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A Show About Nothing: No-Signal Processes in Systems Factorial Technology

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Systems Factorial Technology (SFT) is a popular framework for that has been used to investigate processing capacity across many psychological domains over the past 25+ years. To date, it had been assumed that no processing resources are used for sources in which no signal has been presented (i.e., in a location that can contain a signal but does not on a given trial). Hence, response times are purely driven by the signal-containing location or locations. This assumption is critical to the underlying mathematics of the capacity coefficient measure of SFT. In this article, we show that stimulus locations influence response times even when they contain no signal, and that this influence has repercussions for the interpretation of processing capacity under the SFT framework, particularly in conjunctive (AND) tasks—where positive responses require detection of signals in multiple locations. We propose a modification to the AND task requiring participants to fully identify both target locations on all trials. This modification allows a new coefficient to be derived. We apply the new coefficient to novel experimental data and resolve a previously reported empirical paradox, where observed capacity was limited in an OR detection task but super capacity in an AND detection task. Hence, previously reported differences in processing capacity between OR and AND task designs are likely to have been spurious.

Keywords: assumptions, capacity, no signal, redundant target, systems factorial technology

In the world around us, there are an almost unlimited number of sources of information; yet we take in or process comparatively few of these sources. This is in part because of our limited capacity to process information (Kahneman, 1973). To understand how any cognitive system accounts for processing in complex multisource environments, we must understand several key properties of how the system operates when presented with multiple sources of information. Broadly speaking, any cognitive system may be defined by the combination of four key properties: capacity (efficiency under load), architecture (serial vs. parallel vs. coactive consideration of sources), stopping rule (how many sources must be processed before processing can terminate), and (in)dependence (whether channels processing information are affected by other channels; Townsend, 1974; Townsend & Ashby, 1983; Townsend & Wenger, 2004a).

Systems Factorial Technology (SFT; Little, Altieri, Fific, & Yang, 2017; Townsend & Nozawa, 1995; Townsend & Wenger, 2004a) is a powerful nonparametric framework that allows classification of the architecture, stopping rule, capacity, and independence of a cognitive system. SFT has been used to identify processing architecture in simple detection (Eidels, Townsend, Hughes, & Perry, 2015; Townsend & Nozawa, 1995), visual perception (Fific, Nosofsky, & Townsend, 2008; Little, Nosofsky, Donkin, & Denton, 2013), and recognition memory (Townsend & Fifić, 2004), among other domains (see Algom, Fitousi, & Eidels, 2017; Cooper & Hawkins, 2019; Fitousi & Algom, 2018; Howard, Belevski, Eidels, & Dennis, 2020; Thiele, 2015; Yang, Fifić, Chang, & Little, 2018, for recent applications).

The capacity measures of SFT have been used to show the effect of increased load, often in the form of additional to-be-processed items, on parallel processing (Eidels et al., 2015), comment on dual-task interference in working memory designs (Heathcote et

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al., 2015), and shed light on reading difficulties (Houpt, Sussman, Townsend, & Newman, 2015). The capacity measures of SFT have also been linked with parametric models of processing (Donkin, Little, & Houpt, 2014; Eidels, Donkin, Brown, & Heathcote, 2010), and formal statistics have been developed to facilitate the assessment of capacity (Houpt & Townsend, 2012). The capacity coefficient has been widely applied across a diverse range of psychological domains to further theoretical developments and make novel inferences (see, e.g., Blaha, 2017; Chang & Yang, 2014; Fitousi, 2015; Garrett, Howard, Houpt, Landy, & Eidels, 2019; Hawkins, Houpt, Eidels, & Townsend, 2016; Heathcote et al., 2015; Howe & Ferguson, 2015; Johnson, Blaha, Houpt, & Townsend, 2010; Yamani, Neider, Kramer, & McCarley, 2017; Yankouskaya, Sui, Moradi, Rotshtein, & Humphreys, 2017; Yu, Chang, & Yang, 2014, for just a small selection of recent work).

Fundamentally, capacity analysis relies on comparing response times when some target is presented in isolation or as part of a larger visual display. In the measure of capacity, redundant target response times (i.e., from displays containing two distinct targets) are compared with response times derived from each display where a target was presented in isolation (see, e.g., Altieri, Fifić, Little, & Yang, 2017).[1] For single and double target displays to be directly comparable, it must be assumed that only the target item contributes to the observed processing time (else two nonequivalent processes may be contrasted). In this article, we show that the capacity measure can be affected by nontarget items. Even when a single target is presented in isolation, the null channel (not containing any stimulus) attracts nonnegligible processing time, contrary to previous assumptions. Prior work has shown that distractors can influence the measure of capacity (Little, Eidels, Fific, & Wang, 2015); here, we show that the absence of information can also influence the measure of capacity. We first demonstrate this finding, and discuss its profound implications; finally, a potential remedy is developed and tested later in this article.

The Redundant Target Task

In a prototypical SFT study (see, e.g., Eidels et al., 2015), a small dot of light (the target) requiring detection is presented in either or both of two locations (this is often termed the Redundant Target Task; see, e.g., Altieri et al., 2017; Houpt, Blaha, McIntire, Havig, & Townsend, 2014). The Redundant Target Task can be divided into two cases, based on the decisional stopping rule applied to the task. In the OR task, participants are instructed to respond affirmatively when a target is presented in either Location A *or* Location B *or* in both locations. Only if neither target is present do participants respond negatively. These instructions imply that processing of all target-containing trials should terminate as soon as any target is detected (a self-terminating response rule). In the AND task, participants are instead asked to respond affirmatively only if a target is present in both Location A *and* Location B. Here, if a target is present in only one or neither of the two locations, the participant must respond with a negation.

To set the scene, consider a redundant target detection task where a target item, say the letter *X*, could be presented in two locations, one location only, or neither location. The nontarget locations contain no stimulus, and we refer to them as *no signal* or *null* channels. Importantly, participants are always required to monitor both stimulus locations for potential targets. We will refer to this as the *standard* SFT task throughout this article. In a variant of the task, no signal locations are instead filled by the distractor item(s), Os, so that no-target trials consist of the display OO (yet still require a negative response), and a single-target trial may display XO. In such a task, the decision for participants is identical, the only difference is the presence of a distractor in nontarget locations (see the study by Ben-David, Eidels, & Donkin, 2014). We refer to this variant as the distractor modified redundant-target task. Figure 1 illustrates the OR and AND cases of the task, with white dots specified as targets and dark dots as distractors.

Little et al. (2015) demonstrated that the presence of a distractor modified the distribution of response times from the standard target/no-signal version of the redundant target task, as "with distractors, single-target displays have information to process in both channels" (Little et al., 2015, p.29). For example, the distribution of processing times for single target trials from a serial model would be altered if the distractor was processed before the target compared to the case where only the target was processed. Here, we go further to assert that even in the standard double-factorial paradigm, the no-target channels might also attract processing. This is contrary to the assumptions of the standard capacity measure where it is assumed that "the absence of any information may attract only negligible processing" (Little et al., 2015, p.29). This assumption is implicit in all formulations of the capacity coefficient (Houpt & Townsend, 2012; Townsend & Nozawa, 1995; Townsend & Wenger, 2004b). However, we present compelling empirical evidence that our assertion is true: Nontarget locations contribute to response times even when they contain no signal.

Evidence for Nontrivial Absence Processing

To examine whether or not the no-signal channels are influencing processing, we rely on the fact that SFT designs often manipulate the salience of each target (e.g., the brightness of a dot of light) to selectively influence the completion time of each processing channel (i.e., the time taken to process each source or location). The salience manipulation is useful in the estimation of processing architecture; this requires examining combinations of salience (e.g., trials where both targets are high salience vs. trials where one target is low salience) to ensure that a manipulation designed to speed up or slow down processing in a given channel has the desired effect. This effect is a necessary assumption for applying tools that differentiate processing architecture (see Houpt et al., 2014). To examine the no-signal process, we compare single-target trials in the OR versus AND task designs. If observers can use the absence of a signal to drive a response, then we should find that there is little or no effect of manipulating salience in the single-target trials. Note that we do not suggest salience manipulation is *necessary* for capacity estimation, simply that, when present, it provides a useful check for our arguments.

Because of the difference in decision rules, decisions in OR tasks can terminate when a target is detected. If a parallel self-terminating strategy is used (and assuming stochastic independence between the processing channels; see, e.g., Eidels, Houpt, Altieri, Pei, & Townsend, 2011), response time may be unaffected

[1] Note that a recent development extended capacity measures to cover accuracy as well (Townsend & Altieri, 2012) we do not treat this approach in the present article.

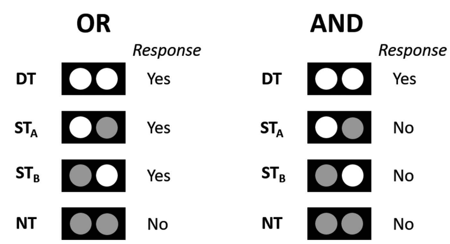

Figure 1. Distractor modified redundant-target detection task. White dots are target items, dark dots are distractors. In the standard detection version of these tasks the dark dots would be absent, and no signal would be presented in that location. DT = double target; ST = single target, (subscript A and B denote individual target locations); NT = no target.

by either distractors or no-signal processes (see Little et al., 2015 and Figure 2a). However, in the AND case, even the benchmark parallel exhaustive model would be influenced by any nontarget (distractor or otherwise) that attracted processing time (Little et al., 2015). Little et al. (2015) note that in the distractor-modified-AND task, participants could frame their exhaustive target detection task as a self-terminating *distractor detection* task. There is no reason equivalent behavior could not be exhibited in the no-signal variant of the task, and under this framing response times would naturally be influenced by the null location(s). Consequently, whether the system truly processes all stimulus locations exhaustively or the framing of the task becomes self-termination on a null location, the nontarget location should always be checked. If this attracts processing time the nontarget location would contribute to the observed response time of the system.

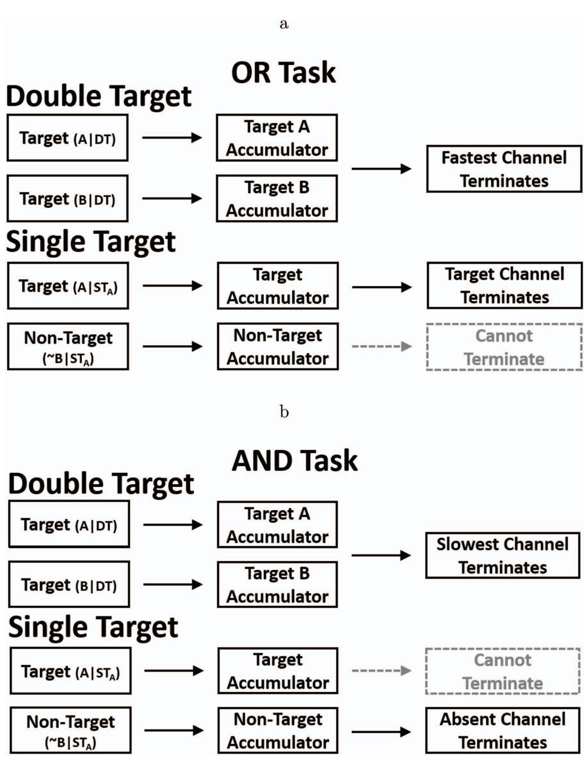

Figure 2. (Top) OR task design. Processing terminates on the fastest target channel to complete on both single and double target displays. (Bottom) AND task design. Processing terminates on the slowest target process in double-target displays but on the absent channel on single-target displays. Single-target channels are defined only for Location A for convenience, but the same relationship holds for Location B with channels reversed. $A|DT$ refers to the channel processing a target in Location A given it was presented in the context of both targets, $\sim B|ST_A$ refers to the process determining Location B did *not* contain a target given only target A was shown, and so on. DT = double target; ST = single target, (subscript A denote individual target locations).

If the observed response times in the standard SFT task are determined exclusively by the target-processing channel, as is typically assumed (Little et al., 2015; Townsend & Wenger, 2004b), low salience targets should be processed slower than high salience targets in both double and single-target trials, for both OR and AND task designs. This salience effect is routinely tested in double-target trials (Houpt et al., 2014) but typically not examined in single-target trials. If the salience effect is present in double-target trials as well as single-target trials (particularly in the AND task), we can safely assume that the no-signal channel attracts negligible processing time. However, if the salience manipulation is successful in double-target but not single-target trials in the AND case, this strongly suggests that the no-signal channel influences the processing time. This influence could manifest in one of two ways; either (a) the system exhaustively processed both channels and the no signal process 'washed out' the target salience manipulation or (b) the system self-terminated on the nontarget location. In either case, the interpretation of the capacity coefficients would be compromised by the processing time attached to the no-signal channel in the same way that distractors affected the coefficient in Little et al.'s (2015) work.

Figure 3 shows a single subject's data from Eidels et al.'s (2015) within-subjects dot detection task, data that are contained within

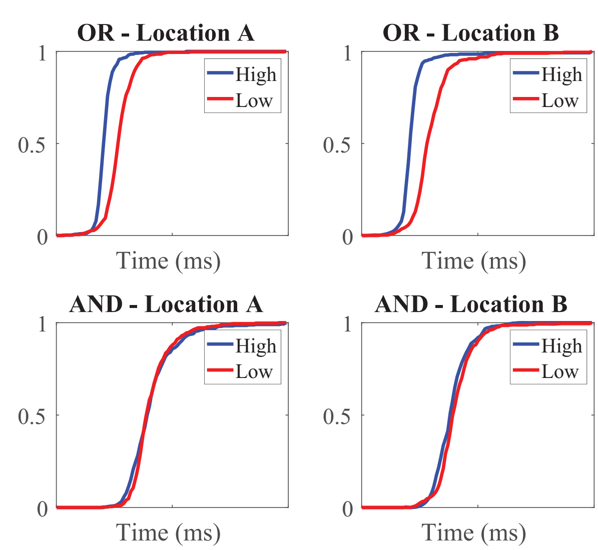

Figure 3. Empirical data displaying differential effects of target salience in OR and AND task. (Top) High- and low-salience single-target trials from an OR task. (Bottom) High- and low-salience single-target trials from the same subject's AND task. All panels show cumulative distribution functions of the response time to single-target trials for both high and low salience targets. See the online article for the color version of this figure.

the 'sft' R package (Houpt et al., 2014), and have been reported in a number of publications (Bushmakin, Eidels, & Heathcote, 2017; Eidels et al., 2015; Houpt & Townsend, 2010; Townsend & Eidels, 2011). These data use a canonical dot-detection task with a within-subjects design (the same subjects completed the OR and AND tasks) and have thousands of trials per subject. The data are often used to assess the suitability of new analysis techniques (Houpt & Fifić, 2017; Houpt, Heathcote, & Eidels, 2017; Houpt, MacEachern, Peruggia, Townsend, & Van Zandt, 2016; Houpt & Townsend, 2010).

In the OR task there is a clear effect of salience on the processing times of single-target trials, as expected. This is shown by the separation between the high and low salience cumulative distribution functions of response time. In the AND task, the same subject shows no salience effect at all (in fact the low and high salience response times almost completely overlap). This pattern holds for most subjects in that data set.

To quantify the missing salience effect, we applied Heathcote, Brown, Wagenmakers, and Eidels's (2010) Bayesian, distribution-free test of stochastic dominance to each pairwise comparison of subject ($n = 9$) by stimulus location (A and B), for both the OR and AND data sets (which were within-subjects). We found that in the OR task all 18 tests showed strong evidence ($BF_{10} > 10$) for stochastic dominance (such that $F_H(t) < F_L(t)$ where $F_H(t)$ is the cumulative distribution function of response times for the high salience single-target trials), showing all subjects responded slower to the low salience item(s) even on single target trials. In the AND task, only four of the 18 comparisons showed even moderate evidence ($BF_{10} > 5$) for stochastic dominance in the AND case, and 10 of the 18 comparisons showed at least moderate evidence in favor of no difference. Thus for most subjects there was no difference in response time to the low and high salience single-target items, contrary to their responses in the OR task. This pattern of results is inconsistent with the assumption that no-signal channels do not contribute to empirically observed response times in standard SFT tasks.

Although these data show differential effects between OR and AND tasks, it is possible that no-signal channels attract processing in the OR paradigm as well. As shown in Figure 2a, decisions in OR tasks should only terminate based on the detection of a target under a task-appropriate self-terminating strategy (assuming context invariant, independent processing channels). Therefore, the effect of no-signal processes would be masked in these response time data. The effect could better be teased apart if serial processing were observed in the OR task; however, the results from the AND task are compelling enough in their own right.

Implications

The above empirical results suggest that the no-signal location attracts nonnegligible processing time. Hence, the assumption underlying the capacity coefficient about how the theoretical single targets map onto the data is incorrect, because people do not process the single targets in the AND task in the manner assumed by the theory. Little et al. (2015) demonstrated the effect of distractor items on processing times for the redundant target task; generally, the introduction of a distractor altered the response time distributions for the single target trials. It is unnecessary to repeat their derivations here; instead, we direct readers to the original article. We suggest that those same derivations generalize to all redundant target tasks, with a modification to generalize the distractor component in Little et al.'s work (the X and Y terms) to encompass all nontarget locations (whether they contain distractors or no-signal). With this modification we propose that the capacity predictions for the five standard SFT models are always of the $R(t)$ form expressed in Table 1 of Little et al. (2015, p. 31). To sum up, nontarget processes can affect the predictions of all models (combinations of architecture and stopping rule) in both the OR and AND task; however, the baseline independent unlimited capacity parallel model in the OR task will not exhibit changes in $C(t)$—see below.

The two parallel models are contrasted in Figures 2a and 2b. In that figure, we depict a parallel exhaustive model that self-terminates on the nontarget location, which seems the most parsimonious strategy in an AND task; however, the capacity predictions are affected even when assuming completely exhaustive processing (cf. Little et al., 2015). One can intuit how serial models will always be affected by the nontarget processing time regardless of stopping rule as the cognitive system has no a priori way to avoid randomly selecting the nontarget location on some trials.

Although the null-channel may influence processing in both OR and AND tasks, the specific combination of self-terminating parallel processing with independent processing channels (the "standard OR model") would not have its capacity predictions altered. To intuit why this is, readers are again directed to Figure 2a. Because the decision rule in the OR task requires at least one target to be identified in both single and double-target trials, *only* the successful termination of a target process should terminate processing. Thus the nontarget location should not contribute to the response time of the system in the specific case of parallel self-terminating processing. For this reason we suspect that reported capacity coefficients from OR tasks may be less affected by our findings, as capacity is of perhaps most interest when processing is parallel (serial models are generally assumed to be quite inefficient, see, e.g., Townsend & Nozawa, 1997), and generally independence is assumed because it cannot be directly tested (Eidels et al., 2011).[2]

In the AND task, even the benchmark parallel exhaustive model with unlimited capacity does not necessarily predict $C(t) = 1$ for all t under the distractor-modified coefficient (Little et al., 2015). The relative processing speed for distractor channels (and now nontargets more generally) can affect the response time distribution of single-target trials and therefore modify the capacity coefficient. In Figure 4, we illustrate the effect of nontarget processing times on the capacity coefficient generated by the benchmark parallel exhaustive model. In these simulated data, we affected the processing speed of only the nontarget decision process relative to

[2] It is worth pointing out here, and we assume throughout the discussion of theoretical predictions, that processing rates across different stimuli maintain context invariance (see e.g., Ashby & Townsend, 1986; Colonius, 1986, 1990; Colonius & Townsend, 1997; Yang et al., 2018). That is, the marginal distribution for a left-hand target is the same regardless of whether the right-hand target contains another target, a distractor, or indeed, no target. The same is assumed for the target in the right channel and the processing of absent information in either location. We note that Townsend and Wenger (2004b) identify cases where context-invariance does not hold but do not treat those cases here.

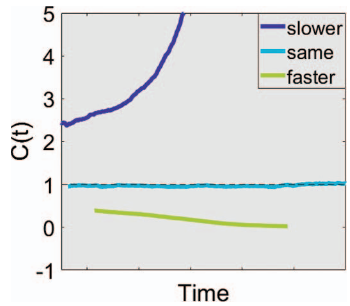

Figure 4. C_{AND} (t) when the Parallel Exhaustive model is simulated to terminate on the nontarget process. The simulation highlights how varying the relative processing time of the nontarget channel compared with the target channel, while holding true capacity fixed, has marked effects on the estimates of the capacity coefficient. Simulations were generated by a Linear Ballistic Accumulator model (Brown & Heathcote, 2008), and bear out the results hypothesized by Little et al. (2015). The terms *slower* and *faster* refer to the speed of the nontarget channel relative to the target—that is, in the slower condition nontarget processes take comparatively longer to complete. See the online article for the color version of this figure.

the target process. The generating model always has "unlimited capacity," in that the processing rate of the target process is identical in both single and double-target trials. We allowed the simulation to self-terminate upon determining that a location contained no-signal in single-target trials (for comparison, most previous approaches have not simulated an absent process at all, cf. Townsend & Wenger, 2004b). All simulations were generated by a Linear Ballistic Accumulator model (LBA; Brown & Heathcote, 2008) with an accumulator for each channel (target and nontarget). We show that manipulating the nontarget processing rates is sufficient to cause C_{AND} (t) to range from limited to super capacity, without any change to the target-processing rate as a function of load. To reiterate, in all cases the generating model is unlimited capacity—the target processing rate is unaffected by the other channel.

Figure 4 shows that *overestimation* of capacity (i.e., $C(t) > 1$ when true capacity is unlimited) results when the nontarget decision processes are slower to complete than target decision processes. In such cases, the single-target response times appear artificially slow relative to the double-target because they are driven by a slower (but unrelated to the target) process. This gives the appearance of a processing benefit under load and thus $C(t) > 1$. Importantly, the overestimation will occur whether we assume self-termination on absent processes, or fully exhaustive processing where the nontarget process is sufficiently slower than the target. Observe that when nontarget processes take the same time as target processes, C_{AND} $(t) = 1$ for all t, as $F_Y(t) = F_A(t)$ (where $F_Y(t)$ is the cumulative distribution function of nontarget processing times). This is essentially a newly identified form of model mimicry (see, e.g., Townsend, 1972) as the result arises from the two processes (nontarget and target) coincidentally displaying similar processing times. As the nontarget process becomes faster or slower relative to the target process, the coefficient ranges from limited capacity to super capacity, respectively.

We draw particular attention to the case in Figure 4 in which the nontarget channel attracts slower processing time than the target. In this case, as noted above, the capacity coefficient incorrectly (based on the "true" model) shows super capacity. In the prototypical SFT studies using dot stimuli, $C(t)$ is typically reported as limited in OR tasks and super in AND tasks (see, e.g., Eidels et al., 2015). This disparity has been observed within the same subject using the same stimuli. Hence, we have a paradox: despite the subject's application of the same architecture (parallel) and a task appropriate stopping-rule (i.e., self-terminating for OR tasks and exhaustive for AND tasks), capacity is not commensurate across the OR and AND tasks (Eidels et al., 2015). We propose that capacity is often empirically overestimated in the AND task because of a slower nontarget process, and we show evidence to support this claim at the end of this article.

We make several observations here: First, it is important to note the shortcoming described in this article relates to the *mapping between the capacity coefficient and empirical data*, and does not invalidate the capacity coefficient itself. This distinction is important, because it allows for the possibility of adapting the empirical setup to match the theoretical underpinnings (we do exactly this below). Second, only single-target trials are affected by the no-signal channel processing. Any double-target focused analyses (including mean interaction contrast [MIC] and the survivor interaction contrast [SIC] calculations) are unaffected as they do not contain a nontarget channel, thus conclusions drawn regarding processing architecture and stopping rule using these SFT measures continue to hold. Any capacity analyses that accounted for the effect of nontarget processes, or from empirical setups that could mitigate those concerns, would similarly continue to hold (however, we are not aware of any such designs).[3]

Third, although in principle the capacity predictions for all models in both OR and AND tasks are affected when nontarget locations are assigned nontrivial processing time, the baseline parallel self-terminating model in the OR task will give identical capacity predictions with or without nontarget influence (assuming independent processing channels; see above). In cases where the capacity predictions in an OR task are affected by nontarget processing, there are other factors, such as serial processing or exhaustive processing, that can explain the inefficient processing; hence further assessment of capacity may be of less importance in those cases. Practically, results from the AND task are more adversely affected as, due to nontarget influence, even the benchmark or standard parallel model in that case can exhibit limited or super capacity coefficients regardless of the true capacity of the system.

Even in the AND task, some researchers employ strategies that may mitigate the effect of processing nontargets—though not for that reason. Most notably, researchers such as Eidels et al. (2015) have previously substituted single-target trials from an OR task into the numerator of C_{AND} (t), contrasted against AND task double-target trials. Those authors cited concerns about different response mappings influencing response times (single-targets are mapped to a *no* response in the AND task where the double-targets are mapped to a *yes* response; see, e.g., Wason, 1959 for evidence that no responses might be slower than yes responses). Although aimed at a different issue entirely, the substitution strategy may

[3] To date, trials containing no target at all have not been utilized within the SFT analyses but are included in the experiment to control the base rate of each response.

have alleviated the effect of nontarget locations, assuming the OR task was completed with a parallel self-terminating strategy. Capacity results reported using this substitution strategy may be more reliable than those generated directly from AND task data. However, substitution is not always possible. First, it requires additional data collection; at minimum, several blocks of pure single-target OR rule trials would need to be collected, removed from the context of the rest of the AND task, relying on the assumption that processing does not change between these experimental contexts. Additionally, one of the prime benefits of the AND task is that it addresses questions that OR tasks cannot, such as questions about holistic processing (see, e.g., Fifić & Townsend, 2010), or classification based on several rules (Little et al., 2013). These factors may not be readily amenable to OR designs (or at least the questions raised by the two designs may be different), yet processing capacity can still be of concern in those cases. Therefore, an approach to remedy the issues identified above within a purely AND task design would be a useful contribution. Unfortunately, the Resilience functions developed by Little et al. (2015) cannot be applied to the no-signal version of the AND task because salience of a null signal cannot be manipulated.

Thus far we have demonstrated that the assumption that no-signal locations do not contribute to processing speed is likely to be incorrect. We then demonstrated how relaxing this assumption allows C(t) to change in ways that do not reflect the actual processing capacity. We next develop a practical solution to this issue. As noted above, the issues outlined thus far relate to the mapping between the theoretical capacity coefficient and the empirical data. That is, the theory does not account for nontarget processing, which appears to be unavoidable in empirical applications. Therefore, if we could suitably modify the empirical setup such that the nontarget processes could be accounted for, the capacity coefficient could be implemented without concern. We suggest that if processing in the AND task could be assumed to be completely exhaustive (i.e., both locations were always processed to completion), it would be possible to factor out the effect of the nontarget channel from the response time distributions. However, the empirical results presented earlier do not preclude self-termination on the nontarget location; in fact, we believe this strategy to be the most parsimonious account of AND task processing.

Hence, for the remainder of the article, we propose a modified version of the AND task that requires full-identification of each stimulus location (i.e., separate target identification for each location). This results in a change from two responses to four, and if we assume a dot task with left and right locations, the design and stimulus space would be as depicted in Figure 5. We hereafter refer to this task as the modified-AND task.

Importantly, in the new task, responses will always terminate on the *slowest* channel regardless of what it contains (see Figure 6). That is, we remove the possibility for self-termination on nontarget channels, because accurate responding requires the unique identification of both Locations A and B. Conveniently, this property allows a modified capacity coefficient to be derived. The derivation relies on the fact that the response time distribution for each display type is known to be an maximum rule combination of both channel completion times. The resulting coefficient relies on an additional assumption that is not made by the existing capacity coefficients: that context invariance holds for no-signal processes

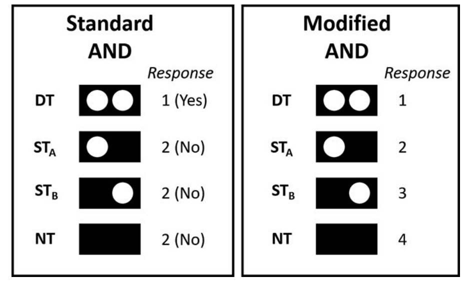

Figure 5. Standard and modified-AND task designs. The modified task requires unique identification of both stimulus locations, and as such the number of response options increases from two to four. DT = double target; ST = single target (subscript A and B denote individual target locations); NT = no target.

(that is, we assume that in the special case where the nontarget location contains no-signal, that process is unaffected by the presence of a target in the neighboring channel, see Colonius, 1986, 1990).

Deriving a New Capacity Coefficient

Before presenting the formal derivations, we provide a brief overview of our mathematical endeavor. As discussed in this article, Townsend and Wenger's (2004b) C_{AND} (t) coefficient provides a powerful and unquestioned assessment of processing capacity. However, the existing empirical application of this coefficient relies on assumptions that we demonstrate to be incorrect. That is to say, the flaws we point out relate to a mismatch between theory and empirical application, and do not discount the relevance of the existing theoretical structures. We modified the empirical setup as described above to force exhaustive processing (see also Eidels, Ryan, Williams, & Algom, 2014 for a different treatment of experimental designs to force specific response strategies). This helps ensure that both target and nontarget processes contribute to the observed response time on every trial. With this knowledge we aim to factor out the influence of nontarget processes on the capacity coefficient. To do this, we build on previous developments concerning the UCIP assumptions (Little et al., 2015; Townsend & Nozawa, 1995; Townsend & Wenger, 2004b). Thus, we begin our derivations using Townsend and Wenger's coefficient as a starting point.

Little et al. (2015) show that attributing nontrivial processing time to distractor channels results in the modification of the standard capacity coefficient (Equation 1) for AND tasks (derived in Townsend & Wenger, 2004b) such that:

$$C_{AND}(t) = \frac{\log[F_A(t) \cdot F_B(t)]}{\log[F_{AB}(t)]} \tag{1}$$

$$\rightarrow \frac{\log[F_{AY}(t) \cdot F_{XB}(t)]}{\log[F_{AB}(t)]} \tag{2}$$

where X and Y refer to the distractor presented in the left or right locations respectively. The work presented in this article suggest these X and Y terms should be generalized to include any nontarget, including cases where no-signal is presented. For clarity, we hereafter replace the X and Y terms with the terms ~A and ~B, respectively, to reflect that for the remainder of the article we

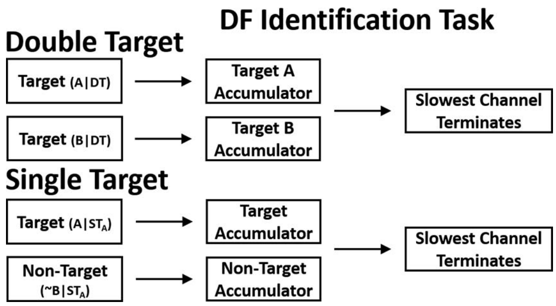

Figure 6. Processing channel behavior in the modified-AND task requiring unique identification of both stimulus locations. Processing terminates on the slowest process in both double and single-target displays because all responses require a unique identification of both components of the display. DT = double target; ST = single target, (subscript A denote individual target locations).

specifically refer to the no-signal variant of the nontarget (i.e., ~A refers specifically to the case where no-signal is presented in Location A). For written clarity we use the terms DT, ST_A, ST_B, and NT to refer to the four possible stimulus displays.

The modified coefficient in Equation 2 includes additional processes not specified in Equation 1 (namely the no-signal channels). The form of the coefficient specified in Equation 2 is the likely result of current empirical applications of the capacity coefficient in AND tasks, given the high probability that single-target response times are contaminated by nontarget processes. That is, with the existing empirical setup we cannot obtain data that match the theoretical coefficient, and feeding such data into the formula instead results in a modified comparison. This modified coefficient may elicit values of C_{AND} (t) that do not reflect the underlying capacity of the system, that is, changes in the X and Y terms alter the function despite the relationship between the target processes remaining constant.

Using the modified-AND task and invoking an assumption that the no-signal process is context invariant, we can derive a modified form of Equation 2 that allows the effects of the no-signal processes to be cancelled out. The no-signal process is assumed to be unaffected by the presence of a target in the other channel.[4] This assumption can be formally expressed as:

$$F_{\sim B\,|\,ST_A}(t) = F_{\sim B\,|\,NT}(t) \tag{3}$$

$$F_{\sim A\,|\,ST_B}(t) = F_{\sim A\,|\,NT}(t) \tag{4}$$

where $F_{\sim B}|ST_A(t)$ is the distribution of processing times for the no-signal process ~B as part of the single-target A only display, and $F_{\sim B}|NT(t)$ is the equivalent no-signal process presented in the context of a double-absent display. Under the assumption that the no-signal process is context invariant, and therefore that both Equalities 3 and 4 hold, the distribution of processing times for the four stimulus displays in the modified task is:

$$F_{DT}(t) = F_{A\,|\,DT}(t) \cdot F_{B\,|\,DT}(t) \tag{5a}$$

$$F_{ST_A}(t) = F_{A\,|\,ST_A}(t) \cdot F_{\sim B}(t) \tag{5b}$$

$$F_{ST_B}(t) = F_{\sim A}(t) \cdot F_{B\,|\,ST_B}(t) \tag{5c}$$

$$F_{NT}(t) = F_{\sim A}(t) \cdot F_{\sim B}(t) \tag{5d}$$

If we expand Equation 2 to its constitute processing channels using logarithmic expansions (see, e.g., Little et al., 2015):

$$C_{AND}(t) = \frac{\log[F_{ST_A}(t) \cdot F_{ST_B}(t)]}{\log[F_{DT}(t)]} \tag{6a}$$

$$C_{AND}(t) = \frac{\log[F_{A\,|\,ST_A}(t) \cdot F_{\sim B}(t) \cdot F_{\sim A}(t) \cdot F_{B\,|\,ST_B}(t)]}{\log[F_{A\,|\,DT}(t) \cdot F_{B\,|\,DT}(t)]} \tag{6b}$$

$$C_{AND}(t) = \frac{\log[F_{A\,|\,ST_A}(t)] + \log[F_{\sim B}(t)] + \log[F_{\sim A}(t)] + \log[F_{B\,|\,ST_B}(t)]}{\log[F_{A\,|\,DT}(t)] + \log[F_{B\,|\,DT}(t)]} \tag{6c}$$

It is apparent that there are two unwanted terms in the numerator of Equation 6c: $F_{\sim A}$ and $F_{\sim B}$. These terms are included due to the unavoidable processing of the absent locations on the single target trials. This means that, compared with the theoretical form of C_{AND} (t) specified in Equation 1, the empirical mismatch form of the equation includes two additional terms, both in the numerator, neither of which is relevant to the capacity analysis.

Notably, Equation 5d from our modified-AND task is equivalent (after log transformation) to the unwanted (nontarget) component of the numerator of 6c, that is, the no-signal components of single target A and single target B. We can therefore use response times from this no-target condition to offset the nuisance terms in the numerator. This new ratio, comparing trials from four different empirical conditions, is specified in Equation 7:

$$C_{ID}(t) = \frac{\log[F_{ST_A}(t) \cdot F_{ST_B}(t)]}{\log[F_{DT}(t) \cdot F_{NT}(t)]} \tag{7}$$

We term the equation $C_{ID}(t)$ [for *identification*] from here onward to indicate we are using terms unique to the modified-AND task that requires full-identification responses. It should be evident here that Equation 7 will reduce to Equation 1 (the theoretical specification of C_{AND} $[t]$), because when expanded it is equal to Equation 1 with identical terms (processes ~A and ~B) added to the numerator and denominator under the assumption of context invariant absent processes. Thus, Equation 7 can be used in conjunction with the modified-AND task to assess capacity in AND paradigms without the influence on nontarget processing. We formally prove this below.

By invoking the assumption of context invariance, (that is, that ~A and ~B distributions are unaffected by the value of the other location) the ~A and ~B processes in the numerator and denominator are identical. Expanding the terms in Equation 7 to constituent processing channels gives:

$$C_{ID}(t) = \frac{\log[F_{A\,|\,ST_A}(t) \cdot F_{\sim B\,|\,ST_A}(t) \cdot F_{\sim A\,|\,ST_B}(t) \cdot F_{B\,|\,ST_B}(t)]}{\log[F_{A\,|\,DT}(t) \cdot F_{B\,|\,DT}(t) \cdot F_{\sim A\,|\,NT}(t) \cdot F_{\sim B\,|\,NT}(t)]} \tag{8a}$$

[4] We only make this assumption for the special case that the nontarget channel contains no signal; we do not expect this property to hold for the generalized distractor case (see Little et al., 2015). Although some readers may be concerned that, as Colonius and Vorberg (1994) note, context-invariance implies unlimited capacity, we believe the fundamental distinction between targets and no signal (or blank) displays can accommodate this assumption.

$$C_{\mathrm{ID}}(t) = \frac{\log[F_{A\,|\,ST_A}(t)] + \log[F_{\sim B\,|\,ST_A}(t)] + \log[F_{\sim A\,|\,ST_B}(t)] + \log[F_{B\,|\,ST_B}(t)]}{\log[F_{A\,|\,DT}(t)] + \log[F_{B\,|\,DT}(t)] + \log[F_{\sim A\,|\,NT}(t)] + \log[F_{\sim B\,|\,NT}(t)]} \tag{8b}$$

Applying the assumption of context invariant nontarget processing, the equation can be simplified to (terms have been reordered for clarity):

$$C_{\mathrm{ID}}(t) = \frac{(\log[F_{\sim A}(t)] + \log[F_{\sim B}(t)]) + (\log[F_{A\,|\,ST_A}(t)] + \log[F_{B\,|\,ST_B}(t)])}{(\log[F_{\sim A}(t)] + \log[F_{\sim B}(t)]) + (\log[F_{A\,|\,DT}(t)] + \log[F_{B\,|\,DT}(t)])} \tag{9}$$

We can now factor out the ∼A and ∼B terms from both the numerator and denominator. To do so, we assume that processing is unlimited capacity, with independent, parallel channels (UCIP processing). Under the UCIP assumption we know that the original formulation of C_{AND} (t) (Equation 1, developed by Townsend & Wenger, 2004b) equals 1 for all t. Because of our context invariance assumption, Equation 9 is equivalent to adding identical ∼A and ∼B terms to both the numerator and denominator of Equation 1 (essentially, adding a constant to the original C_{AND} $[t]$ expression). Thus, Equation 9 equals 1 for all time t under the assumption of UCIP processing with context-invariant nontarget processes:

$$C_{\mathrm{ID}}(t) = \frac{\log[F_{\sim A}(t)] + \log[F_{\sim B}(t)] + \log[F_{A\,|\,ST_A}(t)] + \log[F_{B\,|\,ST_B}(t)]}{\log[F_{\sim A}(t)] + \log[F_{\sim B}(t)] + \log[F_{A\,|\,DT}(t)] + \log[F_{B\,|\,DT}(t)]} = 1 \tag{10}$$

As this equation equals one for all time t, multiplying both sides by the denominator gives:

$$\log[F_{\sim A}(t)] + \log[F_{\sim B}(t)] + \log[F_{A\,|\,ST_A}(t)] + \log[F_{B\,|\,ST_B}(t)] = \log[F_{\sim A}(t)] + \log[F_{\sim B}(t)] + \log[F_{A\,|\,DT}(t)] + \log[F_{B\,|\,DT}(t)] \tag{11}$$

From this expression we can cancel the equivalent terms from either side (again, this operation depends on the assumption of context-invariant processing of absent terms). This results in the simplified expression:

$$\log[F_{A\,|\,ST_A}(t)] + \log[F_{B\,|\,ST_B}(t)] = \log[F_{A\,|\,DT}(t)] + \log[F_{B\,|\,DT}(t)] \tag{12}$$

which reexpressed as a ratio once more becomes:

$$C_{\mathrm{ID}}(t) = \frac{\log[F_{A\,|\,ST_A}(t)] + \log[F_{B\,|\,ST_B}(t)]}{\log[F_{A\,|\,DT}(t)] + \log[F_{B\,|\,DT}(t)]} = 1 \tag{13}$$

The resulting expression in Equation 13 is equivalent to Equation 1, the original formulation of C_{AND} (t), expanded to constituent processing channels. That is, all nontarget processes have been factored out and the coefficient is left comparing only the target-channel completion times in single versus double target displays - the mismatch between theory and empirical data has been resolved. We term the coefficient formalized in Equation 7 $C_{\mathrm{ID}}(t)$ to reflect its application to a full-identification modification of the AND paradigm. The coefficient will take an equivalent value to C_{AND} (t) under the assumption of context invariant absent processing, and the assumption that the response entropy induced by the addition of two extra response options in the modified task is minimal—this seems to be the case given the following experimental results. The capacity space of the coefficient is the same as existing SFT tasks, because the equation resolves to Townsend and Wenger's (2004b) coefficient. Therefore, the UCIP model predicts $C_{\mathrm{ID}}(t) = 1$ for all t, with limited capacity predicting values of <1 and super capacity predicting values >1.

To demonstrate the suitability of $C_{\mathrm{ID}}(t)$ to measuring capacity independent of changes in nontarget processing times, in Figure 7 we present simulated data systematically varying processing both capacity and nontarget processing times within the modified-AND task. These simulations were generated using a Linear Ballistic Accumulator (LBA; Brown & Heathcote, 2008) and response times were obtained by taking a maximum-time combination of the two processes in each simulated trial (as the modified-AND task requires fully exhaustive processing). Capacity was affected by applying a modifier to the target channel drift rate v parameter in double target trials. A modifier >1 speeds target processes when both targets are presented, that is, super capacity. Conversely, a modifier <1 induces limited capacity. Figure 7 illustrates how $C_{\mathrm{ID}}(t)$ reliably reflects the true capacity of the model in all cases. Interestingly, the absolute magnitude of capacity deviations changes with the ratio of target/no-signal processing (affected by fixing the drift-rate v of the nontarget channel to be faster, slower or equal to the target drift-rate). This is a product of the exhaustive decision rule; when the target process is slower than the nontarget process (top left panel) the target-channel will drive response times making the capacity limitation more salient. Another observation

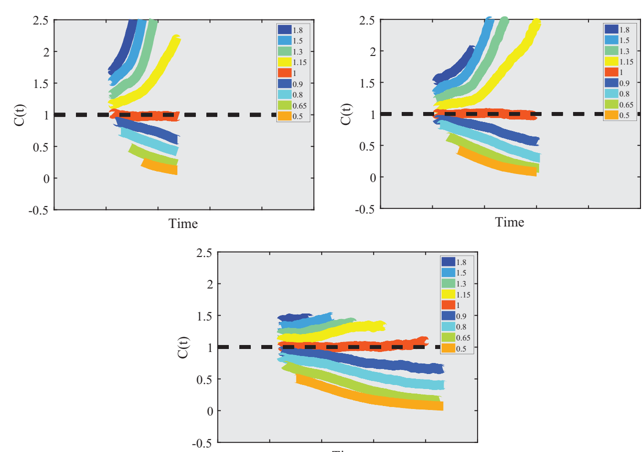

Figure 7. Simulated capacity coefficients from the modified-AND task. Data were simulated using a parallel Linear Ballistic Accumulator (LBA) process, response times (RTs) defined using a Maximum Time rule for all conditions. Capacity was varied by applying a modifier c to the double-target drift rate v parameter, where values of $c > 1$ indicate super capacity, and vice versa. The legend shows the value of c for each simulation. We simulate different relationships between the target and nontarget process (faster, same, slower no-signal process) to show the novel coefficient does not make the same erroneous predictions the original did in Figure 4. See the online article for the color version of this figure.

is that simulated capacity other than strictly unlimited does not predict a fixed value but rather a rising (for super capacity) or descending (for limited capacity) coefficient, at least when generated by an LBA model. We suspect this is related to the change in relative contribution of DT and NT trials across time points. Importantly, the direction of the coefficient is always as expected, that is, $C_{ID}(t)$ is always >1 for super capacity models, <1 for limited capacity models, and $= 1$ for the unlimited model, and unlike the standard-AND case (see Figure 4 above), varying nontarget channel processing rates does *not* change the capacity interpretation.

Interim Discussion

Some readers may be concerned with the additional assumption of context-invariant no-signal processing required for the above derivations (see, e.g., Yang, Altieri, & Little, 2018, for examples where the context variable assumption has been violated in audiovisual tasks). One of the key benefits of SFT has been its nonparametric, distribution independent properties that require minimal assumptions about the underlying processes. Even though the benchmark UCIP models assume context-invariant target processing, we directly test this assumption with $C(t)$. However, we note that previous capacity applications have relied on the (false) assumption that nontarget channels attract negligible processing times, and our new assumption simply replaces the old one. Further, to assess target capacity directly in an AND like task, this added assumption is necessary. Consider a case where context invariance does not hold for absence processing (i.e., the absent process is systematically faster or slower in double-absent vs. single-target trials). In this case, the value of $C_{ID}(t)$ would vary based on the (unidentifiable) degree of violation of context invariance even if the generating target processes were unlimited capacity. As such, the additional assumption is necessary to allow inference, and is line with previous approaches by other authors (see, e.g., Ben-David et al., 2014; Eidels et al., 2010).

An additional observation can be made regarding the effect of base-time on the present equations. Base time refers to processing time that arises as a result of additional processes not attributable to processing the target locations (typically called nondecision time). Townsend and Honey (2007) note that, in general, the effects of base-time have opposite effects in OR and AND paradigms, such that capacity would be underestimated in OR tasks and overestimated in AND tasks (although they note the practical effects are likely to be minimal). In our approach all response times result from an exhaustive combination of two processes. Therefore any base-time concerns are mitigated when considering our $C_{ID}(t)$.

Having established the new $C_{ID}(t)$ measure and demonstrated its effectiveness both analytically and through simulation, the next step is to apply the measure empirically. To test the new measure we performed a small study aiming to approximate the standard Double-Factorial Paradigm dot task. Performance in this task has been well studied (see, e.g., Eidels et al., 2015; Townsend & Nozawa, 1995), providing an established benchmark to assess the new measure and further validate the modified-AND task more generally. This study also allows us to comment on an intriguing theoretical question surrounding processing capacity. In general, participants in the OR version of the dot detection task exhibit slightly to-moderately limited capacity parallel processing (e.g., Townsend & Nozawa, 1995). In the AND version of the task processing is still observed to be parallel, but capacity is often reported as moderately super capacity (Eidels et al., 2015). As noted earlier, C_{AND} (t) may empirically overestimate capacity depending on the relative processing time attached to target and absent processes, whereas predictions in the OR task are unaffected when processing is parallel self-terminating. $C_{ID}(t)$ is robust to this concern; as such the modified-AND task provides a useful foil to the standard AND task for capacity comparisons. We conducted a study in which participants completed three sessions of a dot-detection task, where each session mapped to a different response rule (OR, standard-AND, Modified-AND). This design allowed us to compute capacity measures, C_{OR} (t), C_{AND} (t), and $C_{ID}(t)$ for the three tasks, respectively. The details of the experiment are presented below. The three experimental sessions shared most methodological features so the details are presented together.

Method

Participants

Ten participants were recruited from within the School of Psychology at the University of Newcastle to participate in three experimental sessions (OR, standard-AND [AND], Modified-AND [ID - for identification]) of approximately one hour each, and were remunerated with gift cards (valued $25 per session). All had normal or corrected-to-normal vision. Ages ranged from 23 to 36.

Stimuli and Design

Each experiment used a typical double-factorial design with identical stimuli (bright dots on top and bottom of the screen). At one factorial level target presence/absence was crossed with location (top/bottom). At the second level, target salience (high/low) was crossed with location (top/bottom). Overall, this design resulted in nine unique stimulus combinations: four containing two targets (HH = both targets in high contrast, HL = one high and one low, LH, and LL), four containing one target (top-only target high or low, bottom-only target high or low), and one display containing no targets. Targets could appear in two possible locations, $\pm$ 1 cm from the center of the display. Salience was scaled between 0 (RGB[0,0,0], black) and 1 (RGB[255,255,255], white), with high salience set at .7 (RGB[179,179,179]) and low salience set at.2 (RGB[51,51,51]), both lighter than the black background. The dots were displayed within a 250 $\times$ 250 pixel black box, and the remainder of the screen was set at a constant gray value (RGB[128,128,128]) throughout the experiment. Each dot was approximately 5 mm in diameter, subtending a visual angle of 0.48° at a sitting distance of 60 cm. Each combination of Dot $\times$ Location (i.e., both, one-top, one-bottom, no dots) was presented an equal number of times; thus the proportion of each response option changed between experiments but stimulus presentation was constant. In the OR task participants were required to respond *yes* to double and single-target displays and *no* to double-absent displays. In the AND task participants were required to respond *yes* to double-target displays and *no* to both single target and double absent displays. In the ID task, each of these four displays mapped to a unique response option.

Procedure

Experimental order was randomized between participants using a Latin square design and the procedure was identical on all three experiments, apart from the response mapping. Participants were invited to attend a computer laboratory at the University of Newcastle. At the beginning of each session participants completed a short, untimed practice block designed to introduce them to the response mapping for that session. Following this, a practice block consisting of 80 trials (20 for each of the four display types: double-target, single-top, single-bottom, no-target) was presented. Each trial was preceded by a 500-ms fixation cross, followed by a 500-ms blank screen. Stimuli were then presented for 500 ms, or until a response was made. If a response was not made, the stimulus was removed and a blank, gray screen displayed until either a response was made or 4 s had passed since the stimulus onset. Feedback (*correct* or *incorrect*) was provided after each trial. Following the practice block, a total of 15 experimental blocks were presented, resulting in 1200 experimental trials. These blocks were identical to the practice except feedback was not provided, and the stimulus presentation was shortened to 150 ms.

For both the OR and the AND sessions, response options were *yes* and *no*, mapped to the *A* and *L* keys and counterbalanced between participants. In the OR task the *yes* response was mapped to all three of the target-containing conditions, in the AND case the *yes* response mapped only to the double-target condition. For the ID task, responses were mapped to display type: response keys were *Q* and *S* for single-target top and bottom respectively, both *Q* and *S* simultaneously for double target, and *L* for no target. The experiment program listened for 100 ms to ensure double key presses were accurately detected. Pilot testing suggested that pressing both single-target keys for the double-target display was a natural response option for this task.

Results

Descriptive Statistics

To ensure the Modified-AND task elicits similar processing to the standard-AND task we first consider some basic descriptive details. As shown in Table 1, accuracy was generally high. Each experiment had an average accuracy of more than 90%; the majority of individual data sets had accuracy above this level as well. Importantly, accuracy in the standard-AND and Modified-AND tasks were practically equivalent (there was half a percent difference in accuracy between the tasks), suggesting that the modified task does not adversely impair performance. We present mean response times and accuracy for all conditions per experiment in Table 2.

Analysis of Selective Influence

To test the assumption of selective influence (see, e.g., Houpt et al., 2014) we implemented a distribution free Bayesian test proposed by Heathcote et al. (2010). This test provides a Bayesian equivalent of the more typically used Kolmogorov–Smirnov tests (Houpt & Townsend, 2010) but performs better with small samples (<100), making it more appropriate to use here (each of our four double-target trials had 75 presentations). For all subjects in all

Table 1
Accuracy by Subject for Each Experiment

Participant	OR	AND	ID
Sub01	0.954	0.977	0.974
Sub02	0.873	0.855	0.905
Sub03	0.979	0.979	0.981
Sub04	0.966	0.950	0.968
Sub06	0.940	0.948	0.952
Sub07	0.966	0.978	0.978
Sub08	0.956	0.971	0.903
Sub09	0.913	0.834	0.951
Sub10	0.862	0.919	0.701
Sub11	0.930	0.854	0.904
M	0.936	0.927	0.922

experiments the selective influence checks were successful in the double-target trials, such that $S_{\mathrm{HH}}(t) \lesssim S_{\mathrm{HL}}(t), S_{\mathrm{LH}}(t) \lesssim S_{\mathrm{LL}}(t)$ (where $S_{\mathrm{HH}}(t)$ is the survivor function of response times in the HH condition), and a stochastic dominance relationship between $S_{\mathrm{HH}}(t) < S_{\mathrm{LL}}(t)$ with a Bayes Factor of at least 5.

We also assessed the effect of the selective influence manipulation for single-target displays. We suggested earlier that if the single-target display did not show the same salience effect (particularly in the AND case) as the double-target, the target-processes were not comparable and the capacity coefficient may be tainted. Using the same nonparametric test as above, with two tests per participant (selective influence in the left-target only and right-target only displays), for the OR Task 18 of 20 tests showed evidence for a salience effect in the expected direction with a BF of at least 5. For the AND task, no tests showed evidence for any salience effect. For the ID task, 18 of 20 tests showed evidence for a salience effect in the expected direction with a BF of at least 5. These tests provide useful evidence that the single-target displays in the modified-AND task force exhaustive processing and should allow a more robust capacity coefficient in empirical settings.

Analysis of Architecture and Stopping Rule

To confirm that processing strategies remain consistent between experiments (i.e., that subjects exhibit parallel, task-appropriate processing) we examine two measures, called the MIC and the SIC. Townsend and Nozawa (1995) showed that by contrasting the four double target conditions (HH, HL, LH, LL, where H and L refer to the salience of each target) we can characterize the processing architecture and capacity of a system. In brief, the MIC can be defined as $MIC = MRT_{HH} - MRT_{HL} - MRT_{LH} + MRT_{LL}$, where MRT_{HH} is the mean response time to the HH condition, and so forth. Positive or negative MICs are associated with parallel processing (with self-terminating or exhaustive processing respectively) and an $MIC = 0$ denotes serial processing. By substituting the survivor function of response times in place of the Mean reaction time (RT) above we can compute the Survivor Interaction Contrast. Importantly, an all positive SIC suggests a parallel self-terminating process (which we expect for the OR task) and an all negative SIC suggests parallel exhaustive processing (which we expect for the AND and ID tasks).

We apply a nonparametric Bayesian approach proposed by Houpt et al. (2017) to assess the MIC/SIC. This approach is based

Table 2
Mean RT (With SD) and Mean Accuracy (With SEM) for Each Condition and Experiment

Condition	*M* RT (ms)	*M* accuracy
OR-HH	386.35 (104.40)	0.995 (0.002)
OR-HL	402.58 (120.16)	0.998 (0.001)
OR-LH	398.38 (116.17)	0.996 (0.002)
OR-LL	459.54 (167.20)	0.953 (0.007)
OR-HX	398.23 (129.89)	0.990 (0.003)
OR-LX	458.68 (186.10)	0.862 (0.009)
OR-XH	399.91 (146.10)	0.992 (0.002)
OR-XL	458.10 (156.21)	0.872 (0.009)
OR-XX	536.08 (182.00)	0.891 (0.006)
AND-HH	459.52 (120.24)	0.972 (0.005)
AND-HL	521.53 (150.71)	0.839 (0.012)
AND-LH	529.88 (160.11)	0.835 (0.012)
AND-LL	530.24 (148.10)	0.753 (0.014)
AND-HX	495.17 (168.79)	0.930 (0.007)
AND-LX	501.03 (191.92)	0.963 (0.005)
AND-XH	495.81 (178.60)	0.960 (0.005)
AND-XL	490.65 (175.74)	0.975 (0.004)
AND-XX	451.09 (145.03)	0.991 (0.002)
ID-HH	438.86 (109.15)	0.990 (0.003)
ID-HL	486.89 (121.74)	0.872 (0.010)
ID-LH	483.87 (123.95)	0.885 (0.010)
ID-LL	498.50 (131.32)	0.837 (0.011)
ID-HX	456.82 (133.87)	0.968 (0.004)
ID-LX	498.43 (148.52)	0.880 (0.008)
ID-XH	452.56 (105.25)	0.971 (0.004)
ID-XL	500.33 (150.12)	0.881 (0.008)
ID-XX	528.75 (162.00)	0.956 (0.004)

Note. RT = reaction time. *H*, *L*, and *X* refer to salience levels high, low, and absent, respectively. *AND*, *OR*, and *ID* refer to the three experimental designs.

on a Dirichlet Process, and samples from the empirical response time distributions for each double-target condition. Each posterior sample is classified as belonging to one of five signature SFT models (see, e.g., Houpt et al., 2014) or not matching any model, based on a combination of MIC and SIC computed from the sampled probability distributions. The total posterior classification is compared with the prior weights on the models. We specified a uniform prior on the model space such that all models were equally likely in the prior. Importantly, all subjects showed strong evidence (posterior model probability $>.5$) for a parallel architecture and task appropriate stopping rule (self-terminating in the OR task, exhaustive in both AND tasks). We can confirm these results by examining the empirical SICs in Figure 8, where all the OR SICs are generally all-positive, and both AND tasks show almost entirely negative SICs. This allows us to be confident that any observed differences in capacity are not due to changes in processing architecture between tasks, and also that the capacity predictions for the OR task are not affected by the nontarget processing channels.

Analysis of Capacity

In Figure 9a we present the individual empirical capacity coefficients, computed using C_{OR} (t), C_{AND} (t) and $C_{ID}(t)$ respectively. It is clear that $C(t)$ tends to be higher in the standard-AND case (the red lines) than for either of the other experiments. In fact, for all subjects C_{AND} (t) exceeds 1 at some time. Contrast this with the OR case where no subject shows super capacity, and the Modified-AND case where only two subjects are marginally greater than 1 at any time. Both the OR and ID cases would suggest unlimited-to-moderately limited capacity interpretations, whereas the AND case would suggest super capacity for many participants.

For comparison purposes, in Figure 9b we show the capacity coefficients from the AND experiment computed through the standard C_{AND} (t), and an alternate calculation performed by substituting single-target trials from the participants OR session (consistent with Eidels et al., 2015). Here, we use the standard AND C(t) but use the single-target response times from the OR task. This strategy has been used previously to ensure single and double target trials both result from a *yes* response but should also reduce the influence of nontarget processing. This substitution strategy does reduces the differences between the AND and OR cases—this is because response times for single-target trials in the OR case are not affected by the no-signal process. However, even here two subjects show evidence for super capacity that is not present in the modified version of the task. We suspect this means that the decisional stopping rule can have a nontrivial impact on response time that limits the suitability of the substitution strategy (see e.g., Eidels et al., 2015).

To better understand the reliability of our capacity findings we also examined the average capacity coefficient for each task. We bootstrapped the data to create 1,000 samples for each experimental session, computed a coefficient for each bootstrap × participant combination, then averaged the values at each time-bin. The resulting average capacity coefficients are shown in Figure 9c. The group-level estimates were consistent with the individual $C(t)$ plots, and again highlight the discrepancies between $C(t)$ computed from a standard-AND task versus either the OR or the modified-AND task.

Discussion

In this article, we have provided empirical evidence that the capacity predictions used in most SFT applications may be affected by previously unaccounted for effects of nontarget processes. We showed that while theoretical predictions of most models are affected, in the OR task the effects are limited to cases where capacity may be of less importance to the researcher. We identified major issues with capacity analysis in the standard-AND task, such that it would be impossible to reliably assess processing capacity in those tasks. We proposed a modification to the AND task requiring participants to fully identify both stimulus locations on all trials. This modification allowed the derivation of a modified version of C_{AND} (t) that is robust to the effects of nontarget processing channels under certain (reasonable) assumptions. Relying on those assumptions, along with useful properties of the modified-AND task, we were able to show that the $C(t)$ could be empirically estimated without bias using our modified capacity coefficient, termed $C_{ID}(t)$, computed from data collected in the modified experimental task.

We applied the new coefficient, alongside the existing C_{OR} (t) and C_{AND} (t), to provide evidence that processing capacity for two dots of light is limited under both self-terminating and exhaustive decisional stopping rules, when the effect of nontarget channel processing times are accounted for with the modified coefficient. These results suggest that the standard-AND task may often em-

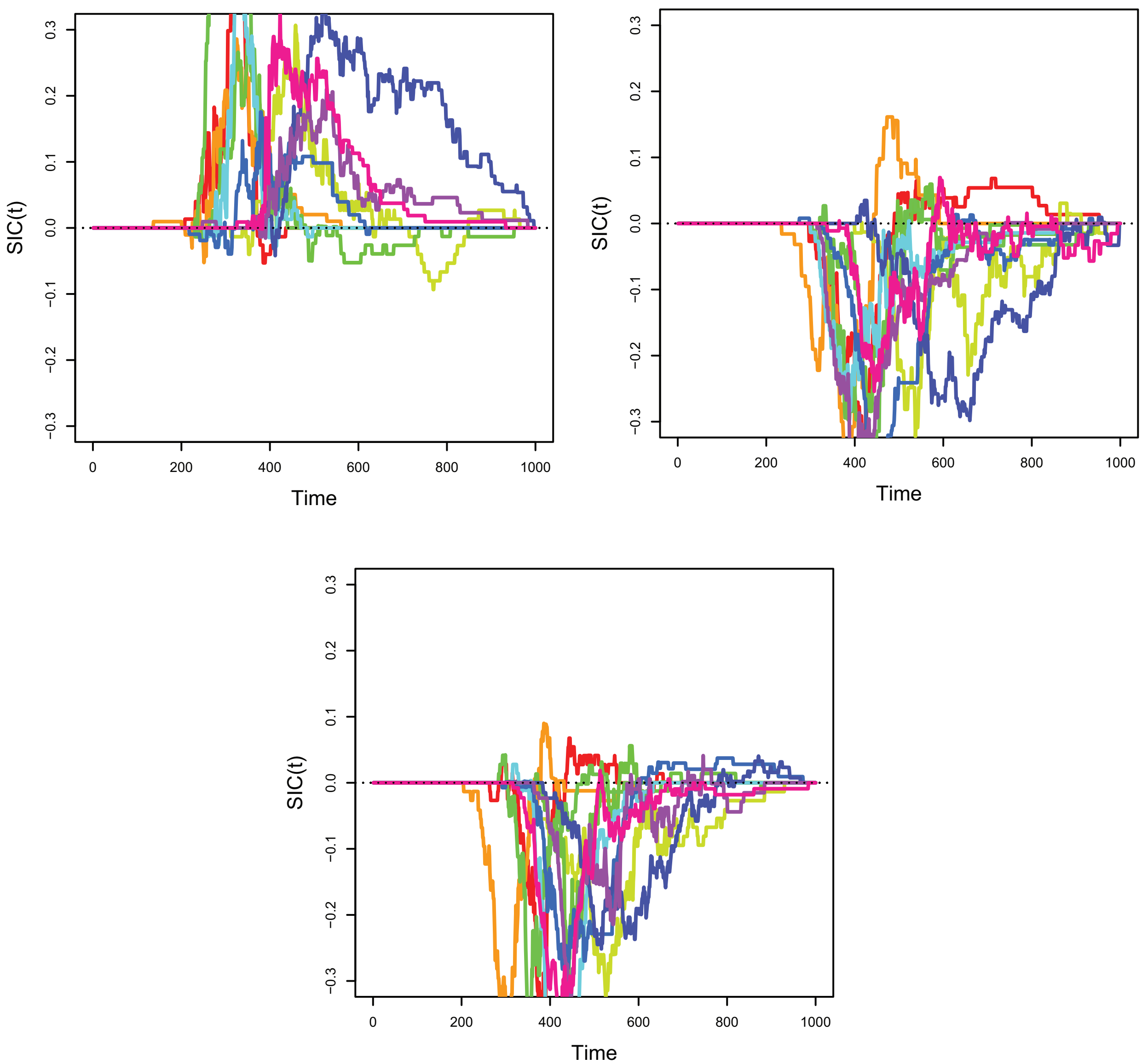

Figure 8. Empirical survivor interaction contrasts (SICs) for each person in each experiment. All subjects showed evidence for parallel processing with a task appropriate stopping rule. See the online article for the color version of this figure.

pirically overestimate processing capacity and highlights that these previously unidentified effects have likely tainted earlier reported findings. The modified-AND task provided results that were much more consistent with the standard OR findings than the existing AND task. This result highlights the importance of accounting for the effect of the no-signal channel—previously published results (e.g., Eidels et al., 2015; Townsend & Nozawa, 1995) reported fundamental processing capacity differences even when the same subjects viewed the same stimuli using the same processing architectures. Our findings suggest the previously reported super capacity in AND tasks was inflated by the effect of the no-signal channel. Occam's Razor suggests processing capacity probably does not change with task instructions when our results are taken into account.

A reviewer raised the question of whether the differences we report between single target conditions in the OR and AND tasks could be remedied by changing the task instructions such that instead of *target* and *no target* the options were more neutral (e.g., *condition A* or *condition B*). This is, in effect, what our novel task achieves (albeit with the extension to four responses). We suspect that simply relabeling instructions in the standard AND task would not be sufficient to overcome the potential for self-termination on the nontarget channel. An alternate account for the single-target discrepancy is that the salience effect could simply be weaker in the AND task. This would certainly explain why we see little-to-no difference between the high and low salience single targets. However, this account does not explain why the salience effect is strong for double-target trials in both AND and OR tasks. Additionally, a

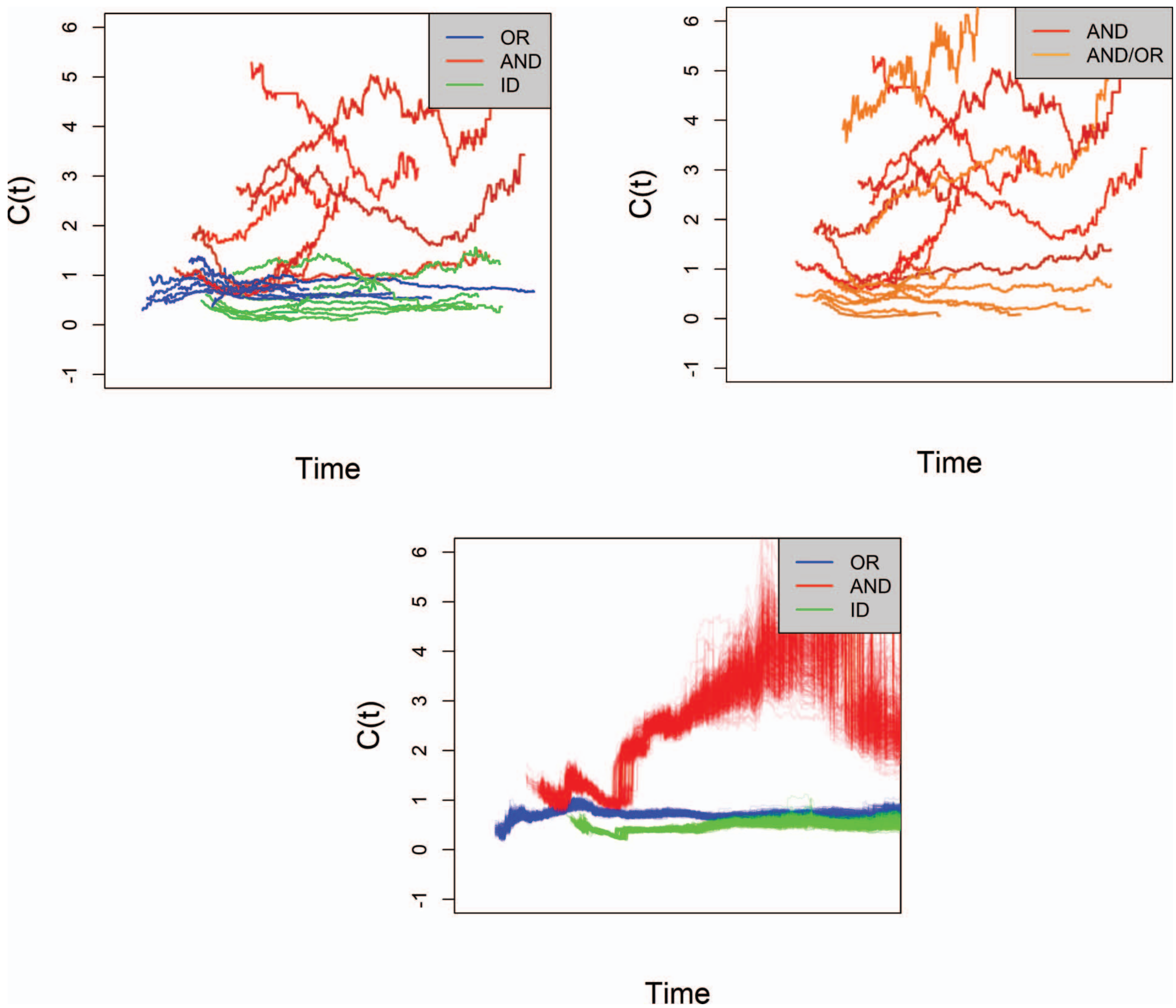

Figure 9. Top Left: Empirical capacity coefficients for each participant in each Experiment, computed with the standard specification of the respective C(*t*). (Top Right) Comparison of the standard specification of C_{AND} (*t*) with the substitution strategy used by various authors—double target response times from the AND task contrasted against single target response times from the OR task (within subjects). (Bottom) Group level averaged capacity coefficients for each task. The colored regions represent 1,000 bootstrapped average capacity coefficients for each of the tasks. See the online article for the color version of this figure.

weak salience effect on its own would not explain the super capacity that we observe in standard AND tasks, nor would it explain why the issues are resolved in our novel ID version of the task. We encourage further exploration of these issues but suspect capacity analysis in the standard AND task will prove untenable.

Importantly, the modified-AND task proposed herein retains all the benefits of the double-target analyses in regular AND tasks, and we have shown that neither accuracy nor processing strategies were affected by the change in task. The task provides unique benefits on single-target displays as it ensures fully exhaustive processing and allows the researcher to account for the effect of nontarget processes when considering capacity. The modified-AND task proposed here is, in essence, a 2×2 identification task with the addition of a salience manipulation. Until now, investigating properties such as processing architecture and stopping rule in such tasks was difficult, if not impossible (Howard, Eidels, Silbert, & Little, 2017). We have shown in this article that we can utilize the full suite of analyses from the Systems Factorial Technology (Townsend & Nozawa, 1995) framework in this modified task, and did so to investigate stopping rule, architecture, and capacity. Our task can naturally extend to the distractor-modified task used by authors such as Little et al. (2015) and Ben-David et al. (2014) by incorporating a salience manipulation on the distractor items, and implementing the unique identification response strategy developed herein. In theory, our task could also be amenable to existing identification-based analyses (e.g., General Recognition Theory, Ashby & Townsend, 1986; Multidimensional Scaling, Kruskal, 1964; see, e.g., Howard et al., 2017 for further discussion). The developments presented herein provide a useful alternative to the distractor-based Resilience functions of (Little et al., 2015) when the presence of a distractor is not warranted but when researchers wish to explore processing capacity without the effect of nontarget processing channels. Importantly, our work highlights the importance of empirically validating critical assumptions; previous authors have assumed nontarget channels to attract little to no processing, which we have shown here is unlikely to be true.

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