see that the functions tend to lie below a value of 1, suggesting that the additional distracting item interfered with the processing of the light stimulus. Further, we see essentially no difference between the functions under speed and accuracy emphasis.

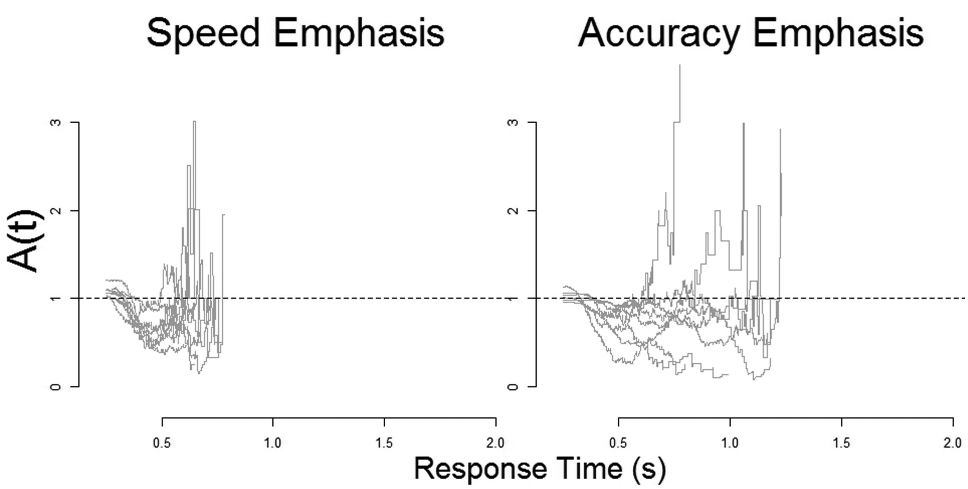

Figure C1. The impact of the distracting dark stimulus on the processing of the light stimulus under speed- and accuracy-emphasis conditions in Experiment 2.

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