Switch it Up! How Context Influences the Efficiency of Redundancy Gains in a
Peripheral Task

Zachary L. Howard ^{1,*}, Alexander Thorpe ², and Elizabeth L. Fox ³

¹School of Psychological Science, University of Western Australia

²School of Psychology, University of Newcastle

³Air Force Research Laboratory, Wright-Patterson AFB, Ohio

*Correspondence may be addressed to zach.howard@uwa.edu.au

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Abstract

Optimizing the time and accuracy with which peripheral tasks can be monitored concurrent with a central primary task is of paramount importance for human factors researchers developing human systems. Nonetheless, the design of peripheral task are often evaluated in isolation, and their effectiveness is assumed to generalize to multi-task contexts. Our work acknowledges that peripheral displays may be utilized in a variety of operational contexts. Across four experiments we examine peripheral task detection speeds under several contextual factors related to operator workload and task-set. We use the capacity coefficient from the Systems Factorial Technology framework to quantify the extent that context influences redundant signal enhancements in a peripheral detection task. Across four experiments we manipulated the presence, difficulty and stability of the primary task to simulate different workload contexts. Using a novel time-varying estimate of workload capacity, we show that efficiency in detecting redundant peripheral targets decreases with high primary task demands, contrary to previous findings. Our results also indicated higher capacity in less stable environments but a correspondingly greater workload impairment in these conditions. Implications for system design include consideration of the expected operator workload, as well as attention recruiting strategies to improve peripheral task detection speeds.

KEYWORDS: capacity, workload, redundancy gains, peripheral detection

Switch it Up! How Context Influences the Efficiency of Redundancy Gains in a Peripheral Task

Introduction

In almost all cognitively demanding situations, the human operator must divide attention between tasks. A driver must monitor the road, while also scanning mirrors, monitoring speed, and being aware of any signs of mechanical failure. Pilots must attend to gauges related to airspeed, altitude, and communications, while monitoring weather conditions and warning systems. A submarine commander must monitor the course and depth of their vessel but be ready to respond to alerts for emerging contacts or imminent safety threats. It is imperative in these complex scenarios that peripheral signals (which often require ongoing monitoring until an action is required) are processed as quickly as possible in order to optimize safety and performance. In domains with isolated and centrally located alerts, it is known that redundancy in signal presentation (e.g., two warning lights containing the same information) can facilitate detection speeds (Miller, 1982). However, human resources are limited, and dividing attention between central and peripheral demands leads to competition for common resources, and may cause performance deficits (Norman & Bobrow, 1975). Even in simple detection tasks performance can suffer due to bandwidth limitations in the cognitive system (Townsend & Eidels, 2011), in which case redundant signals may not be optimal. It is possible that the *context* (here defined as the operators task set and how they are changing) in which an operator is making perceptual judgments contributes to the viability of redundancy gains. For example, perhaps different attentional strategies are recruited when multitasking, or when tasks are demanding more cognitive resources. A more thorough understanding of the role of operating context, particularly in the detection of peripheral signals that, in part, contribute to highly demanding situations, is needed to shape optimal development of safety systems.

In Experiments 1A and 1B we provide novel evidence that not just overall performance, but the efficiency of processing two peripherally presented and redundant visual targets is influenced by the presence and/or difficulty of a primary task. In

Experiments 2A and 2B, we found that longer periods of stability (here defined as the length of blocks of consistent primary task difficulty) led to *reductions* in processing efficiency compared to the shorter blocks used in Experiments 1A/1B, and that the more stable workload altered the influence of task difficulty on processing efficiency. These data suggest there may be attentional benefits when one must more often re-calibrate to a new primary task load, but that stability can reduce the influence of task demands (perhaps by facilitating adaptation). We show that performance speed-ups (or lack thereof) from redundant peripheral signals are related to the context the signals are presented in and the reserve amount of resources available to the operator - a novel finding with interesting human factors and theoretical implications. Our work motivates continued development of adaptive systems that can dynamically account for contextual effects to suggest optimal multi-task conditions (load and stability) for the use of redundant peripheral signals. Below we present a brief theoretical overview of the redundant signals effect before introducing our context manipulations: level and type of primary task workload, and stability of task demand. We then describe our modeling approach to measure redundancy gains and processing capacity, before introducing our experiments.

Redundant Signals and Processing Capacity

The Redundant Signals Effect (RSE) describes the phenomenon where people are typically faster to detect signals when multiple redundant sources of information are presented, compared to either single source of information alone. While this outcome can be produced by a highly efficient information pooling process (often termed “coactive” processing, e.g., Duncan, 1980; Miller, 1982), the RSE is also predicted by a simple “race” between the redundant information channels (assuming no resource limitations; Miller, 2016; Raab, 1962). A sophisticated mathematical modeling technique developed as part of the Systems Factorial Technology (SFT) framework, the Capacity Coefficient $[C(t)]$, describes the efficiency of a redundant target processing system relative to a baseline race mode (Howard, Garrett, Little, Townsend & Eidels,

2021; Townsend & Eidels, 2011), and can be interpreted as a measure of the efficiency of a “system” (e.g. cognitive processing system). Capacity coefficients have been used in numerous applied investigations in recent years (see Houpt, Sussman, Townsend & Newman, 2015; Hsieh, Fifić & Yang, 2020; Yamani & McCarley, 2016, 2018, for a few examples), and can provide critical information about cognitive processing. For example, while redundant signals may be detected faster than an isolated signal, it is possible each *individual* target is detected slower when multiple sources are simultaneously presented due to resource bottlenecks (Garrett, Howard, Houpt, Landy & Eidels, 2019; Townsend, 1990). In this case, a redundant signal may increase operator workload relative to a single, highly salient signal which might be preferred instead. The capacity coefficient compares single and dual target performance against a baseline model, and capacity can broadly be either limited (less efficient than the baseline model), unlimited (equal to baseline), or super (more efficient than the baseline model). In this manuscript, we draw a distinction between *workload* (which we define at an operator level, relating to the current task demands), and *capacity* (which we define at a within-task level, relating to efficiency of dual-target processing). These terms are often used interchangeably; however here they refer to distinct attributes of a cognitive system.

To make optimal use of the RSE, system designers should work to develop systems that attract unlimited or super capacity processes. However, parallel processing of redundant signals does not guarantee unlimited or super capacity performance. It is typical to find limited capacity in simple visual detection (Eidels, Townsend, Hughes & Perry, 2015) and even multimodal tasks (Fox, Glavan & Houpt, 2014). Recently, Morey, Thomas and McCarley (2018b) suggested that one reason redundancy gains may diminish is due to high operator workload. Cognitive resources such as working memory (Yu, Chang & Yang, 2014) are distributed across an individual’s concurrent tasks, and it is generally accepted that humans have a finite pool of cognitive resources which can be dedicated to their total task-set (Kahneman, 1973). If an operator attempts to complete several tasks simultaneously, there are less resources available to dedicate to

each task. This relationship has been shown and often measured by increased response times in a secondary task (e.g., Strayer, Cooper, Turrill, Coleman & Hopman, 2015). It follows that contexts with high levels of primary demands leave few spare attentional resources for one to allocate toward the completion of other tasks, and that the degree to which redundancy gains are found may therefore depend on the overall workload (or more broadly, the operational context) of the operator. This is consistent with our own observations in highly demanding numerical cognition tasks (Garrett et al., 2019) where redundancy gains were minimal at best, implying a relationship between the size of the RSE and overall operator workload.

Context Effects

We recently applied evidence accumulation models to a secondary task workload measure (the detection response task, DRT; International Organization for Standardization, 2016) extensively used in domains such as driving (Strayer, Cooper, Turrill, Coleman & Hopman, 2017) and aviation (Innes, Howard, Thorpe, Eidels & Brown, 2020). We found that the context behind a change in primary task load (whether primary tasks were added or merely made more difficult) altered aspects of the detection process to that secondary task. Within the domain of accumulator models, the addition of a task involved an adjustment of participants' response threshold that was not observed when increasing the difficulty of the task only (Howard, Evans, Innes, Brown & Eidels, 2020). Thus the *type* of manipulation, not just the absolute level of workload, played a part in the decision strategy of participants. Overall, responses slowed regardless of the type of workload manipulation, and showed reduced processing efficiency under high workload. This suggests that the primary and peripheral visual tasks compete for the same resources (Wickens, 2002, 2008), but operating context influences other aspects of the decision process. Both workload and processing capacity have been indexed by the processing rate parameters of cognitive models (Castro, Strayer, Matzke & Heathcote, 2019; Eidels, Donkin, Brown & Heathcote, 2010; Howard et al., 2020) which hints at a shared underlying mechanism

and motivates investigation of co-dependencies.

To overcome reduced detection time under high workload, peripheral tasks might include redundant signals that, for instance, both flash to indicate the same system malfunction. Redundant signals often enhance detection rates and response times in simple perceptual studies (e.g., Miller, Beutinger & Ulrich, 2009), yet redundancy gains are often minimal at best in human-systems research (Fox et al., 2014; Seagull, Wickens & Loeb, 2001; Wickens, Goh, Helleberg, Horrey & Talleur, 2003). Theoretical accounts such as Multiple Resource Theory would predict that redundant presentations of visual information create resource competition and reduce capacity as task load increases (Wickens, 2008), however more recent information quality research suggests that information uncertainty in itself taxes the residual resource pool (Endsley & Kaber, 1999; Innes, Howard et al., 2020; Liu, Peterson, Vincenzi & Doherty, 2016; Steinhauer, Karlsson & Andler, 2013). Thus, providing additional task-relevant redundant stimuli could conceivably *reduce* performance deficits by improving the processing efficiency of each individual process, or *increase* deficits through resource competition. Strategic allocation of cognitive resources based on the type and number of concurrent tasks may also influence this relationship.

Several recent studies have considered the influence the operators workload context plays on processing capacity. Thorpe et al. (2020) found increasing load *within* a task led to impaired processing capacity (measured using a novel continuous-to-discrete variation of capacity analysis) in that same task. Conversely, Morey et al. (2018b) and Morey, Thomas and McCarley (2018a) found no evidence that processing efficiency (measured by standard capacity and resilience functions; Houpt & Townsend, 2012) in a *secondary* task, consisting of redundant, peripherally displayed targets, changed with the addition or difficulty of a primary task. There is a key distinction between the studies in that Thorpe et al. (2020) did not consider capacity within a *dual* task environment, where attention must be split between the primary and peripheral components. Thus, to-date, there is no evidence that primary task workload impairs processing capacity to a peripherally presented task.

Current Study

Given the critical importance redundant signals may play in optimal system design, and our own recent evidence of how peripheral and primary tasks interact (Howard, Innes, Eidels & Loft, 2021), the question of whether operator workload context impairs peripheral target redundancy gains requires further scrutiny. Recent advancements in Bayesian modeling techniques (Fox & Hout, 2021) allow a more sensitive assessment than traditionally measured processing capacity. We use these techniques (described in the Method section) to examine whether redundant-target capacity in a peripherally-presented visual detection task can be modulated by context (i.e., primary task factors). Through Experiments 1A and 1B we aimed to determine whether processing capacity for redundant, peripherally presented signals varied as a function of two context factors, task load (low/high), and type of load manipulation (multitasking vs difficulty), in an independent visual tracking task using our previously developed multitasking paradigm (Howard et al., 2020; Innes, Evans, Howard, Eidels & Brown, 2020). We leveraged existing work to assume independent and parallel processing (i.e., the race model) of basic redundant visual stimuli (e.g. Eidels et al., 2015; Fox & Hout, 2016) in our peripheral task, and estimated the capacity coefficient using a novel time-varying parametric model. We found that, contrary to earlier reports (Morey et al., 2018b), capacity to detect peripheral redundant targets was impaired by higher primary task demands, although this was modulated by the type of task load manipulation (i.e., the addition of, or the increased difficulty of, a primary tracking task).

Method - Experiment 1A and 1B

Participants

A total of 202 ($n=103$ in Exp 1A, $n=99$ in Exp 1B) undergraduate psychology students from the University of Newcastle participated in the Experiment (randomly allocated to 1A or 1B at sign up). Participants were reimbursed with course credit, and were required to have normal or corrected vision, and be able to read English.

Participants completed the experiment online, without supervision from an experimenter. The study was approved by the Human Research Ethics Committee (approval no. H-2019-0254).

Tasks

Participants completed two simultaneous tasks. In the Moving Object Tracking task (MOT) participants were required to track the movement of zero, one, three or four small discs for a period of 15 seconds. The dots moved smoothly around the display area for 15 seconds. The “target” discs were initially colored blue, and turned to red after three seconds. There were always 10 discs in total, and non-target discs were colored red for the entire 15 seconds. Each disc was circular with a diameter of 14 pixels, corresponding to a visual angle of approximately 6° at 60 cm viewing distance assuming a 24” monitor. Discs moved randomly throughout a 150x150 pixel box for the 15 second duration at a rate of 15 frames per second. Discs could overlap briefly if their paths crossed, and discs bounced randomly away if they reached the edge of the display area. Both Exp 1A and 1B contained a “high” and “low” workload condition which alternated between blocks. For Exp 1A this involved tracking either three (high) or zero (low) dots simultaneously (i.e., the low workload condition was a single task). In Exp 1B the conditions were to track either four (high) or one (low) dot simultaneously, such that participants were always dual-tasking and the manipulation was simply the difficulty of that task. These contextual manipulations have been described and motivated elsewhere (Howard et al., 2020).

Throughout the tracking period, participants were asked to respond to intermittently presented targets (red squares) presented at the top of the screen. This task followed the design of our previously published adaptation of the Detection Response Task (DRT; Innes, Evans et al., 2020), and the display was almost identical to our previous applications (Howard et al., 2020; Howard, Innes et al., 2021), except that the task was adapted to fit within the Redundant Target Paradigm (Little, Altieri, Fific & Yang, 2017). The DRT stimulus was a red (RGB[255, 0, 0]) square that could appear

in one or both of two locations slightly left and right of center. The DRT window was equal in length to the MOT window, but presented at the top of the MOT window such that the DRT targets would appear in the participants' peripheral vision. Stimulus presentation adhered to ISO 17488 (International Organization for Standardization, 2016; Young, Hsieh & Seaman, 2013), with a DRT trial being displayed every 3-5 seconds (sampled uniformly). Displays were slightly biased toward double target trials (60/40), but single targets were equally likely to be presented in the left or right location. Unlike traditional redundant-target applications there was no “non-target” stimulus due to the ongoing nature of the detection task. The maximum time to respond to the DRT stimulus was 2.5s. However, the stimulus was displayed no longer than 1s, response-terminated. The DRT display was not shown outside of the 15-second tracking periods, so there were no DRT presentations during instructions, breaks or MOT decision time.

Figures 1a and 1b illustrate the concurrent display of the tasks for both single and dual target DRT displays. The timelines of the MOT and DRT are illustrated in Figure 2. Both tasks were administered on the participant's computer concurrently, with the DRT stimulus displayed as either one or two red squares presented in a box above the MOT display.

Procedure

After signing up, participants completed a 60-mins online experiment on their own device. Participation required a computer with access to an Internet browser and a keyboard. Participants were randomly allocated to either the “Multitasking” (Exp 1A, $n=103$) or “Difficulty” (Exp 1B, $n=99$) condition at sign-up. Participant numbers reflect the available sign-ups within the study timeframe, and are comparable or greater than reported in our earlier work (Howard et al., 2020; Howard, Innes et al., 2021; Innes, Evans et al., 2020) and similar studies Morey et al. (2018a, 2018b). The procedure between Exp 1A and 1B was identical apart from the number of dots requiring tracking in the high and low workload conditions.

Figure 1. Illustration of the concurrent display of the MOT (red dots) and DRT (red square[s]) displays. The DRT component flashed on intermittently and the red dots moved around the display randomly throughout a trial. DRT signals could be either a single target (left panel) or double target (right panel), both requiring the same response.

After initial instructions regarding both the MOT and DRT tasks, a practice block consisting of 15 MOT trials (of 15 seconds each), with a tracking load of 2 target dots, was presented. Each MOT trial was initiated by the participant, with the number of dots to be tracked (targets; zero, or three in the Multitasking condition, one or four for the Difficulty condition) noted before each trial and block. DRT stimuli (one or two squares presented above the MOT display area) were presented every 3-5 s during the tracking period only, and required a key press response ('T') upon detection. After the 15 second tracking period finished, the DRT presentation ceased, the dots stopped moving, and the interrogation stage commenced. A single dot was colored white and participants were asked "was the white dot one of the targets?", with a yes/no response indicated using the keyboard ("O" and "P" respectively). This question was repeated for each of the ten dots, one at a time.

After 15 practice trials at a fixed difficulty (2 dots), participants completed a total of 120 MOT trials. Ten blocks of 12 MOT trials were presented, with the task difficulty

Figure 2. Timeline of both MOT and DRT tasks for all experiments. Note the DRT stops at the MOT interrogation phase to ensure there is no response competition.

(tracking load) alternating each block. The first tracking load was randomly selected. Participants were encouraged to take short breaks between trials and blocks. The total number of DRT trials in a block could vary slightly, depending on the random sampling of presentation times, within the 3-5 second intervals.

Analysis

Our primary analysis was to estimate the workload capacity to the redundantly presented DRT signals across different types and levels of workload in the primary tracking task. To do this, we implemented a novel variation of the Systems Factorial Technology capacity coefficient (SFT; Houpt & Townsend, 2012; Townsend & Nozawa, 1995). SFT has been well treated elsewhere (Houpt, Blaha, McIntire, Havig & Townsend, 2014; Little et al., 2017), but we provide a brief overview of capacity analysis here for the readers' benefit. Assuming a design in which either one or two (redundant) signals may be presented to a participant on a given trial, the capacity coefficient is

defined as the ratio of the cumulative hazard function of response times to redundant signals, $H_{12}(t)$, relative to a baseline performance. The baseline is derived from an unlimited capacity, independent, parallel (UCIP) processing model. The capacity coefficient that applies to this experiment is

$$C_{OR}(t) = \frac{H_{12}(t)}{H_1(t) + H_2(t)} \quad (1)$$

The “OR” in Equation 1 refers to the first-terminating structure of the experimental task (the first detected DRT stimulus is sufficient to make a response, reflecting the redundant nature of the stimuli). The capacity coefficient classifies processing into three different categories: limited, unlimited, and super. Limited capacity [$C(t) < 1$] refers to a decrease in performance as the number of sources of information increases. Unlimited capacity [$C(t) = 1$] refers to performance that remains consistent with the baseline performance even as more sources of information are added. Super capacity [$C(t) > 1$] refers to an increase in performance as the number of sources of information increases. Notably, performance here refers to the processing of *each target individually*; while overall response-time might decrease for redundant targets even under limited capacity, the processing system would be performing sub-optimally in this case. The formula above describes a function over time, but it is typical to summarize the capacity coefficient to facilitate interpretation. Previously, this has been achieved by computing the Cz statistic developed by Houpt and Townsend (2012). However, this non-parametric approach may not have sufficient power to detect temporal variations in capacity, and the Cz statistic reduces the data from all trials down to a single observation.

Fox and Houpt (2021) have recently developed a technique that models a trial-varying capacity coefficient. This technique assumes a Weibull distribution with two parameters (shape and scale) adequately characterizes response times. To estimate the capacity coefficient using this model, we must estimate the shape and scale parameter for dual (redundant) and single target performance, respectively. To calculate the capacity-OR coefficient, we take ratio of the $H(t)$ estimate of the Weibull

when two targets are present to the sum of the $H(t)$ estimate of the Weibull when a single square is present. The model relies on Bayesian updating of the parameters of the Weibull for each trial-type to obtain a posterior estimate of performance based the Bayesian combination of a prior (belief before new data), and the likelihood of the new data. To simplify the model, we assume each Weibull has a fixed shape parameter and use a conjugate of the Weibull, the inverse gamma function, to characterize our prior.

To apply the model, we chose to follow most of the assumptions demonstrated in Fox and Houpt (2021). We briefly describe our choices and their importance next, but an interested reader can find a more complete description in Fox and Houpt (2021). In our application of the model, we started with two hyperparameters: a shape (fixed) and scale (updated across trials) parameter value. We estimated the shape and scale of the Weibull distribution at the individual-level, using a maximum likelihood fit to response times from *all* distribution types. Hence, capturing a parameter value that adequately captures most response times for that individual. We fix the shape parameter and allow the scale to update across trials. This provides us a single estimate of capacity across all times on any given trial; we denote this as $C(s)$. We assumed a UCIP model prior, as it is the baseline comparison for the capacity coefficient. Therefore, we used Monte Carlo sampling from a Weibull distribution with individual-based hyperparameters to estimate a UCIP combination of two distributions for an OR process (i.e., minimum of the two) and fit those data to a Weibull distribution using a Brent method optimization of the maximum likelihood function.

We used a Bayesian method to update the scale parameter and estimate the posterior belief of performance across time for each single channel and multi-channel performance, respectively. We allowed individual variability in estimates of the scale hyperparameter fixed at the single-channel level (CH1, CH2) and the UCIP combination of the single-channels for the multi-channel distribution (CH12). We had roughly a 3:1 ratio of observations given to the prior over the likelihood, and the prior was updated using the posterior from previous estimates. Lastly, we assumed older observations contribute less to the capacity estimate than newer ones, and a squared

exponential function describes the drop-off rate (i.e., a decreasing weight given to previous trials). Our instantiation of the model minimized uncertainty in the estimate while providing fairly high temporal precision.

We utilised the trial-varying capacity model to obtain a precise estimate of capacity at each and every trial, compared with aggregated measures such as Cz. We subject these capacity estimates to Bayesian ANOVAs to determine whether capacity varies with Load Type or Task Load.

Results - Experiment 1A and 1B

In order to model the time-series of DRT trials, we excluded participants who had a hit-rate of less than 90% on the DRT across either the entire experiment or in any one block of trials, and participants who responded with a mean RT of less than 100ms across the whole experiment or in any one block of trials. These criteria resulted in the exclusion of nine participants from Exp 1A, and twelve from Exp 1B, leaving total $n=94$ and $n=87$ respectively. Throughout the manuscript, we report Bayesian statistics (e.g., Wagenmakers, Love et al., 2018; Wagenmakers, Marsman et al., 2018) computed in JASP (Love et al., 2019). In place of p -values we report Bayes Factors, which we express as BF_{10} or BF_{01} depending on the direction of evidence. We adopt the general convention that a Bayes Factor between 3-10 is weak-to-moderate evidence for an effect, and that a Bayes Factor over 10 is strong evidence (Goodman, 2005). We report Bayesian Credible Intervals (BCI) in place of Confidence Intervals. In all ANOVAs reported below we include a random “Subject” term to account for individual differences in response times and capacity. This can be considered a more powerful alternative to Repeated Measures ANOVAs when multiple observations per cell are available (Rouder, Morey, Speckman & Province, 2012).

Descriptive Statistics

To confirm the workload manipulation worked, we compared correct response times to single targets (to remove any differential redundancy influences) between Low and High workload conditions. In Exp 1A, we found reliable evidence that response

times were slower in the High load condition ($M=544\text{ms}$, 95% BCI [539, 548]) than in the Low load condition ($M=398\text{ms}$, 95% BCI [396, 401], $BF_{10} > 1000$). Redundant targets were slightly faster ($M=449\text{ms}$, 95% BCI [447, 452]) than single targets ($M=468\text{ms}$, 95% BCI [465, 471], $BF_{10} > 1000$), and in a Two-Way ANOVA including Load, Number of Targets, and their interaction, there was strong evidence *against* an interaction, $BF_{01} = 11.30$ (suggesting load did not influence the RTE at the mean level). In Exp 1B, we again found reliable evidence that response times were slower in the High load condition ($M=533\text{ms}$, 95% BCI [528, 537]) than in the Low load condition ($M=483\text{ms}$, 95% BCI [479, 487], $BF_{10} > 1000$). Redundant targets were faster ($M=487\text{ms}$, 95% BCI [485, 490]) than single targets ($M=507\text{ms}$, 95% BCI [504, 510], $BF_{10} > 1000$), and in a Two-Way ANOVA including Load, Number of Targets, and their interaction, there was again strong evidence *against* an interaction, $BF_{10} = 72.45$. A complete summary of response times is provided in Table 1.

Table 1

Mean Response Time to DRT by Experiment, Load, and Number of Targets

Experiment	Load	No. Targets	Mean	SD	N	95% Credible Interval	
						Lower	Upper
1A	Low	1	398	177	15817	396	401
		2	383	178	15871	381	386
	High	1	544	278	14569	539	548
		2	521	273	14491	517	526
1B	Low	1	483	215	13205	479	487
		2	463	203	14048	460	466
	High	1	533	264	12699	528	537
		2	512	251	13536	508	517

In Exp 1A, performance (as percentage of dots correctly classified as target/distractor) on the MOT was reliably worse in the High load conditions ($M=76.6\%$, 95% BCI [76.3, 77.0]) than Low load conditions ($M=99.4\%$, 95% BCI [99.4,

99.5], $BF_{10} > 1000$). This was also true for Exp 1B (High M=65.4%, 95% BCI [64.9, 65.8], vs Low M=96.3%, 95% BCI [96.2, 96.5]). These results imply participants were not simply attending to one or the other task as load increased.

Processing Capacity

All mean-level processing capacity across trials was limited capacity, $C(s) < 1$. To investigate variation in the degree of limited capacity across conditions, we combined the data from Exp 1A and 1B and subjected the model-estimated processing capacity at each trial to a Two-Way Bayesian ANOVA, including Task Load (Low vs High), Condition (Difficulty vs Multitasking), and their interaction. Task Load was a within-subject variable, while Condition was a between subject manipulation. The overwhelming posterior evidence favored the full model, including both main effects and their interaction (Posterior Probability [pp]>0.99). Task Load influenced capacity such that $C(s)$ was higher in the Low load conditions (M=0.841, 95% BCI [0.837, 0.844]), compared with High load conditions (M=0.791, 95% BCI [0.788, 0.795], $BF_{10} > 1000$). Participants in the Difficulty condition (Exp 1B) showed higher overall capacity (M=0.835, 95% BCI [0.831, 0.838]) than those in the Multitasking (Exp 1A) condition (M=0.801, 95% BCI [0.798, 0.804], $BF_{10} > 1000$). Condition interacted with Load such that the reduction in capacity from Low to High load was less in Exp 1B (see Figure 3).

Figure 3. Model estimated $C(s)$ for participants in Experiments 1A and 1B, by Task Load and Condition. Error bars represent 95% Bayesian Credible Intervals around the mean.

Interim Discussion

In Experiments 1A and 1B we demonstrated that processing capacity to peripherally presented redundant targets is sensitive to the contexts of both operator workload, and the type of manipulation used in the primary task. As expected, processing capacity decreased with task load in both cases, likely a reflection of competing resources between the central and peripheral tasks. Perhaps surprisingly, workload (measured by DRT-RT on single target trials) in the “high” condition was slightly higher in Experiment 1A (three dots - $M=544\text{ms}$) compared with Exp 1B (four dots - $M=533\text{ms}$). This traded off against the lower tracking accuracy in 1B (65% vs 77% in 1A). We suspect that three dots may be an approximate limit for most participants, however in earlier applications we found context effects such that pairing three dots with one dot did not sufficiently increase DRT-RT, and pairing four dots with a no-tracking condition led to participants ‘giving up’ in the tracking condition (e.g., Howard et al., 2020, p. 945). Therefore, we expected the “workload” imposed by tracking either three or four dots to be approximately equal. Naturally the observed

workload in the zero-tracking condition of Exp 1A was lower than the single-dot tracking in Exp 1B, by design, as we wished to examine whether the change in context (i.e., increase in difficulty vs addition of a difficult task) influenced the efficiency of redundant target processing.

An unexpected result was that *capacity* was both higher overall, and less influenced by load, in Exp 1B, where task load was manipulated only by altering the difficulty of the primary task. This result is surprising for several reasons. First, earlier studies only explored a single vs dual-task manipulation and found no evidence of a capacity impairment (Morey et al., 2018a, 2018b). Therefore, we might have expected the more pronounced effect in the previously unexplored case of increasing primary task difficulty. Perhaps more notably though, as observed above, overall workload in Exp 1B was higher than Exp 1A. This is to be expected, as the ‘low’ load condition requires one dot to be tracked (i.e., dual tasking, compared to Exp 1A where only the detection task requires attention). However, if processing efficiency to redundant targets were purely a function of resource competition, we should expect greater capacity deficiencies in Exp 1B. The surprising nature of this finding is compounded by the interaction we observed between Load and Condition. From Figure 3 it is clear the $C(s)$ is approximately equal in the ‘Low’ workload conditions of Exp 1A and 1B, despite the difference in both specified and measured workload. The interaction is such that, while capacity decreases with task load in both Exp 1A and 1B, decrements are much more pronounced in Exp 1A. The actual workload (measured by DRT response times) is almost the same in the equivalent condition in Exp 1B (three vs four dots to-be-tracked).

These results cannot be purely explained by a resource competition account. Instead, we hypothesize that the magnitude of capacity adjustment may be related to the *stability* of the workload context. In other words, the transition rate of primary task load may influence how one processes multiple signals, and the degree to which redundancy gains are observed in a peripheral detection task. In both Exp 1A and 1B, task load changes relatively frequently (12 trials of 15 seconds duration, i.e. workload changes after every three minutes of on-task time). This rapid change in task demands

may couple with the added change in task *set* in Exp 1A (i.e., switching from single to dual tasking) to result in a greater capacity decrement under high load. While our task replicated our own previous applications (Howard et al., 2020; Howard, Innes et al., 2021), Morey et al. (2018a) used a comparatively predictable workload context (20 trials of 60 seconds, i.e., 20 mins of on-task time at a consistent level of demand).

It is not inconceivable that the way in which cognitive resources are allocated, and/or the efficiency with which cognitive resources can be utilized, may change based on how (in)frequent transitions in primary task load are. It has been demonstrated that both a participant’s performance and their perception of task difficulty can change depending on what previous tasks have been experienced (Baumeister, 2014; Hagger, Wood, Stiff & Chatzisarantis, 2010; Kurzban, Duckworth, Kable & Myers, 2013). *Hysteresis* describes a delayed reaction or adaptation to changing task demands (Morgan & Hancock, 2011) that influences measurable workload, and there is substantial evidence that workload effects carry forward long after a trial or task has finished (Bowden, Loft, Wilson, Howard & Visser, 2019; Hancock, Williams & Manning, 1995; Jansen, Sawyer, van Egmond, de Ridder & Hancock, 2016), and that sudden changes in workload affect subsequent task performance (Cox-Fuenzalida, 2007). These findings are evidence that cognitive resources are dynamic and context-sensitive. It remains unknown how (or if at all) *capacity* can be re-allocated dynamically, but it seems likely (given the results of Experiment 1) that operational context may play a part in determining how efficiently a cognitive system can respond to redundant information.

To determine whether workload stability might account for some of the context differences observed between Experiments 1A and 1B, we conducted a second set of studies where we more than doubled the amount of on-task time between workload transitions. This manipulation allowed participants to experience less frequent changes in primary task demands than participants in Exp 1A and 1B. Therefore, in Experiment 2 we investigate three contextual effects: primary task demands (low, high), a within-subjects factor, task load type (difficulty vs multitasking), a between-subjects

factor, and stability (comparing Experiment 2 results to Experiment 1), a between-study factor.

Method - Experiment 2A and 2B

Participants

A total of 205 ($n=101$ in Exp 2A, $n=104$ in Exp 2B, randomly allocated at sign-up) undergraduate psychology students from the University of Newcastle participated in the Experiment and were reimbursed with course credit. Participants were required to have normal or corrected vision, and be able to read English. Participants completed the experiment online, without supervision from an experimenter.

Tasks

The MOT and DRT tasks remained identical to Experiments 1A and 1B. The only change from Experiment 1 to 2 was the distribution of trials. In both Experiment 2A and 2B trials were presented in four blocks of 30, with task load (0 and 3 dots in Exp 2A, 1 and 4 dots in Exp 2B) alternating between blocks.

Procedure

The procedure of Experiment 2 followed that of Experiment 1. Participants were recruited and participated online using their own device. Practice and Instructions were identical to Experiment 1, with the only difference being in the distribution of trials (four blocks of 30, compared with 10 blocks of 12). Total MOT trial numbers remained identical ($n=120$), and DRT trial numbers varied with random sampling.

Results - Experiment 2A and 2B

As with Experiment 1, we excluded participants who had a hit-rate of less than 90% on the DRT across either the entire experiment or in any one block of trials, and participants who responded with a mean RT of less than 100ms across the whole experiment or in any one block of trials. These criteria resulted in the exclusion of 12

participants from Exp 2A, and 13 from Exp 1B, leaving total $n=89$ and $n=91$ respectively.

Descriptive Statistics

We again compared correct response times to single targets between Low and High workload conditions to establish the success of the workload manipulation. In Exp 2A we found reliable evidence that response times were slower in the High load condition ($M=517\text{ms}$, 95% BCI [512, 522]) than in the Low load condition ($M=391\text{ms}$, 95% BCI [389, 395], $BF_{10} > 1000$). Redundant targets were detected faster ($M=434\text{ms}$, 95% BCI [432, 436]) than single targets ($M=453\text{ms}$, 95% BCI [450, 456], $BF_{10} > 1000$), and in a Two-Way ANOVA including Load, Number of Targets, and their interaction, there was weak evidence *against* an interaction, $BF_{01} = 4.77$. In Exp 2B, we again found reliable evidence that response times were slower in the High load condition ($M=523\text{ms}$, 95% BCI [518, 528]) than in the Low load condition ($M=456\text{ms}$, 95% BCI [452, 459], $BF_{10} > 1000$). Redundant targets were detected faster ($M=470\text{ms}$, 95% BCI [467, 472]) than single targets ($M=489\text{ms}$, 95% BCI [485, 492], $BF_{10} > 1000$), and in a Two-Way ANOVA including Load, Number of Targets, and their interaction, there was no evidence for or against evidence an interaction, $BF_{10} = 1.13$.

Comparing correct response times to single targets across Experiments 1A, 1B, 2A and 2B, there was inconclusive evidence ($BF_{10} = 1.07$) whether response times differed with Block length, with RT in the short ($M=475\text{ms}$, 95% CI [473,478]) and long ($M=479\text{ms}$, 95% CI [478,481]) block groups approximately equal. However, there was strong evidence ($BF_{10} > 1000$) for an interaction between Block Length and Load, such that RT in low load blocks was slightly faster in Experiment 1 (short blocks, 5ms difference) but RT in high load blocks was faster in Experiment 2 (longer blocks, 15ms).

In Exp 2A, performance (as percentage of dots correctly classified as target/distractor) on the MOT was reliably worse in the High load conditions ($M=74.1\%$, 95% BCI [73.8, 74.5]) than Low load conditions ($M=96.2\%$, 95% BCI [96.0, 96.3], $BF_{10} > 1000$). This was also true for Exp 2B (High $M=64.7\%$, 95% BCI [64.3,

Table 2

Descriptives - RT

Manipulation	Load	No. Targets	Mean	SD	N	95% Credible Interval	
						Lower	Upper
Multitasking	Low	1	394	182	12015	391	398
		2	381	176	18309	378	383
	High	1	521	275	11395	516	526
		2	496	256	16846	493	500
Difficulty	Low	1	462	202	12373	458	466
		2	447	201	18625	444	450
	High	1	528	276	11837	523	533
		2	504	265	17687	500	508

65.1], vs Low M=95.8%, 95% BCI [95.7, 96.0]), suggesting participants were not only attending to one task as load increased.

Processing Capacity

Once again, all mean-level processing capacity across trials was limited capacity, $C(s) < 1$. We combined the data from Exp 2A and 2B and performed a Two-Way Bayesian ANOVA on model estimated $C(s)$ by Task Load (Low vs High) and Condition (Difficulty vs Multitasking), and their interaction. Task Load was a within-subject variable, while Condition was a between-subject manipulation. The overwhelming posterior evidence favored the full model, including both main effects and their interaction (Posterior Probability [pp]>0.99). Task Load influenced capacity such that $C(s)$ was higher in the Low load conditions (M=0.755, 95% BCI [0.753, 0.758]), compared with High load conditions (M=0.735, 95% BCI [0.732, 0.738], $BF_{10} > 1000$). There was strong evidence that capacity did not change between Multitasking (Exp 2A) and Difficulty (Exp 2B) manipulations, $BF_{01} = 20.04$. However, there was an interaction between Load and Condition such that $C(s)$ decreased with Load in Exp

2A, but *increased* with load in Exp 2B (see Figure 4). Pooling all data from Experiments 1A, 1B, 2A and 2B revealed a reliable difference in processing capacity such that $C(s)$ was higher in the short (unstable) block conditions of Exp 1A and 1B ($M=0.802$, 95% BCI $[0.799, 0.805]$), than the longer (stable) blocks of Exp 2A and 2B ($M=0.745$, 95% BCI $[0.743, 0.747]$, $BF_{10} > 1000$).

Figure 4. Model estimated $C(s)$ for participants in Experiments, by Task Load and Condition. Error bars represent 95% Bayesian Credible Intervals around the mean.

Discussion

In the present study, we first revisited the question of whether the capacity of a human operator to respond to redundantly presented peripheral targets changes with the presence, and difficulty of, an independent primary task. We applied a more powerful and time-precise estimate than previous authors, and in Experiments 1A and 1B found, contrary to earlier work (Morey et al., 2018a, 2018b), that capacity to detect redundant signals was higher when more spare resources were available (that is, when primary task load was low). This result was consistent with limited resource accounts of human cognition (e.g. Kahneman, 1973) and suggests that the process(es) governing redundancy gains are at least partly subject to the same resource restrictions as other

cognitive tasks. As both our primary and peripheral tasks focused on delivering *visual* information, it is likely that the tasks tapped the same resource pool (Wickens, 2002, 2008) and that adding redundant peripheral targets led to sub-optimal processing because of this interference.

An unexpected outcome of Experiment 1A and 1B was the differential effect on capacity that Multitasking and Difficulty based load manipulations had. Specifically, despite higher *overall* workload in Exp 1B, capacity was almost equivalent between the tasks in the low load condition, but participants in Exp 1A were much more affected by the workload increase. A pure resource competition account could not explain this phenomena as in all cases workload should have been (and was measured to be) equal or higher in Exp 1B, leaving less residual processing resources to detect the peripheral targets. We suggested that the relatively frequent workload transitions in both experiments may have increased the perceived difficulty of the additional task in Exp 1A, leading to strategy changes. To consider this explanation, we repeated the study with much longer blocks of consistent task demands, aiming to create a more “stable” workload environment.

Somewhat contrary to expectations, participants in the more frequently changing workload conditions showed greater capacity (higher efficiency) than participants in the more stable conditions (i.e. capacity was overall higher in Experiment 1 compared with Experiment 2). In addition, in the longer, more stable blocks of Experiment 2, capacity *increased* when switching from an easy to more difficult tracking task (Exp 2B), but still decreased with the addition of a task (Exp 2A). In this sense the interaction of manipulation and workload was different between the shorter and longer blocks. We suspect the more frequently changing conditions may have led to strategic changes such as increased vigilance, leading to increased efficiency when attending to redundant signals (i.e., higher capacity in Experiment 1 vs 2). Whether these changes are due to a greater overall level of attention resources or simply a more efficient allocation of those resources when multiple stimuli were present is unclear from the present data, although the relatively minimal differences in overall RT between Experiment 1 and 2 may hint

at the latter. Regardless, participants were unable to maintain that efficiency in the face of increased task demands, perhaps because they did not have time to acclimatize to those demands before the task changed again. In the highly predictable workload conditions of Experiment 2, participants were able to effectively modulate their processing in response to the difficulty manipulation, showing very little difference in capacity between low and high task load conditions (in fact capacity slightly increased from low to high load). While the reversal of capacity changes between Exp 1B and 2B was unexpected and difficult to explain, the percentage reduction in capacity was also smaller in Exp 2A (6.86%) compared to Exp 1A (8.04%), hinting at some modulation of the workload impairment that might be more pronounced in the difficulty-only conditions.

Importantly, whatever the explanation, our results clearly demonstrate the effect of operational *context* on processing capacity to peripheral tasks. Workload (i.e., overall detection time) was comparable across both the type of manipulation and degree of environmental stability, discounting a pure resource competition account. Instead, it seems that the way in which primary task demands fluctuate has a measurable impact on ones ability to efficiently integrate redundant visual sources presented in the periphery. Further investigation is needed to explore the dynamic interaction between “higher overall but more sensitive to workload” capacity in unstable environments versus “lower but less susceptible to change” capacity in more predictable environments. Once the underlying mechanisms are better understood, it may be possible to boost redundancy gains observed in the detection of critical information presented in an operator’s peripheral vision. For example, systems could be specifically designed to introduce frequent transitions in primary task load as a means to increase operator vigilance. Furthermore, with the time-varying advancements of capacity analysis developed by Fox and Houpt (2021) researchers should investigate whether capacity takes time to “settle in” in a more traditional redundant-target detection task. This may illuminate a potential explanation for our block-length results.

Several notable limitations of our experimental design should be addressed. First,

by design, the “low” workload conditions between our multitasking and difficulty conditions are not comparable in terms of task structure. In the difficulty conditions (Exps 1B and 2B) participants were required to track the movement of dots in the primary task, whereas they were not required to do so in the multitasking “low” conditions. It is plausible, therefore, that the DRT component was not “peripheral” in Exps 1A and 2A low load blocks, which could disrupt our reported capacity comparisons. Happily, we suspect that this is not an issue as the estimated capacity scores between the two “low” workload conditions in each study are very comparable (if the task attracted primary attention we might expect to see much higher capacity in the zero-tracking block). Further, we have previously used this design to explore the influence of task context (Howard et al., 2020) and replicated the design here. An alternative approach could have been to present three conditions to participants (e.g., zero, one and four dot conditions) - however this design necessarily contaminates the “context” we aimed to manipulate and seems counter-productive to our aims.

A related concern pertains to the comparison between the short and long block conditions. It might seem preferable that this key manipulation be performed within-subjects. However, the very act of exposing participants to an alternative design might change the way they acclimatize to the context and disrupt the comparisons. Therefore, while the between subject comparisons may be less than ideal, we prefer them over the alternatives. Finally, as our studies were run online it is plausible that display sizes and types varied wildly across participants. While we accept this to be true, this would only lead to additional noise which should be offset by the much larger sample size online data collection facilitates. As a sanity check, both the estimated DRT response times (difference of 4ms) and MOT accuracy (difference of 0.8% accuracy) were comparable between the two studies, which were delivered to the same student population. Therefore, we do not believe the data are confounded in any meaningful way.

Our results present the first evidence that workload can change the efficiency of redundant target processing. In fact, to our knowledge our results are the first that

demonstrate the malleability of redundant target capacity independent of the changes to the detection task at all. Although an important first step, there remain several unknowns that limit the extent to which results can immediately generalize. For example, we paired a visual tracking task with one or two additional visually-presented targets. According to Multiple Resource Theory (Wickens, 2002), these tasks would all share a resource capacity pool. Visually presented target capacity may therefore be impaired by visual load (such as the tracking task), but be unaffected by load presented in an alternative modality. There is some preliminary support for this argument in the fact that visually presented targets, similar to those used here, are often found to be limited capacity (e.g. Eidels et al., 2015; Townsend & Nozawa, 1995), yet multisensory targets can often show facilitory effects consistent with super capacity (Altieri, Townsend & Wenger, 2014; Diederich & Colonius, 2004, 2019). However, others have struggled to identify redundancy gains even with multi-modal stimuli (Fox et al., 2014). This leads to a further consideration: In the present study, capacity was always slightly-to-moderately limited. The effect of cognitive load on generally *super capacity* processes (e.g. holistic or multisensory processes) remains unclear. Optimally designed warning systems might seek to take advantage of stimuli known to attract super capacity processing, thus more focused exploration of those cases is warranted. Likewise, we were unable to push workload to an extent that redundant signals were processed *slower* than single targets, leading to critically limited capacity. That is, although we observed sub-optimal processing of redundant visual information sources, there was still an overall speed advantage in presenting two targets. In more extreme cases where the redundancy gain might reverse it is likely that processing *architectures* may become a more relevant consideration as well, given that super and limited capacity are often associated with co-active or serial processes, respectively (Colonius & Townsend, 1997; Townsend, 1972, although see also Townsend, Liu, Zhang & Wenger, 2020; Townsend & Nozawa, 1997 for alternative cases).

It should also be noted that detection speed, accuracy and efficiency are not the only considerations for peripheral displays. We adapted the DRT, which purportedly

recruits minimal processing resources (although recent research suggests this may not be as true as first thought, e.g., Biondi, Balasingam & Ayare, 2020; Castro et al., 2019; Palada, Neal, Strayer, Ballard & Heathcote, 2019). Under the assumption that the peripheral display does not detract from primary task performance, optimizing the detection speed and accuracy to the secondary task should be the goal, and redundant signals may assist with this aim. However, if optimizing the peripheral detection process impairs ordinary operation of a task or system, the outcomes may be considered sub-optimal (e.g., if the pilot cannot adequately fly the plane, the information presented in peripheral dials becomes irrelevant). In addition to optimizing the salience, accuracy and speed with which a signal can be detected, system designers should also consider the totality of multitasking performance with additional measures (e.g. Fox, Houpt & Tsang, 2021). Finally, a key point of note in our study is that despite variations and limitations in processing capacity, we universally observed redundant targets were processed *faster* than single targets alone. While optimizing capacity is ideal to maximize the absolute efficiency of the cognitive system, we have not found any evidence that cognitive workload negates the Redundant Target Effect, therefore it is clear that redundant targets remain useful when minimizing detection time is the key outcome.

Conclusion

Interfaces and cockpits may seek to utilise redundant signals to enhance detection speeds. We show that redundancy gains are influenced by both the overall cognitive workload of the operator and their operational environment, highlighting the need to embed consideration of the expected operating circumstances within the system development pipeline. Our results highlight the important role that the relative stability (here defined as block-length) of overall workload plays in determining how efficiently peripheral targets can be detected in a dynamic environment. Less stable workload conditions led to greater processing efficiencies, suggesting that decreased operator attention in predictable environments, and/or increased vigilance in

unpredictable situations likely trade off against other benefits of environmental stability. Our results may support the development of automated systems that aim to continuously engage the attention of the operator in order to maximize peripheral processing capabilities, but also point to the need to consider optimal task modalities to enhance redundancy gains.

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