Visual Target Processing Efficiency under Dual-Task Load

by

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Table of Contents

SUMMARY

Multitasking is common in operational workspaces, from air traffic control through to military command and control. Within many of these environments, efficient processing of visual information, such as warning alerts or cues, is fundamental. In this thesis, I explore whether increasing task load reduces visual processing efficiency. More specifically, I examine whether efficiency decreases when people are engaged in a demanding concurrent task, and whether display characteristics such as clutter, target salience, and signal location modulate processing efficiency.

In the first study, participants performed a visual target recognition task either by itself, or while engaged in a visuo-manual tracking task. Analysis of response times revealed that processing was consistently limited-capacity when targets were large enough to be discriminated in peripheral vision (Experiments 1 & 2), and was super-capacity when targets were small enough to demand serial visual attention (Experiment 3). However, I found no difference in visual processing efficiency as task-load increased.

The second study replicated Study 1, but for displays absent of any distractors. Consistent with the earlier experiments, processing capacity was consistently limited capacity and did not vary as a function of task load.

The third study assessed the effect of target location on visual processing under load by manipulating the location of target information within the visual field. Participants responded to targets appearing at either high or low eccentricities (Experiment 1), or else in the upper or lower visual field (Experiment 2), while performing the tracking task. Processing efficiency was consistently capacity-limited and did not vary between target locations in either experiment.

The fourth study examined changes in processing efficiency associated with manipulating both task load and target–distractor discriminability. Overall, highly

discriminable targets were processed with greater efficiency than poorly discriminable targets, but efficiency was again similar across load conditions. These findings suggest increasing the discriminability between targets and distractors is more effective for increasing processing efficiency than reducing task load.

The fifth study applied the basic dual-task paradigm from the earlier experiments to a higher-fidelity simulated military task. Participants monitored for visual targets within a simulated humanitarian aid scenario while either monitoring (low load) or teleoperating (high load) an unmanned vehicle. Despite greater mental workload during teleoperation, monitoring performance did not vary between conditions and was extremely poor across the board.

These studies demonstrate one robust central finding: that increasing task load does not reduce processing efficiency for visual information. The studies also show that, in general, processing efficiency is limited capacity, being less efficient than a standard parallel model. Finally, I find that target salience, but not target location or distractor presence, is effective at increasing capacity. These findings have implications for display design of complex operational environments that optimise operator responding under concurrent task load.

DECLARATION

I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

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LIST OF TABLES

LIST OF FIGURES

GLOSSARY OF ABBREVIATIONS

AOC/POC – attention/performance operating characteristics

BCI – Bayesian credible interval

BMS – battlefield management system

c – response bias

C(*t*) – capacity coefficient

CDF – cumulative distribution function

Cz – standardised capacity coefficient

d – Cohen's *d*

d' – sensitivity

Diff – difference between conditions

EPIC – Executive Process/Interactive-Control

FAR – false alarm rate

FLANDERS – Flinders Handedness Survey

h(*t*) – hazard function

H(*t*) – cumulative hazard function

HR – hit rate

Hz – hertz

IC – interaction contrast

kph – kilometres per hour

LVF – lower visual field

M – mean

MA – meta-analysis

MCMC – Markov chain Monte Carlo

NASA-TLX – NASA Task Load Index

PRP – psychological refractory period

R(*t*) – resilience coefficient

R_1 – response 1

R_2 – response 2

RMSE – root mean squared error

RSE – redundant signals effect

RT – response time

Rz – standardised resilience coefficient

S_1 – stimulus 1

S_2 – stimulus 2

SD – standard deviation

SDT – Signal Detection Theory

SE – standard error

SFT – Systems Factorial Technology

SIM/SUCC – simultaneous/successive

SSQ – Simulator Sickness Questionnaire

SST – serial self-terminating

ST-ST – single-target self-terminating

UCIP – unlimited capacity independent processing

UVF – upper visual field

VBS3 – Virtual Battlespace 3

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CHAPTER 1: INTRODUCTION

Measuring Capacity:

An Introductory Guide to Assessing Attentional Limitations

The following chapter comprises an unpublished manuscript reviewing various methods for measuring attentional limitations in visual processing.

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Measuring Capacity:

An Introductory Guide to Assessing Attentional Limitations

> "*Capacity, carefully defined, carefully measured by converging operations, and carefully localized in a specific system architecture, can help us predict and explain behavior.* " (Kantowitz, 1985, p. 172)

There is a limit to the amount of information we can process at any particular moment in time. Not only are we limited in how much information we can take in from a quick glance at a detailed painting, but we also cannot keep up with 10 different conversations at once. The nature and severity of these limits is less clear, however. Since the mid-1900s, psychologists have attempted to measure *cognitive processing capacity*. Cherry (1953; 1954) began this work with a series of dichotic listening experiments, with the aim to understand how people process two sets of speech simultaneously. By assessing what information was picked up automatically from an unattended message while attention was focused on the other ear, Cherry identified limits in the ability to process concurrent auditory channels. A few years later, Miller's (1956) seminal work on storage capacity in the short-term memory system demonstrated limits on the number of items that could be held in short-term memory. Taking into account these examples, Moray (1967) developed a general model of human information processing as a limited-capacity system.

Early attempts to explain human information processing drew on information theory (Attneave, 1959; Garner, 1962), also known as communication theory (Shannon, 1948). This approach viewed the human as a communication channel through which information passed at a given number of 'bits' per second. Although cognitive psychologists later lost interest in information theory, the desire to measure the transmission of information from an external source through the human information processing system continued. Over the 60-odd years since information theory was introduced, a variety of different techniques for assessing processing capacity have emerged. This broad range of techniques lead us to our central question: how can we best diagnose capacity limitations?

Here, we review a variety of methods used by cognitive psychologists to examine capacity limitations in human performance. Though we recognise the importance of capacity limitations in memory and auditory processing, here, we focus on the methodologies used to assess limitations in visual perception. In the first section, we introduce how capacity has been defined over the years, and touch upon issues relating to capacity measurement. In the second section, we discuss a variety of techniques that involve manipulating display characteristics, such as set size, within a single set of stimuli. In the third section, we introduce a selection of dual-task methodologies that assess resource competition between concurrent tasks. In the fourth section, we discuss a more current technique that addresses some of the earlier paradigms: Systems Factorial Technology (SFT; Houpt, Blaha, McIntire, Havig, & Townsend, 2013; Houpt, Blaha, Base, & Burns, 2013). Finally, the last section recounts several of the main issues researchers should consider in the search for capacity limitation. By the end of this paper, we aim to provide clear insights into how to best measure the elusive concept of capacity.

The What, When, Where, and How of Capacity

Conceptualisations of capacity typically fall into three general categories. These categories view capacity as either the amount of space available, the amount of cognitive effort expended, or the rate of processing or 'bandwidth'. Space-based definitions conceive of capacity as the quantity of information that can be processed; the larger the capacity, the more information that can be processed at any one time. Sperling's (1960) early research assessed the number of items a person could immediately recall from a visual display; he described this phenomenon as the 'span of apprehension'. Similarly, Broadbent (1965) viewed capacity within the context of available 'states' or resources within the nervous system. In his view, capacity referred to the size of the set of available states. Effort-based definitions of capacity focus on the amount of work a cognitive system must invest to successfully perform a task. Examples of these include Kahneman's (1973) notion of expending psychological 'effort' or Navon and Gopher's (1979, p. 215) description of the "amount of resources invested". Finally, speed-based definitions of capacity focus on the speed or efficiency of information processing. These definitions focus on changes to channel processing rates as a system's load is increased (e.g., Townsend & Nozawa, 1995; Wenger & Townsend, 2000). Townsend and Ashby (1983, p. 13) defined capacity as "how a system reacts with regard to speed and accuracy when its processing load is varied".

The goal of measuring capacity is to identify how efficiently a cognitive system is working. Townsend and Ashby (1983) provide general definitions for how we can conceptualise different levels of capacity performance based on the speed or processing efficiency definition. *Limited capacity* refers to a model where an increase in the number of items to be processed slows processing rates or decreases accuracy. *Unlimited capacity* refers to the situation where an increase in the number of items to be processed does not change individual channel processing rates or accuracy. In other words, performance under an unlimited capacity model is unaffected by an increase in set size or task load. Finally, in a *super-capacity* system, increasing load increases processing rates or task accuracy.

One important consideration when assessing a system's capacity is to first specify the level of processing we wish to measure. We can consider the finer-grained processing of the individual channels or subsystems, or else we can focus on the more course-grained collective operation of subsystems reflected in performance of the system as a whole (Townsend & Ashby, 1983). Take, for example, the situation of a detective unit attempting to solve crimes. To reach a solution, a unit assigned to the case must investigate some number of leads. Imagine a unit of four agents is assigned the case. The unit would constitute a *multi-*

channel system, with each agent acting as a separate 'channel' for following up possible leads. Alternatively, if the agency assigned a single detective to the case, the unit would constitute a *single-channel system*. Imagine that the number of leads to be investigated is the workload, and that each case may have between 1 and 10 critical leads to be pursued.

Regardless of the number of channels operating in the system, if we are interested in understanding how quickly individual detectives (i.e., channels) are able to follow a lead to its conclusion, we are focusing on processing efficiency at the level of the *individual units.* In this case, if the time required for detectives to follow up each lead increases as the total number of leads increases—perhaps because the agency's resources limit the rate at which detectives can follow up multiple leads simultaneously—we can say the detectives are performing with limited capacity. If individual detectives are able to chase leads at the same rate, regardless of the number of possible leads, performance is unlimited capacity. Such a situation would constitute one example of *context invariance*; the assumption that the processing rate for any given channel does not vary with changes to the number of channels operating (Ashby & Townsend, 1986; Blaha & Houpt, 2015). Note that context invariance does not only apply to unlimited capacity systems, but may also occur in other systems, such as in serial processing. Lastly, if increasing the number of leads to follow up increases how quickly individual detectives chase up each lead, the detectives are operating with super-capacity.

If, on the other hand, we are interested in assessing capacity of the agency as a whole, we are focusing on the efficiency of the *system*. From this perspective, each detective represents a single channel that contributes to how quickly the detective agency solves the case. When measuring capacity at the system level, we compare system performance relative to predictions of an unlimited capacity model in which channels operate completely independently and in parallel. We call this the *standard parallel model*, or the *unlimited* *capacity independent processing* (*UCIP*) *model* (Houpt & Townsend, 2012). We go into more details about the UCIP model in a later section. For now, it is important to understand that if, relative to the UCIP, the agency takes longer to solve the case as the number of leads to be investigated increases, we can describe the agency as functioning with limited capacity. If increasing the number of leads does not change how quickly the agency solves the whole case relative to the UCIP, we have evidence for unlimited capacity. Finally, if a greater number of leads results in the agency solving the case faster than predicted by the UCIP, we can say the detective agency is operating with super-capacity.

A critical point, here, is that the system may operate at a different level of capacity than its individual units. There are several reasons for why this situation may occur. One reason is the system's *architecture*, or in other words, the way in which the different processing channels are structured (Townsend & Ashby, 1983; Townsend & Nozawa, 1995). Systems that require one channel to finish processing before the next can begin are described to be operating under a serial architecture. In our detective analogy, if, to solve the case, each lead needed to be investigated in a specific order, we would describe the process as serial. For instance, if finding the gun used as a murder weapon (first lead) leads an officer to investigate the shooting range from which the gun was stolen (second lead), we would have a serial process. In contrast, a system that allows all items to be processed concurrently is parallel. In our detective example, parallel processing would be occurring if the detectives can process all leads simultaneously, such as chasing up questionable offshore accounts while also carrying out DNA swabs and so on. Finally, systems that operate in parallel but that allow information to be accumulated across channels are coactive. Under a coactive architecture, all detectives could be working in parallel; however, rather than working independently, detectives could exchange information between one another. For example, two detectives that interview separate subsets of eyewitnesses and then meet to collate their results would constitute coactive channels. In this situation, though all detectives are working in parallel with unlimited capacity, the benefit from working in a coactive manner allows the agency as a whole to operate with super-capacity.

Another system characteristic that can affect information processing is the system's *stopping rule*. If a system is operating with a *self-terminating stopping rule*, processing of individual items can stop as soon as any one target of interest is processed. An example of this stopping rule would be if a case involves both leads critical to solving the case and dead ends, and the detective agency must continue investigating all possible leads until a critical 'case-cracking' lead is solved. Alternatively, a system may operate with a *first-terminating stopping rule*, which is where all possible items are targets, and the first channel on which a target is processed leads to a response. This type of stopping rule would occur if a case involved any number of possible leads, but each individual lead was enough to solve the whole mystery. Hence, the first lead solved results in a conviction. Finally, if a system must process all items in a set before ending processing, the system is described as using an *exhaustive stopping rule*. In the case of the detective agency, an exhaustive stopping rule would require all possible leads to be investigated before the murderer could be identified. Changing the stopping rule changes the benchmark against which we assess capacity for any given system. Thus, though changing a system's stopping rule will not change how efficiently that system processes, it will change how we interpret the system's processing.

Finally, information processing can also vary depending on whether the channels operating are *stochastically dependent* or *independent*. Independently-operating channels, such as detectives working independently of one another, will not influence how other concurrent channels (i.e., detectives) process. Alternatively, if channels are stochastically dependent, finishing times for different channels are correlated. For example, two detectives could be stochastically-dependent if the time one detective takes to investigate a lead is based on the time of the other detective. In situations that violate stochastic independency because of inter-channel correlations, a system may operate with limited- or super-capacity, even if the individual channels are operating with unlimited capacity.

We can also differentiate resource models of information processing from structural or bottleneck models. *Resource models* assume a store of fungible mental assets or energy that can be divided or reallocated between cognitive processing operations. Interference between concurrent tasks occurs when task demands exceed the available resources (Kahneman, 1973). Resource models allow information to be processed in parallel when demands are low (and therefore do not exceed resources). However, when demands exceed resources, resource models suggest information will process in serial. Whereas some resource models emphasise a single, general capacity resource, which can be depleted by general cognitive load (Gopher & Sanders, 1984), others suggest there are different types of resources available and concurrent tasks will only interfere when tasks require similar resource pools (e.g., Navon & Gopher, 1979; Wickens, 1981; Wickens, 2008). Resource models contrast with *structural*, *bottleneck*, or *single-channel models* that argue resources cannot be shared at the bottleneck stage (e.g., Harold Pashler, 1994a; Ruthruff, Pashler, & Klaassen, 2001). Therefore, if multiple items require processing, each item must be processed one at a time. If an item is easy to process, rather than leaving spare resources available to process other items, as assumed by resource models, bottleneck models assume that the specific item will simply process faster. Thus, at no stage in the bottleneck can resources be shared between competing demands. The central difference between these two types of models, therefore, comes down to system architecture: whereas traditional capacity models allow parallel processing if demands are low enough, bottleneck models necessarily assume serial processing of information.

Before moving on to the methods, we first want to clarify that our focus of the current paper is about assessing capacity at the system-level. Thus, in the following sections we discuss a range of different ways in which researchers have attempted to capture processing efficiency for a whole cognitive system, rather than just for the individual channels.

Single-Task Paradigms

Early methods for assessing capacity involved manipulating the characteristics of a single stimulus input. These approaches, also known as *single stimulation* paradigms, assess performance at different levels of difficulty to measure how performance changes as a function of task difficulty (Kantowitz, 1985). Thus, in single stimulation studies, capacity is inferred from changes in speed or accuracy as a function of changes to different variables, such set size or display sequence.

Choice Reaction Time Paradigms

Some of the earliest studies in the field of human information processing began by testing the relationship between the number of different response alternatives and response time (RT) to detect a target. In the 1950s, Hick (1952) and Hyman (1953) provided early attempts at measuring processing capacity by analysing the set size/RT relationship. By asking participants to respond to one stimulus out of a set of *n* possible items, each tied to a different response, both Hick (1952) and Hyman (1953) examined changes in RT as the number of possible items increased. They found that that RT was proportional to the number of stimulus alternatives.

Later on, Sternberg (1966) developed a memory scanning paradigm to assess how efficiently people could retrieve items from memory as the number of remembered items increased; he described this number as their ‘span of immediate memory’. Observers in Sternberg’s experiments memorised a list of 1 to 6 digits and were then presented with a test item. Immediately afterwards, they would make a speeded ‘Yes’/‘No’ response to indicate whether the test item had been in the initial list. Similarly to the Hick-Hyman (Hick, 1952; Hyman, 1953) findings, Sternberg found a direct linear relationship between list length and RTs. He argued that the increase in RT associated with each additional item in memory was too great to be explained by parallel processing, and instead suggested that this pattern provided evidence that items in memory were processed in serial (though see McElree & Dosher, 1989, for a contrary conclusion).

Both the choice RT and memory scanning paradigms have become popular methods for attempting to assess processing efficiency and system architecture (e.g., Jensen, 1979; Rensink, 2000; Treisman & Gelade, 1980; Wickens, Braune, & Stokes, 1987). In their seminal paper on feature integration, for instance, Treisman and Gelade (1980) compared RT search slopes for basic, single feature items (e.g., a red O among blue Os), with slopes of more complex, conjunction feature items (e.g., a red O among blue Os and red Vs). Compared to single feature search, which produced very shallow RT slopes, conjunction search RTs increased dramatically with increases in display set size. Treisman and Gelade argued that rudimentary features are registered in parallel at an early stage of visual processing, but that veridical perception of feature conjunctions requires serial processing.

Despite its popularity, the manipulation of set size as a technique for assessing capacity has been criticized for several reasons. Critics have pointed out that changes in RTs as set size increase not only reflect changes in processing rate, but can also be influenced by statistical decision noise (e.g., Huang & Pashler, 2005; Huang, Pashler, & Junge, 2004). *Statistical decision noise* refers to the accumulating risk of error that results when set size increases. Assume that each item among some set of n has a non-zero probability p of producing an error response. The probability that all n items are processed without error is then $(1-p)^n$, where $1-p$ is greater than zero but less than one. Thus, as n increases, the probability that all n items are processed without error decreases, even if p, the probability that any single item will be processed erroneously, remains constant (Huang & Pashler, 2005).

Eye movements may also affect the steepness of RT slopes. Because larger set sizes make detection more difficult, observers are more likely to serially scan items in larger displays than they are in smaller displays. The additional time resulting from fixating individual items can then increase RTs for larger displays, creating steeper search slopes than for smaller displays.

More fundamentally, Townsend and colleagues (e.g., Townsend, 1971; Townsend & Thomas, 1994; Townsend & Wenger, 2004) have shown that RT slopes are non-diagnostic for measuring capacity or architecture. Contrary to Sternberg's argument that positive RT slopes are evidence of serial processing, Townsend demonstrated limited-capacity parallel processing may produce positive linear RT functions, mimicking the effects of a serial model. Thus, set size slopes are limited with regards to drawing inferences about capacity as they tend to conflate architecture with capacity.

Whole versus Partial Report

In an attempt to measure the 'span of apprehension', Sperling (1960) introduced the methods of *whole* and *partial report.* In whole report, participants are presented a brief display of multiple items and are then asked to recall as many items as they can. In partial report, participants are again presented with a brief display of multiple items, but they are only asked to recall a subset of the display. Most importantly, participants are not cued which parts to report until after the stimulus has disappeared. Thus, participants are required to encode the whole display before recalling the relevant items from memory. Using the whole report method for set sizes of between 3 and 12 items, Sperling discovered participants were only able to recall, on average, 4-5 items from the whole display, showing a clear limit to their performance on the task. When participants viewed a display but were cued to recall only a subset of items using partial report, participants again showed a 4-5 item limit on their recall, but this limit was specific to the cued items. In other words, participants could recall items from the cued subsets, indicating they had successfully encoded all items at the perceptual level. Because participants were able to successfully recall approximately the same number of items in both partial and whole report, Sperling concluded that the capacity limit of 4-5 items occurred at the level of short-term memory. In contrast, as recall was high for items that were cued, he concluded that visual capacity was unlimited. Sperling's findings were pivotal in distinguishing between capacity limits in perception and memory, showing that a person's capacity to perceive visual information is much greater than his or her capacity to remember it.

Detection Methods

To circumvent the short-term memory constraints that limit whole report performance, Estes and Taylor (1964) devised an alternative method of 'apprehension span' that required only a present/absent decision about a single target within the display. An array of letters was displayed briefly, and the participant's task was to determine which of two pre-specified target letters appeared in the display. The set size varied between 3 and 16, but unlike the studies discussed above that focused on set size effects on RT, Estes and Taylor shifted the focus of analysis to detection accuracy. By modelling the detection data, Estes and Taylor estimated the mean number of items processed within a display as the number of elements increased. Similarly to the whole/partial report methods, the detection method showed no evidence of a capacity limit with increasing set size (Estes & Taylor, 1964, 1966).

Although they found evidence of unlimited capacity, and thus, the location of items within the display should not have affected performance, a possible limitation of Estes and Taylor's (1964) original study was that as set size increased, so too did the spread of the items from more central to more peripheral locations. To account for this potential eccentricity effect, further studies manipulated set size while holding the spread of items approximately constant (Estes & Taylor, 1966; Estes & Wessel, 1966). Estes and colleagues (Estes & Taylor, 1966; Estes & Wessel, 1966) varied set sizes among 8, 12, and 16 items by ensuring that each row and column contained 2, 3, or 4 items, respectively, minimising any eccentricity effects due to set size. Similarly to their original study, they found the number of items processed within a display increased with the number of items within the display, and hence, they found no evidence of a capacity limit.

In a further attempt to control for stimulus eccentricity, Eriksen and Spencer (1969) developed a rapid letter sequence paradigm. On each trial, the participant saw a sequence of letters and was asked to report whether or not the sequence contained a designated target letter. The items appeared in a set of ten locations forming an imaginary circle around a fixation point. The experimenters manipulated sequence length from 1 to 9, along with the interval between successive items. Increasing the interval between items was expected to enhance processing of each individual element, and hence, any evidence for a capacity limitation would appear as greater detection accuracy as the inter-stimulus-interval increased. Surprisingly, the increased time interval between stimuli did not aid performance; detection accuracy remained approximately constant as the interval between stimuli increased from 5 ms to 3000 ms. However, as with the previous detection methods, Eriksen and Spencer also found a clear decrease in performance as a function of sequence size; though correct detection rates were consistent across sequence size, false alarm rates increased with sequence length. Eriksen and Spencer suggested that the lack of any inter-stimulus-interval effect was incompatible with a limited capacity model. Because processing efficiency of sequence items did not increase with increases in inter-stimulus-intervals, Eriksen and Spencer argued that a serial encoding process could not account for their findings. Instead, they suggested their results could be explained by either a multichannel encoder that could process multiple channels concurrently, or else an attentional filter that could screen out irrelevant information (Broadbent, 1958). Furthermore, they suggested that the sequence length effect on error rates reflected statistical decision noise rather than indicating a performance limitation (Eriksen & Spencer, 1969). Thus, Eriksen and Spencer argued that they had had found evidence of an independent parallel model with processing efficiency being independent of other items being processed.

Simultaneous versus Successive Displays

Shiffrin and Gardner (1972) devised an alternative method for assessing visual capacity, in which some number of stimuli to be processed are either presented simultaneously for an interval of *i* ms, or in successive intervals of *i* ms each. The logic of the method is simple: both the simultaneous and successive displays require the same number of items to be processed (e.g., 4 items total), and are therefore matched for statistical decision noise. However, manipulating whether all items appear simultaneously or in successive intervals varies processing load that is imposed within a given amount of time. Thus, poorer performance with simultaneous displays than with successive displays provides evidence for a capacity limitation.

In the simultaneous displays of Shiffrin and Gardner's (1972) study, for example, the four corners of a square were each occupied with one item, one of which was a target. In the successive displays, two of the items appeared in one interval and the other two appeared in a second interval immediately afterwards. The exposure duration for all intervals was equal. For instance, if the total exposure duration of the simultaneous display was 50 ms, the exposure duration for each interval in the successive displays was also 50 ms. Following the displays, participants reported the location of a target item. Because successive displays reduced the number of items to be processed at any one time, they should have allowed better performance than simultaneous displays, but only if capacity was limited. If capacity was unlimited, the two display types should have produced similar levels of performance. Shiffrin and Gardner found no effect of display type in their study and thus inferred that perceptual processing capacity was unlimited.

More recent studies using the *simultaneous/successive* (*SIM/SUCC*) paradigm have found no evidence of capacity limits in symmetry detection (Huang et al., 2004), but have noted larger differences between simultaneous and successive displays when an observer must monitor for two or more targets (Duncan, 1980b). SIM/SUCC paradigms have also revealed differences in processing between different types of visual search tasks. Huang and Pashler (2005) used a SIM/SUCC paradigm to test for capacity limits in a difficult feature search, a conjunction feature search, and a spatial configuration search. Spatial configuration search, where a target is defined by the spatial arrangement of line segments rather than any single feature, has been shown to engender less efficient processing than that of conjunction or single feature search (Wolfe, 1998). Despite finding very steep RT search slopes across tasks, Huang and Pashler observed a successive advantage only for the spatial configuration task. In other words, both the difficult feature search and difficult conjunction search showed no evidence of a capacity limit even though their steep RT slopes appeared to indicate highly inefficient processing (Sternberg, 1966). These findings reiterate that RT search slopes are not an accurate measure of capacity.

Though the SIM/SUCC paradigm is considered better than many of the previous techniques already presented, it is still limited as the time between the two intervals in the successive display could introduce memory losses that could reduce performance (Duncan, 1980a). For example, if a target appeared in the first interval of a successive display, the participant might forget its location before the response is prompted. Thus, even if visual perception was limited capacity, memory losses could wash out any difference between successive and simultaneous displays, mimicking the effect of unlimited capacity.

SIM/SUCC designs that minimise memory load, such as using a binary response choice, reduce the likelihood that memory will contaminate performance.

Partial Discrimination

During the 1990s, Palmer and colleagues (Palmer, 1990, 1994; Palmer, Ames, & Lindsey, 1993) devised a method for assessing capacity that could circumvent the sensory and decisional confounds associated with visual search set size effects. Recognising that previous methods had confounded set size with eccentricity and positional uncertainty, Palmer (1990) developed a different type of paradigm. Palmer's paradigm involved discriminating between features of briefly presented displays. In Palmer's studies, the feature of interest was line length. In each trial, the participant viewed a fixation display, before viewing a brief study display containing between one and four stimulus lines of varying lengths positioned around a central fixation point. Finally, a test stimulus line appeared in one of the four locations of the study stimuli. The participant's task was to judge whether the test stimulus line was longer or shorter in length than the line that had appeared in the same location in the study display. Participants responded by making a two-alternative forced-choice judgement.

By positioning items equally close to fixation, Palmer (1990) ensured that increasing set size from one to four items did not increase the eccentricity of items within the displays, and by positioning items equally distant from one another, he controlled for sensory effects such as lateral masking. By ensuring that sensory, decision, and response processes were matched across set sizes, Palmer could conclude any effect of set size on discrimination accuracy was due to attentional limits. His data showed that the threshold for discriminating between line lengths increased as the number of items in the display increased. He concluded that increases in set size compromised perception and memory for line lengths.

In a follow-up experiment, Palmer included a cueing paradigm to further control for potential sensory interference. To do this, Palmer differentiated between the total number of items that were displayed in a set and the number of cued or ‘relevant’ items. Holding the total number of items fixed while manipulating the number of cued items controlled for sensory interference while varying attentional load. In one experiment, he manipulated the displayed set size between 2 and 4 items, holding the number of relevant, or cued, items constant. Participants saw a fixation display, and then received a cue that directed them to attend to the two items on one of the diagonals of an imaginary square. Following the cue, a line segment appeared in each of the two cued locations, or else a line segment appeared in all four locations. Finally, a test stimulus appeared in either one of the two cued locations. The participant’s task was to determine whether the test stimulus matched the length of the item that had just appeared in the same location. Data showed no evidence of a display size effect, ruling out a sensory explanation of the set size effects seen in the first experiment.

A second cueing experiment tested for any effect of attention, this time holding display size constant at 4 items while manipulating the relevant set size to either 2 or 4. Data showed a decrease in performance as the number of relevant items increased, implying an attentional explanation for the set size effect on line discrimination thresholds. In later studies, Palmer and colleagues examined discrimination set size effects for larger sets sizes and complex displays (Palmer et al., 1993) and for a variety of stimulus types (Palmer, 1994). Data revealed similar set size effects across different search tasks and stimuli, and they were fit well by a model that assumed attentional capacity limitations absent of statistical decision noise.

General Issues with Single-Task Paradigms

Over the history of using single-task or single-stimulation methods for measuring capacity, several important issues have emerged. One of the main issues concerns set size effects on RT and how these effects are interpreted. As mentioned above, a set size effect can result from a processing capacity limitation, but can also result from sensory limitations, decision noise, or similar confounds. In contrast, the later paradigms, such as the SIM/SUCC and partial discrimination paradigms, control for those potential confounds.

Another important point to mention here is that, in general, single-task paradigms have revealed similar conclusions about visual capacity. Across a variety of different paradigms, from the whole and partial report method (Sperling, 1960) to detection tasks (e.g., Eriksen & Spencer, 1969; Estes & Taylor, 1964, 1966) and even the SIM/SUCC paradigm (Shiffrin & Gardner, 1972), researchers have found a consistent pattern: that many basic judgements, such as basic letter recognition, are made with unlimited capacity. In contrast, it is only for more complex tasks, such as line length discrimination (e.g., Palmer, 1990, 1994; Palmer et al., 1993) or spatial configuration (e.g., Huang & Pashler, 2005), where we start finding clear limits to capacity. In other words, capacity limits appear to arise in situations where there is a controlled allocation of attention.

Dual-Task Paradigms

Dual-task paradigms, or *double-stimulation*, methods measure capacity by assessing performance reductions associated with performing two or more tasks concurrently (Kantowitz, 1985). The expectation in a dual-task paradigm is that by ‘saturating channel capacity’ (Poulton, 1965), the combined capacity demands of the two tasks will cause interference (Millar, 1975). The standard dual-task paradigm involves comparing single-task performance on each task to the performance observed when the two tasks are carried out at the same time (e.g., Bourke, 1997; Duncan, Martens, & Ward, 1997; McLeod, 1977; Talsma, Doty, Strowd, & Woldorff, 2006). Here, we focus on specific dual-task paradigms commonly used to assess processing capacity: the psychological refractory period paradigm, the subsidiary task method, and the analysis of attention (or performance) operating characteristics.

The Psychological Refractory Period

One of the most well-known dual-task paradigms is the *psychological refractory period* (*PRP*) method, in which the participant receives two separate inputs, each requiring a separate response. The PRP refers to the delay in the response (R_2) to a second stimulus (S_2) that closely follows a primary stimulus (S_1) compared to when R_2 is performed on its own (Craik, 1948; Telford, 1931). Welford (1952) proposed the *single-channel hypothesis* to explain the PRP, positing a bottleneck in the response-selection stage of information processing. According to this model, the temporal proximity between the S_1 and S_2 reveals a processing bottleneck on the responses to the two stimuli, where the response to S_2 can only occur once the response stage for S_1 has completed. As such, the bottleneck theories attribute the PRP to a structural limitation rather than a capacity shortfall (Harold Pashler, 1994a, 1994b; Ruthruff, Pashler, & Hazeltine, 2003; Ruthruff et al., 2001).

Despite much support for a bottleneck model to explain the PRP (e.g., Marois & Ivanoff, 2005; Harold Pashler, 1994a, 1994b), some theorists have argued that an analytic focus on R_2, the response time to the second stimulus, ignores a key finding also common in most studies: that R_1, the response time to the first stimulus, is also inflated in the dual-response condition (Herman & Kantowitz, 1970; Noble, Sanders, & Trumbo, 1981; Tombu & Jolicœur, 2002, 2003). Central bottleneck models predict that R_1 will not change as the interval between S_1 and S_2 decreases (e.g., Harold Pashler, 1994a). In contrast, resource models assume a graded capacity allocation between tasks, and thus predict that decreasing the time between stimuli, as well as increasing the difficulty of the second task, should delay R_1. Tombu and Jolicœur (2002) tested the effect of secondary task difficulty on the delay of R_1. Consistent with a shared resource model, they inferred that increasing the difficulty of the secondary task led to a greater amount of capacity allocated to S_2, driving resources away from S_1 and hence delaying R_1. Incorporating aspects from both resource-sharing and bottleneck models, they proposed a *central capacity sharing model* that assumed information processing comprises of both limited and unlimited capacity stages (Tombu & Jolicœur, 2002, 2003). According to the model, the limited capacity stages were during the central components of information processing. Tombu and Jolicœur used the model to account for evidence of both attentional bottlenecks and capacity sharing models in the PRP paradigm.

However, not all researchers agree that the common delay of R_1 in the PRP paradigm is evidence of limited capacity. Noble et al. (1981) examined the effects of a variety of task characteristics (such as the inter-stimulus interval or the processing demands of the first task) on the R_1 delay, and found that the delay was independent of these task changes. This finding contradicted the predictions of capacity sharing models, which predict that increasing task demands should affect the R_1 delay. As such, the authors argued that their findings were not evidence of a limited capacity model, but reflected *concurrence costs*, the general ‘overhead’ costs of performing two tasks concurrently (Navon & Gopher, 1979). Such costs could mimic the effect of a shared resource allocation between tasks, despite being the result of natural performance decrements expected by performing two tasks at the same time.

As an alternative to both the bottleneck and capacity-sharing models, Meyer and colleagues (Meyer et al., 1995; Meyer & Kieras, 1997) introduced an *adaptive executive control model* that involved, what they described as, an *Executive Process/Interactive-Control* (*EPIC*) architecture. Meyer et al. argued the bottleneck model was inconsistent with evidence that in many situations people can perform multiple tasks concurrently, or evidence that training can reduce the PRP effect. In contrast to the bottleneck model, the EPIC architecture assumes that people can select responses and perform operations for different tasks simultaneously, and that dual-task interference is caused by sensory or motor limitations. Moreover, it assumes that interference between tasks can be reduced by changes to task prioritisation and scheduling (i.e., concurrent [parallel] versus sequential [serial] scheduling), or through practice. Thus, Meyer et al.'s model assumes that the PRP effect is a consequence of task strategy, not evidence of a cognitive limitation. Schumacher and colleagues (2001) argued in favour of Meyer et al.'s adaptive executive control model after finding minimal PRP effects on concurrent choice RT tasks following practice. They interpreted their findings as evidence that performance can vary depending on factors such as instructions and task priorities. In addition, they argued that inter-individual differences in the size of dual-task interference could be explained by personal preferences with task scheduling; daring scheduling produces concurrent task performance, whereas cautious scheduling results in performing tasks in succession.

However, the notion of a strategic or voluntary explanation for the PRP has been criticised (e.g., Ruthruff et al., 2003, 2001). Ruthruff et al. (2003) tested whether the PRP could be explained by a bottleneck model or EPIC's strategic model. Because EPIC assumes dual-task interference is caused by non-cognitive peripheral sources rather than cognitive limitations, Ruthruff et al. used a paradigm that eliminated all non-cognitive sources of interference, and that equally weighted the priority of each task. Despite controlling for these alternative sources of interference, Ruthruff et al. still found considerable dual-task interference, and hence, argued cognitive limitations are critical to explaining the PRP. The validity of the adaptive executive control model has also been questioned by studies showing little or no reduction in the PRP following changes to task prioritisation instructions (e.g., Levy & Pashler, 2008; Ruthruff et al., 2003).

There is still debate around whether the PRP is best explained by a resource sharing model, a bottleneck model (Ruthruff et al., 2003, e.g., 2001), or a combination of the two (e.g., Tombu & Jolicœur, 2002, 2003). Navon and Miller (2002) questioned the use of the

PRP 2-stimulus, 2-response paradigm for testing between single bottleneck and resource capacity theories. They argued that, because the paradigm is "inherently biased in favor of queuing" (Navon & Miller, 2002, p. 227), this method will generally show a bottleneck, regardless of the underlying processing model.

Subsidiary Task Method

The *subsidiary task* method differs from the PRP in that participants are instructed to prioritise a primary task, allowing performance on a secondary (subsidiary) task to represent the amount of *spare* or *reserve* capacity (Brown, 1966). Though this method may employ any of a variety of tasks, possibly the most well-known choice of subsidiary task is the *probe RT* task (Posner & Boies, 1971), described in full below. Given that different primary tasks may engender different effects on subsidiary task performance (Brown, 1966), some researchers have suggested that spare capacity is best measured using a battery of subsidiary tasks, rather than any single task (Kahneman, 1973).

Probe reaction time tasks. Speeded probe RT is commonly used as a subsidiary task for measuring spare capacity in conjunction with a concurrent task. Posner and Boies (1971) devised a probe RT paradigm in which the participant responds to auditory probes (subsidiary task) while performing a same/different letter match task (primary task). In the letter match task, a letter first appeared (encoding stage), followed by a second letter shortly thereafter, and the participant was then required to make a rapid 'same'/'different' judgement using a key press. Posner and Boies manipulated the timings of the probes at different stages during the primary task to assess changes in the amount of probe interference. In addition, they measured RTs both to probes on the subsidiary task and to letter stimuli on the primary task to assess performance changes at different levels of interference. Posner and Boies found probe RTs increased when the probe occurred at specific times during the primary task, such as during the response phase of the letter match task. They used these findings as evidence that the probe RT reflected fluctuations in the attentional demands of the primary task, concluding they had found evidence of limited capacity performance. Moreover, probe RTs did not increase during the appearance of the first letter (i.e., the encoding stage) of the letter match task. Thus, they concluded that the stimulus encoding required in the early stages of the letter match task did not require processing capacity, but that post-encoding, conscious processes, such as rehearsal or response selection, demanded attentional resources.

To test Posner and Boies' (1971) conclusion that letter encoding during the primary task did not demand processing capacity, Comstock (1973) replicated the original probe RT paradigm. In contrast to Posner and Boies, she found increased probe RT interference when probes occurred during the encoding stage of the letter match task. She concluded that both the encoding of stimuli and response execution required resource capacity. Similar conclusions have been made by other researchers who have found processing limitations during stimulus encoding due to interference from a competing probe (e.g., Millar, 1975; Ogden, Martin, & Paap, 1980; Paap & Ogden, 1981; Shwartz, 1976). These varied findings highlight one of the issues regarding inferring interference via changes in RTs on the letter-match task and to the probes.

In addition to interpretation issues, several researchers have also questioned whether the probe RT task is a valid measure of central capacity (e.g., Kantowitz, 1985; McLeod, 1978; Shwartz, 1976). Shwartz (1976) modified Posner and Boies' (1971) original study to test for between- and within-modality effects on probe RT performance, pairing a visual primary task with either a visual or auditory probe task. He found that responses were slower to visual probes than to auditory probes. Because the probes occurred during the encoding stages of the letter-match task, he suggested this effect provided evidence for a capacity limitation during the perceptual processing stage.

Following on from Shwartz's (1976) findings, McLeod (1978) further tested whether probe RT was an effective measure of central capacity, irrespective of response modality. For this purpose, he combined the primary letter match task with an auditory probe task, but he manipulated response modality. Half of the participants responded to the auditory probes manually, with a button press, and the other half responded by making a vocal "bop" sound. Data showed clear differences in RT between the two modalities. Not only were vocal responses slower than manual responses, but the magnitude of probe interference on the different stimuli in the letter match task differed depending on probe modality. More specifically, whereas vocal probe RTs did not differ between same and different letter match trials, manual probe RTs were longer when letter match trials were different than when they were the same. Thus, similarly to Shwartz, McLeod argued that the probe RT task was not a valid measure of a generalised central capacity, but instead gave evidence of modality-specific resource limitations.

Despite some findings identifying clear inter-modality differences in probe RT interference, others have argued that interference is generally consistent across task type (e.g., Proctor & Proctor, 1979). Recognising limitations in the design of Shwartz' (1976) study comparing auditory and visual probes on RT, Proctor and Proctor (1979) tested whether the shape of the probe RT function varies over time, depending on probe type. In contrast to Shwartz, they found no difference between auditory and visual probes in influencing the probe RT function, so long as participants were aware of the modality of the probe. Whereas both types of probes produced identical RT functions when participants were aware of the probe modality, RTs to auditory probes were considerably longer than those to visual probes when the probe modality was not known. Surprisingly, the delayed RTs on the auditory task directly contrast the earlier modality-specific findings that show longer RTs when pairing the visual primary task with a visual probe (e.g., Shwartz, 1976). Proctor and Proctor argued that this auditory task interference represented evidence that interference was due to central capacity processes, and moreover, that auditory tasks are more sensitive to changes in primary task resources than visual tasks.

Performance Operating Characteristics and Attention Operating Characteristics

An alternative method to measuring the effects of a primary task on secondary task performance is to plot the performance trade-offs between two concurrent tasks in the form of an *attention operating characteristic* (*AOC*) (Kinchla, 1969; Kinchla, 1980; Sperling & Melchnor, 1978) or a *performance operating characteristic* (*POC*) (Norman & Bobrow, 1975). This method visualises changes in performance of one task as a function of performance on the other task. AOC/POCs are created by manipulating one variable of task performance, such as task priority, task difficulty, or allocation of attention to each task, while holding all other variables constant. The logic behind the AOC/POC is based on the shared resource model. If attention is limited capacity, increasing performance on one task should result in a corresponding decrease in performance on the other task. Unlimited capacity, in contrast, is assumed if performance on either task is robust against changes to performance on the other task. Thus, unlimited capacity performance should appear as perfect and consistent performance on the second task as performance on the first task increases. Norman and Bobrow (1975) argued that to successfully interpret an AOC/POC in terms of capacity limits, researchers should manipulate task priority, rather than task difficulty. However, others have suggested that manipulations of both task priority and task difficulty are critical for successful interpretations of the AOC/POC (e.g., Navon & Gopher, 1979).

Early studies using the AOC/POC paradigm focused on speeded detection of luminance signals (Kinchla, 1969) and visual recognition (Sperling & Melchnor, 1978). Following on from these studies, in the late 1980s and early 1990s, Bonnel, Miller, and colleagues (Bonnel & Miller, 1994; Bonnel, Possamai, & Schmitt, 1987; Bonnel, Stein, &

Bertucci, 1992; Miller & Bonnel, 1994) developed a concurrent line length discrimination paradigm to test resource allocation between simultaneous tasks. Within the original paradigm (Bonnel et al., 1987), two separate pairs of vertical lines appeared in each display, one pair either side of fixation. Each trial, the participant made a 'same'/'different' judgement about whether the two lines in each separate pair were equal in length. To gauge performance across the spectrum of resource allocation, participants were instructed to devote between 0% and 100% of their attention to the line pair on one side of fixation and the complementary percentage to the opposite line pair. Bonnel and colleagues plotted AOC/POCs showing discrimination performance (*d*') for line pairs to the right of fixation against performance for line pairs to the left for each level of attention allocation, illustrating the changes in performance that resulted as cognitive resource allocation moved from one 'task' to the other. The plots showed that varying the attention allocation from one stimulus pair to the other created a graded trade-off function. Comparing their findings to predictions of different task-switching and resource-sharing models, the authors concluded that the curves were evidence of a shared attentional capacity between the two tasks, rather than an 'all-or-none' model (Bonnel & Miller, 1994). However, given the clear performance trade-offs between the two tasks, processing was limited capacity.

Because the analysis of AOC/POCs allows a quantitative measure of resource allocation between two concurrent tasks, Navon & Gopher (1979) suggested that the AOC/POC method is a better method of gauging capacity limitations than simply comparing a dual-task condition with a single-task. Despite this advantage, there are several issues that must be considered when implementing this paradigm (see Kantowitz & Knight, 1976, for a comprehensive review). One concern relates to the key assumptions of the method. AOCs/POCs assume there is a fixed amount of capacity available to complete tasks, and that all possible resources are consumed by performing the two tasks concurrently (Gopher &

Sanders, 1984; Kantowitz & Knight, 1976). If, together, the two tasks do not consume all available resources, the AOC/POC may give the misleading impression that capacity is unlimited, with increases in performance on one task showing little, if any, interference on the other task. Thus, the method cannot provide an accurate measure of capacity for situations in which two tasks consume less than all of the available resources. Moreover, these methods cannot account for theories that suggest total capacity can vary in response to task demands (e.g., Kahneman, 1973; Young & Stanton, 2002b). The AOC/POC method also assumes that the participant can control how they allocate capacity or resources between tasks and is not suitable for situations where a person has no control over their capacity allocation.

Another issue is how to interpret performance using the AOC/POC paradigm (Broadbent, 1982; Gopher & Navon, 1980; Gopher & Sanders, 1984; Kantowitz & Knight, 1976). Though a trade-off in performance is generally accepted as representing some form of shared-resource or limited capacity model, there may be multiple explanations for similar shapes of the AOC/POC (Broadbent, 1982; Gopher & Sanders, 1984). Without further modelling of the data, such as the methods used by Bonnel and Miller (e.g., Bonnel & Miller, 1994; Bonnel et al., 1987, 1992; Miller & Bonnel, 1994), it may be difficult to clearly deduce a specific underlying model. Finally, it is important to ensure that participants do not change how they perform the two tasks concurrently compared to when they perform each task alone. This issue is known as the assumption of *process invariance* (Gopher & Sanders, 1984). For process invariance to hold, both tasks must be performed as separate tasks, even when performed concurrently. The assumption of process invariance states that resource demands of two concurrent tasks should equal the sum of the resource demands for each individual task (Gopher & Sanders, 1984). In situations where tasks become cumulative to form a different task or where participants change strategies to accommodate both tasks, the assumption of process invariance is violated and, thus, it becomes extremely difficult to interpret the critical effect of the change in task priority.

Some critics have questioned the value of the AOC/POC technique as a true method for assessing capacity limitations. Kantowitz (1985) criticised the AOC/POC for only providing a way to plot data rather than being a true research paradigm, likening the technique to a histogram. He stated the technique had "no more special implications for assessing capacity limitations" than other graphical representations of data (Kantowitz, 1985, p. 155). However, Bonnel and Miller's (Bonnel et al., 1992; Miller & Bonnel, 1994) modelling suggests the AOC/POC method can provide valuable insights into cognitive processing capacity and resource allocation.

General Issues with Dual-Task Paradigms

Regardless of the type of dual-task paradigm employed (i.e., whether it assesses spare capacity or performance trade-offs), researchers must be aware of several issues when assessing performance changes between concurrent tasks. One of these issues is the type of interference at play. Performance losses in a concurrent task paradigm may result from cognitive resource competition, or else may be due to other factors such as structural interference, concurrence costs, or peripheral constraints. As mentioned earlier, *structural limitations* refer to bottlenecks in particular stages of processing, such as during response selection. If two tasks require a similar type of response, interference between the two tasks may result in temporary bottlenecks during the response stage of processing. Though this interference is inherently structural rather than capacity-related, the reduced performance may easily be misinterpreted as a capacity limitation. Similarly, *concurrence costs* refer to 'overhead' costs associated with performing more than one task concurrently (Navon & Gopher, 1979). As explained by Damos (1991, p. 101), "performing two tasks concurrently is inherently different from performing one task, regardless of its complexity". Concurrence costs are basic costs associated with performing two tasks together that would not be present when performing one task alone. Concurrence costs may change the capacity allocated to each task, mirroring a capacity limitation. Finally, *peripheral constraints* are non-cognitive sensory or physical limitations that may affect the ability to perform tasks concurrently. For example, sensory limitations could include not being able to look in two different directions at the same time. Physical or effector limitations occur when concurrent tasks require similar motor responses.

Similar to structural limitations and concurrence costs, dual-task performance may be affected by factors not present in single-task conditions. As stated earlier, process invariance is the condition that each task is performed in the same way when tasks are concurrent than when performed alone. If the participant changes their strategy for performing the tasks when moving from single- to dual-task, it becomes difficult to pull apart the factors leading to any dual-task costs. For example, if a participant unitises the individual tasks into one combined task or confuses the response mappings for individual tasks, the dual-task condition may be confounded with *emergent processes* (Duncan, 1979) that are absent from the single-task conditions. Moreover, if changing the difficulty of the first task also affects the difficulty of the second task, performance on the tasks may become intertwined, making it particularly difficult to pull apart performance on each task (Navon & Gopher, 1979).

A major question with many dual-task paradigms relates to the assumption that the two tasks performed concurrently consume all available capacity (Gopher & Sanders, 1984; Ogden, Martin, & Paap, 1980; Tombu & Jolicœur, 2003). A performance decrease under dual-task conditions is assumed to represent evidence that the tasks' total capacity demands exceed available capacity; however, this assumption is not necessarily true. As just mentioned, factors other than capacity saturation may cause performance losses. Moreover, the capacity-saturation notion contradicts theories that suggest available resources may change or even increase with greater task demands up to a point (e.g., Kahneman, 1973; Young & Stanton, 2002b). Though variable-capacity theories generally argue that capacity will eventually reach a set limit, they assume that up to that point, increasing task demand will allow a greater amount of resources to be allocated to the tasks to maintain performance (Kahneman, 1973; Young & Stanton, 2002b). Thus, paradigms based on the idea that capacity can become saturated under dual-task load are limited to theories that assume capacity is ‘fixed’ (Navon & Gopher, 1979).

The many issues associated with comparing single- and dual-task performance raise the question of whether a single-task is a meaningful baseline against which to test for processing capacity limits. Though some researchers have argued that a single-task baseline control is essential for assessing dual-task processing demands (e.g., Ogden et al., 1980), others have explained that manipulating task factors, such as priorities or instructions, is a better option than comparing dual- and single-task performance (e.g., Gopher & Sanders, 1984). In fact, Gopher and Sanders (1984, p. 236) go as far as to say that single tasks are “only relevant to augment interpretation of dual task trends”. In any case, regardless of how dual-task performance is measured, some argue that researchers must always protect performance on the primary task while under dual-task conditions if they are to successfully interpret secondary task effects on capacity (Gopher & Sanders, 1984).

Alternative Methods of Assessing Capacity

In the previous sections, we discussed a variety of single- and dual-task methods, along with their advantages and disadvantages, for assessing visual processing capacity in the laboratory. In the current section, we discuss an alternative, more robust measure of capacity limitations. Prior to exploring this method, we will briefly touch upon an alternative measure used to assess capacity that forms the basis of this technique: the redundancy gain.

The Redundancy Gain

The *redundancy gain* or *redundant targets effect* refers to the effect of faster processing when presenting two or more items mapped to a common response than when presenting only one of the items alone (Grice & Reed, 1992; Miller, 1982, 2015; Todd, 1912). Redundancy gains are assessed using a *redundant-targets paradigm*. Each trial, a target may appear in one of two channels (single target conditions), or it may appear in both (redundant-target condition). The redundancy gain is the difference between the mean redundant-target condition and the mean of the mean RTs (or alternatively, the faster mean RT [cf., Biederman & Checkosky, 1970]) of the two single-target conditions. Because the redundancy gain provides a measure of performance changes as the number of items to be processed increases, it has been used as a measure of processing efficiency (e.g., Miller, Beutinger, & Ulrich, 2009; Mullin & Egeth, 1989).

Mean RTs alone, however, cannot distinguish between limited, unlimited, and super-capacity models. Without benchmarks against which we can compare redundancy gains, we have no concrete way of assessing the type of processing occurring in a system. For example, shorter RTs with dual targets than with a single target may represent highly efficient super-capacity processing, with substantial processing benefits resulting from the concurrent targets. Alternatively, however, the same findings could instead represent performance of a limited-capacity system in which processing is only marginally improved with the addition of a second target. To provide a better measure of dissociating unlimited capacity from super-capacity, Miller (1982) devised an upper bound on unlimited capacity parallel processing, known as the *race model inequality.* Miller's inequality states that, in an unlimited capacity system, the cumulative distribution function of the redundant-target condition cannot exceed the summed cumulative distribution functions of the two single-target conditions. Performance that violates this bound can provide evidence in support of super-capacity processing. Similarly, Grice and colleagues (Grice, Canham, & Gwynne, 1984) delineated a lower bound on unlimited capacity; values beyond this bound are evidence of limited capacity processing. However, both Grice et al.'s and Miller's bounds are conservative, and neither can distinguish between gradations of capacity (see Colonius & Diederich, 2006, for an alternative opinion). Moreover, although performance that violates either Grice et al.'s or Miller's bounds provides evidence against an unlimited capacity model, neither is necessary to reject unlimited capacity parallel processing. Thus, a more fine-grained measure of capacity is needed to distinguish variations of processing efficiency between the Grice and Miller bounds.

Systems Factorial Technology and the Capacity Coefficient

An alternative method for assessing processing capacity that builds upon the redundant-targets effect is built into a set of methods known as Systems Factorial Technology (SFT; Houpt et al., 2013; Houpt, Blaha, Base, & Burns, 2013). SFT provide a series of measures for assessing characteristics of cognitive systems. Most relevant to the present purposes, SFT provides a measure of *workload capacity*, the efficiency with which a system operates as the number of different channels under load—in other words, set size or *workload*—increases (Houpt & Townsend, 2012; Townsend & Eidels, 2011; Townsend & Nozawa, 1995).

Workload capacity is measured using the *capacity coefficient*, $C(t)$, which is the ratio of the cumulative hazard functions at different levels of workload (Houpt & Townsend, 2012; Townsend & Eidels, 2011). The capacity coefficient can assess differences in processing between single- and redundant-target displays (Townsend & Nozawa, 1995). To assess processing as the number of target items increases, a redundant-target paradigm is used. The capacity coefficient measures changes in capacity over time using the *hazard functions* for speeded responses. The hazard function, denoted $h(t)$, provides a measure of moment-to-moment variations in cognitive effort (Neufeld, Townsend, & Jette, 2007; Wenger &

Townsend, 2000). With regards to visual detection paradigms, the hazard function provides the instantaneous probability that a response will be executed at time t given that it has not yet been executed (Townsend & Ashby, 1983). The integral of the hazard function up to time t is known as the *cumulative hazard function*. In a standard unlimited capacity parallel model, the cumulative hazard function of the redundant-target condition is equal to the sum of the cumulative hazard functions of the two single-target conditions (Townsend & Nozawa, 1995). $C(t)$ is the ratio of the cumulative hazard function of the redundant-target condition over the cumulative hazard functions of the two single-target conditions.

The capacity coefficient has many advantages, not least being its ability to discriminate between different capacity models. Mullin and Egeth (1989, p. 111) articulated quite succinctly that “a major obstacle to resolving the processing capacity issue is the difficulty of designing methodologies that distinguish unlimited-capacity from limited capacity models”. One of the main benefits of the capacity coefficient is that it provides easily interpretable performance benchmarks specifically for doing just this—for distinguishing between different levels of efficiency. As mentioned earlier on, the *unlimited capacity independent processing* (*UCIP*) model (Houpt & Townsend, 2012), is the standard parallel model, where individual channel processing rates are unaffected by task load. The capacity coefficient benchmarks processing based on this model. A $C(t)$ of 1.0 indicates performance is equivalent to UCIP predictions (Houpt & Townsend, 2012). In other words, it represents unlimited capacity processing where the individual channels are unaffected by other concurrent channels. A $C(t)$ greater than 1.0 provides evidence for super-capacity, or that an increase in workload results in a speed up in the individual channel processing rates. Finally, a $C(t)$ below 1.0 indicates processing is limited by an increase in the number of channels processing; the more channels processing concurrently, the slower each individual channel processes. Thus $C(t)$ provides a way to clearly discriminate between different models of capacity.

The capacity coefficient can also be used to assess differences in processing single-target displays in the presence or absence of a distractor item (Blaha, 2011; Blaha & Houpt, n.d.; Houpt et al., 2013). Here, we can calculate capacity by dividing the cumulative hazard function for the condition in which the single target appears alone by the cumulative hazard function for the condition including the single target plus n distractors. In addition, we can use $C(t)$ to assess capacity in redundant-target paradigms that use a first-terminating stopping rule, where the first target processed leads to the response, as well as designs using an exhaustive stopping rule, where a response is made only after all items are processed.

In a recent paper, Blaha (2017b) identified the similarities between the capacity coefficient and dual-task measures of capacity for assessing cognitive processing. She demonstrated that both measures were based on similar assumptions about measuring performance, the resource requirements involved, and the difficulty of the secondary task. Unlike dual-task methods, however, the capacity coefficient can distinguish capacity from other aspects of human information processing such as system architecture, stopping rule, and inter-channel contingencies (Houpt et al., 2013). Because the capacity coefficient measures moment-to-moment fluctuations in processing rather than just capacity for a single time point, it provides a much more fine-grained analysis of processing capacity than most of the methods we have discussed so far.

The standard capacity coefficient assesses processing for redundant-target displays relative to single-target displays in which the target appears alone, unaccompanied by distracting information. A recent extension of the standard coefficient, known as the *resilience coefficient*, $R(t)$, assesses redundant-target processing relative to processing of a single target accompanied by a distractor, providing a measure of distractor costs (Cheng, Moneer, Christie, & Little, 2017; Houpt & Little, 2017). Capacity and resilience coefficients can be converted to normalised values that allow the comparisons across experimental conditions or studies (Houpt & Townsend, 2012). Given its many benefits, the capacity coefficient may be useful for assessing processing capacity for a variety of perceptual tasks, including divided attention, selective cueing, and paradigms manipulating set size (Wenger & Townsend, 2000). Finally, though our interest in this paper focuses on processing efficiency for visual information, the capacity coefficient can also be applied to auditory or multi-modal displays (e.g., Fox, Glavan, & Houpt, 2014).

General Issues with Measuring Capacity

A particularly critical issue on the topic of capacity assessment is how we operationalise processing efficiency from the outset. How we define the elusive concept of capacity will directly affect which method or paradigm is most appropriate for measuring it. Most current definitions describe visual processing capacity as the efficiency with which information can be processed at any one time as the number of active processing channels increases (e.g., Houpt & Townsend, 2012; Townsend & Eidels, 2011). As such, effective capacity measures must manipulate the number of items for processing to see how processing changes with increases in workload.

Related to this issue is the question of how we operationalise workload (Eriksen & Spencer, 1969). Kantowitz (1985, p. 140) explained that capacity “becomes meaningful and measurable only when the size of the element [i.e., unit of load] is first specified”. In some cases, load refers to the difficulty of a specific task; for example, we might wish to measure capacity for a tracking task by manipulating the difficulty of the tracking. More commonly, studies manipulate the number of items within a display, such as individual letters, shapes, or more complex figures, intending to manipulate the amount of information to be processed. As the number of items within the display increases, the number of ‘units of information’ also increases. However, specific factors, such as learning or experience, may influence how we define 'units of information' (Eriksen & Spencer, 1969). With practice or experience, particular individual items or elements may be grouped into larger, more complicated 'units' of information. Because different paradigms may use differing definitions of load, one must be cautious when comparing capacity across studies. For example, a complex multiple-display task that incorporates numerous pieces of updating information may provide very different conclusions about processing capacity than a basic visual search letter task, despite both tasks manipulating between one and 20 'units of information'.

One misinterpretation of capacity stems from confusion over whether one is measuring processing of an entire system or rather just processing of the individual channels comprising the system. As we saw at the beginning of this paper with our analogy of the detective agency solving a crime, a complete system that displays super-capacity performance may not necessarily mean each channel is operating at a super-capacity rate. Similarly, inefficient processing does not necessarily mean that processing is capacity-limited (e.g., Huang & Pashler, 2005). Another issue to consider is that a system can only exhibit evidence of unlimited capacity up to the maximum set size available—determining capacity beyond the maximum number of items is not possible (Mullin & Egeth, 1989). This issue is especially important if the capacity of a particular system varies qualitatively depending on set size (Huang & Pashler, 2005). For instance, a system may exhibit unlimited capacity performance for set sizes of up to 10 items but begins exhibiting limited capacity beyond that set size. As such, paradigms which limit display size to only a small number of items risk limiting the conclusions that can be drawn about a particular system.

A final challenge when measuring processing efficiency is distinguishing capacity from other human information processing concepts such as system architecture. Architecture—which primarily focuses on whether a system processes in parallel or in serial—though related to capacity, is a separate and distinct concept (Townsend & Nozawa, 1995). As such, methods that combine capacity and architecture measures may provide inaccurate interpretations of the underlying processing system. The RT slope method, for instance, has been criticised for assuming that longer RTs represent inefficient processing and, hence, serial architecture (Townsend & Wenger, 2004; Townsend, 1971; Townsend, 1990). Instead, a similar RT slope may provide evidence for a parallel model operating with limited capacity. These findings emphasise the importance of employing methods that allow a direct test to differentiate processing capacity and system architecture. As it stands currently, SFT (Houpt et al., 2013; Houpt & Townsend, 2012), with its ability to distinguish between various aspects of information processing, may be the best methodology for capturing a cognitive system's processing in the laboratory.

Given the various issues with many of the current paradigms used for assessing capacity, is it better to assess processing using a range of techniques rather than just one? Kantowitz (1985) recommended researchers use a variety of methodologies to provide a more comprehensive view of processing than can be obtained from any single method. Similarly, Gopher and Sanders (1984) suggested a cognitive system's information processing is best measured using the AOC/POC (Kinchla, 1969; Norman & Bobrow, 1975; Sperling & Melchnor, 1978) in conjunction with an RT slopes paradigm (Hick, 1952; Hyman, 1953; Sternberg, 1975). Though, as mentioned earlier on, the RT slopes task may be a poor choice for measuring capacity per se, both Kantowitz, and Gopher and Sanders raise valid points about whether processing should be measured with a battery of different tasks. One option for combining measures is to incorporate a single-task measure of capacity within a dual-task paradigm to assess processing changes (of the individual information units) as task load increases. In other words, an effective measure of capacity could involve incorporating one of the single-task methods discussed earlier, such as a SIM/SUCC paradigm, into a dual-task paradigm that also measures performance on a concurrent task. Such a situation would not only allow us to measure workload in terms of the number of items appearing within the SIM/SUCC displays, but we could then also assess the effects of different levels of task load created by the concurrent task. Damos and Wickens (1977) employed a similar design to assess processing by incorporating a choice RT task with a secondary tracking task. Similarly, to assess the effects of ageing on processing efficiency, Wickens et al. (1987) asked participants to complete a variety of processing tasks, including three different modalities of Sternberg's (1966) memory tasks, both alone and while performing a concurrent tracking task. These combined methods for assessing information processing may provide a more comprehensive picture of performance, allowing one to more clearly delineate unlimited capacity from limited and super-capacity processing.

Current Aims

In many operational environments, such as in air traffic control or in the pilot flight deck, we need to convey visual information or alerts to an operator who is already engaged in an ongoing task. To be able to do this effectively, we need to understand whether the concurrent task compromises processing efficiency for visual information. Moreover, we need to know whether other task characteristics, such as distractor presence or target salience, might influence efficiency. Systems Factorial Technology (SFT) provides a novel and close-to-ideal method for assessing capacity under a range of different conditions. Though SFT has recently been used to model overall system efficiency for multiple concurrent tasks (Fox & Houpt, 2018), the use of SFT for assessing visual information processing when a person is loaded by a demanding secondary task remains unexplored. Given SFT is highly sensitive and provides easy to interpret benchmarks for efficient processing, this method may be especially valuable for assessing capacity under dual-task load. As such, the current thesis combined two separate capacity measures—dual-task paradigms and SFT—to examine visual processing efficiency while loaded by a secondary visuo-manual task. Using this approach, this thesis aimed to address two main questions regarding processing efficiency under load. Firstly, it examined whether increasing task load reduces processing efficiency for visual information, and secondly, it explored whether specific task characteristics help drive processing under load.

This thesis is comprised of five experimental chapters directed at addressing these aims. Chapter 2 is a published article comprising three experiments that examine the effect of dual-task load on peripheral visual target processing efficiency for distractor-present displays. Chapter 3 is a published proceedings paper comprising a follow-up experiment to those in Chapter 2, and explores dual-task effects on processing for distractor-absent displays. Chapter 4 is a manuscript in preparation comprising two experiments. It examines visual field effects, in this case, eccentricity effects and upper versus lower visual field differences, on processing capacity while under dual-task load. Chapter 5 is a manuscript in preparation that assesses the benefits of salience—or target–distractor discriminability to be exact—in maintaining processing efficiency while under both single- and dual-task load. Chapter 6 comprises a manuscript in preparation of an applied study completed in collaboration with Defence Science and Technology Group that extends the dual-task paradigm to a simulated military environment. Within this study, I use changes in signal detection theory (SDT; Green & Swets, 1966; Stanislaw & Todorov, 1999) over time to examine operator processing efficiency under both high and low levels of cognitive demand. Finally, in Chapter 7 I provide a general summary and interpretation of these findings gathered across all five studies, providing some general conclusions about visual information processing efficiency under dual-task load.

CHAPTER 2: STUDY 1

Redundant-Target Processing is Robust against Changes to Task Load

The following chapter is a version of an article that was published in *Cognitive Research: Principles and Implications* in March 2018. The article comprises three experiments exploring the effects of dual-tasking on processing efficiency for peripheral visual targets in distractor-present displays. Two additional experiments that were included in an earlier version of this manuscript (Experiments 1c and 1d) can be found in Appendix A.

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All three authors formulated the design of the study. SAM collected the data and wrote the first draft of the manuscript. Both SAM and JSM carried out the data analysis. JSM and NAT provided revisions on the manuscript.

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Abstract

Monitoring visual displays while performing other tasks is commonplace in many operational environments. Although dividing attention between tasks can impair monitoring accuracy and response times, it is unclear whether it also reduces processing efficiency for visual targets. Thus, the current three experiments examined the effects of dual-tasking on target processing in the visual periphery. A total of 120 undergraduate students performed a redundant-target task either by itself (Experiment 1a) or in conjunction with a manual tracking task (Experiments 1b – 3). Target processing efficiency was assessed using measures of workload resilience. Processing of redundant targets in Experiments 1-2 was less efficient than predicted by a standard parallel race model, giving evidence for limited capacity parallel processing. However, when stimulus characteristics forced participants to process targets in serial (Experiment 3), processing efficiency became super-capacity. Across the three experiments, dual-tasking had no effect on target processing efficiency. Results suggest that a central task slows target detection in the display periphery but does not change the efficiency with which multiple concurrent targets are processed.

Significance Statement

High workload environments often mean dividing attention between multiple visual tasks or displays. The current study examined aspects of visual display design that might influence target detection in multi-task environments. Using paired target discrimination/manual tracking tasks, we investigated the effects of target redundancy on participants' ability to notice eccentric visual signals while engaged in a central task. Our goal was to assist display design by identifying factors that help multi-tasking operators to notice visual alerts and alarms in their peripheral vision.

Redundant-Target Processing
is Robust against Changes to Task Load

Operators in high-stress domains often need to divide attention between the central and peripheral visual fields. A pilot, for example, must also monitor for cockpit alerts while maintaining awareness of an aircraft's position in space (Wickens, Sebok, McCormick, & Walters, 2016), and operators in air traffic control must remain responsive to critical alerts while managing the flow of air traffic (Imbert et al., 2014). Similarly, the increasing use of head-worn displays in professional roles means many operators are required to switch attention between tasks within their central visual field and peripheral events projected onto the headset (Pascale et al., 2015). Within each of these domains, performing effectively means processing information presented centrally, while also discriminating between critical and non-critical 'noise' events in the visual periphery. For system designers, this issue implies a need to understand the task and display characteristics that maximise peripheral detection and discrimination under conditions of high central load.

An obvious technique to improve target detection is to increase target salience, the feature contrast between the target and its surroundings (Itti & Koch, 2000; Theeuwes, 2010). Unfortunately, visual heterogeneity reduces feature contrast (Humphreys, Quinlan, & Riddoch, 1989; Nothdurft, 1992), and in a cluttered, dynamic environment like the cockpit, even events designed to be highly salient can go undetected (Nikolic, Orr, & Sarter, 2004; Steelman, McCarley, & Wickens, 2013). Alternative strategies for ensuring rapid target detection are, therefore, useful. One converging strategy is to present targets redundantly, that is, on multiple channels simultaneously. Redundant presentation generally speeds target detection (Miller, 1982; Todd, 1912), and is endorsed in human factors engineering as a method of promoting information security (Wickens & Hollands, 2000; Wickens, Prinet, Hutchins, Sarter, & Sebok, 2011). For example, vehicle collision warning systems often employ redundant visual or auditory signals to alert a driver of a potential collision (Ho, Reed, & Spence, 2007). Similarly, in aircraft settings, pilots respond faster to missile approach warnings as the number of informational channels delivering the warning increases (Selcon, Taylor, & McKenna, 1995).

Like a manipulation of salience, however, redundant information display is not guaranteed to aid performance. Constraints on processing resources can modulate the efficiency with which concurrent events are processed (Townsend & Eidels, 2011), limiting the benefits produced by a redundant target (e.g., Eidels, Townsend, Hughes, & Perry, 2014; McCarley, Mounts, & Kramer, 2007; Townsend & Nozawa, 1995). Moreover, under some conditions, the addition of the second target may produce no redundancy gain at all (Grice et al., 1984). More surprisingly, within a multi-task environment redundant signals may actually be disruptive. Wickens and colleagues (Seagull, Wickens, & Loeb, 2001; Wickens & Gosney, 2003) have reported evidence that redundant audio-visual target presentation in a monitoring task can disrupt performance in an ongoing tracking task. These results suggest that the demands of encoding or recognising redundant targets can divert processing resources from a concurrent task, producing interference. In the current experiments, we pursue this effect by examining the converse possibility, that the demands of a concurrent central task might limit the efficiency of redundant signal processing.

Measuring the efficiency of redundant-target processing

In a standard redundant-target task, participants make a speeded response to a target presented in either of two channels (e.g., on a visual channel and an auditory channel). On single-target trials, a target appears in only one channel (e.g., only the visual channel); on redundant-target trials, the target is presented in both channels (e.g., on both the visual and auditory channels). The observer responds as soon as a target is detected in either channel, a condition known as a *first-terminating* stopping rule (Colonius & Vorberg, 1994). Under these conditions, redundant signals generally produce faster responses than single targets, a phenomenon known as a *redundant signals effect* (*RSE*) or *redundancy gain* (Miller, 1982). For example, for a driver approaching a railway crossing, the presentation of both a red flashing light and a loud bell is likely to allow faster detection, and consequently a faster braking response, than either warning presented alone.

The RSE, however, may differ in magnitude under different task constraints, and in some cases, may be entirely absent. The size of the RSE reflects variations in a cognitive system's *architecture* and *workload capacity* (Townsend & Eidels, 2011; Townsend & Nozawa, 1995), where architecture refers to the arrangement of channels (e.g., serial or parallel), and workload capacity refers to the efficiency with which the channels operate concurrently. In addition, the RSE can also reflect variations in inter-channel dependencies (Townsend & Wenger, 2004a). The simplest model of the RSE is the *unlimited-capacity independent parallel* (*UCIP*) model, wherein multiple channels operate with stochastic independence and each channel's rate of processing remains unchanged, regardless of the total number of channels under operation (Townsend & Eidels, 2011). Under a first-terminating stopping rule, the UCIP model produces a redundancy gain simply because the processing time of the system as a whole is based on the output of the fastest channel on each trial. This mechanism is known as *statistical facilitation* (Raab, 1962). *Super-capacity* occurs when an increase in the number of operating channels (i.e., workload) results in a corresponding increase in the individual channels' processing rates, producing a larger RSE than predicted by the UCIP model. Conversely, *limited capacity* exists when an increase in workload decreases the processing rates of the individual channels, producing a smaller RSE than predicted by the UCIP model. In situations where capacity is highly limited, the redundancy gain may be no different to that of a serial model.

Importantly, unless capacity is extremely limited, mean RTs alone cannot distinguish gradations in parallel processing capacity within a redundant-target task. To establish whether a system is limited, unlimited, or super-capacity, we therefore need to analyse the data at the level of the RT distributions. As a means of distinguishing between statistical facilitation in the UCIP model and actual processing speed-ups with multiple channels, Miller (1982) established an upper bound on performance for the UCIP model, known as the *race-model inequality*. The inequality holds that in the UCIP model, the cumulative distribution function (CDF) of the redundant-target trials cannot exceed the combined CDFs for the two categories of single-target trials. Evidence that the CDF for the redundant-target trials exceeds the summed CDFs for the single-target trials at any time t thus disconfirms the UCIP model and implicates a super-capacity model instead. Analogously, Grice, Canham, and Gwynne (1984) identified a lower bound on UCIP performance, providing a test of extreme capacity limitations. The Miller and Grice inequalities, however, are both conservative tests that are insensitive to modest variations in capacity. Townsend and Nozawa's (1995) workload capacity coefficient, $C(t)$, provides a more fine-grained measure of efficiency, sensitive to variations in between the Miller and Grice boundaries.

$C(t)$ rests on the conceptualisation of the hazard function for speeded responses as a gauge of moment-to-moment cognitive expenditure. In a speeded task, the hazard function, $h(t)$, indicates the instantaneous probability with which a response will occur at time t, given that a response has not yet occurred (Townsend & Ashby, 1983). The cumulative hazard function, $H(t)$, is the integral of the hazard function up to time t. Importantly, within the UCIP model, the cumulative hazard functions for multiple operating channels are additive. In other words, if processing follows the UCIP model, the value of the cumulative hazard function in the redundant-target condition at time t is equal to the sum of the values of the cumulative hazard functions of the two single-target conditions at time t. Taking advantage of this constraint, Townsend and Nozawa (1995) define the capacity coefficient, $C(t)$ as,

$$C(t) = \frac{H_{AB}(t)}{H_A(t) + H_B(t)}\ ,\ t\ >\ 0, \tag{2.1}$$

where $H_{AB}(t)$ refers to the cumulative hazard function of the redundant-target condition, and where $H_A(t)$ and $H_B(t)$ refer to the individual cumulative hazard functions for a target present only on channel A or channel B, respectively. Under the UCIP model, in which the cumulative hazard functions for channels A and B are additive, $C(t) = 1.0$. Values of $C(t)$ greater than 1.0 indicate that $H_{AB}(t) > H_A(t) + H_B(t)$, implying super-capacity. Conversely, values less than 1.0 indicate that $H_{AB}(t) < H_A(t) + H_B(t)$, implying limited capacity. In extreme cases capacity may be fixed, $C(t) = 0.5$, implying a zero-sum trade-off between channels and producing performance akin to that predicted by a serial model.

A transformation of $C(t)$ that can be used to compare performance across experiments is the standardised capacity score, *Cz* (Houpt & Townsend, 2012). *Cz* provides a summary capacity measure collapsed over time and suitable for comparison between experimental conditions. Values follow a standard normal distribution, with a score of 0 indicating UCIP-level processing, positive scores indicating super-capacity, and negative scores indicating limited capacity.

The capacity coefficient was developed for examining judgements of displays wherein, on single-target trials, the position of the potential second target is empty. Recent developments have extended the approach to accommodate analysis of displays in which single-target conditions include a distractor in place of the empty space (Little, Eidels, Fific, & Wang, 2015). The measure of processing efficiency in this case has been termed *resilience, R*(t) (Little et al., 2015). $R(t)$ is calculated with the formula used to calculate $C(t)$, except that the cumulative hazard functions in the denominator of the equation represent single-target conditions on which a distractor is present,

$$R(t) = \frac{H_{AB}(t)}{H_{AX}(t) + H_{XB}(t)}\ ,\ t > 0, \tag{2.2}$$

where $H_{AX}(t)$ is the cumulative hazard function for single target A accompanied by a distractor, X, and $H_{XB}(t)$ is the cumulative hazard function for single target B accompanied by the X. $R(t)$ can, in turn, be converted to a measure of normalised resilience (Houpt & Little, 2017), referred to here as *Rz*, analogous to *Cz.* Resilience differs from capacity because, when a distractor is present on single-target trials, it can divert processing resources from the target, slowing target detection (Allen, Madden, Groth, & Crozier, 1992; Ben-David, Eidels, & Donkin, 2014). Resilience, therefore, reflects both the changes in target processing rate that occur as the number of targets increases, and the potential release from interference that occurs when a distractor is replaced by a target.

Interpretation of resilience scores is more involved than interpretation of the workload capacity scores. By definition, channels in the UCIP system operate at the same rate regardless of processing load. Thus, the UCIP model predicts a benchmark value of $R(t) = 1$ ($Rz = 0$), just as it predicts a benchmark value of $C(t) = 1$ ($Cz = 0$). More generally, a parallel self-terminating model predicts that $R(t)$ will not vary as a function of distractor discriminability, and that redundant-target processing will be equally efficient in the experimental designs with and without distractors, that is, $C(t)$ and $R(t)$ will be equal (Little et al., 2015).

In contrast, a serial self-terminating (SST) model predicts that $R(t)$ will vary with the relative discriminability of the target and distractor. For simplicity, assume a case in which the cumulative hazard functions for targets A and B are identical, both with distractors, ($H_{AX}(t) = H_{XB}(t)$), and without, ($H_A(t) = H_B(t)$). On redundant-target trials, the first item processed will always be a target. The cumulative hazard function for redundant-target trials will, therefore, equal the cumulative hazard function for single-target trials without distractors, i.e., $H_{AB}(t) = H_A(t)$. This reduces Equation 2 to,

$$R(t) = \frac{H_A(t)}{2 \times H_{AX}(t)}\ ,\ t\ >\ 0, \tag{2.3}$$

On single-target trials, assuming the target position is unpredictable, the number of items that are processed will vary randomly from trial to trial; on some trials only the target will be processed, and on the remaining trials, the distractor will be processed before the target. The difference between $H_{AX}(t)$ and $H_A(t)$ will thus reflect the time needed to process the distractor on those trials on which the target is not processed first. When the time needed to process the distractor is negligible relative to the time needed to process the target, $H_{AX}(t)$ will equal $H_A(t)$, and $R(t)$ will be fixed. When the time needed to process the distractor becomes more substantial, $H_{AX}(t)$ decreases and $R(t)$ becomes larger. In other words, the SST model predicts that resilience will be limited when distractor interference is negligible and will increase as distractor interference becomes larger.

But regardless of the underlying architecture, values of $R(t) < 1$ or $Rz < 0$ imply that redundant targets are processed slower than predicted by the UCIP model, and values of $R(t) > 1$ or $Rz > 0$ imply that redundant targets are processed faster than predicted by the UCIP model (Houpt & Little, 2017). By analogy to the terminology applied to workload capacity, we will describe these effects as limited capacity and super-capacity, respectively. However, it is important to note that these labels describe performance of the multi-channel system as a whole and do not necessarily connote changes in the processing rates of the individual channels. As described above, for example, changes in distractor discriminability within an SST system may change $R(t)$ from less than 1 to greater than 1, even if the target processing rate remains constant.

Redundant presentation of peripheral signals will thus aid detection only if the signals are processed with spare capacity or resilience. Unfortunately, existing data do not make it clear that this will be the case. Some evidence suggests redundancy gains should be greater for more difficult single targets (Diederich & Colonius, 2004). Thus, targets appearing concurrently with a manual tracking task may produce greater redundancy gains than targets appearing alone. Moreover, empirical data suggest attention is weighted toward the central visual field (Carrasco et al., 1995; Carrasco & Yeshurun, 1998; Wolfe, 1998), and modelling likewise suggests that elemental processing resources are denser in the central retina than in the eccentricity (Miller & Ulrich, 2003). A demanding task in the central visual field might further shift attention away from the retinal eccentricity (Leibowitz & Appelle, 1969; Reimer, 2010), engendering *visual tunnelling* (Williams, 1985). For example, observers have higher detection thresholds for luminance probes in the visual periphery when performing a concurrent central task, with more difficult central tasks producing larger threshold increases (Leibowitz & Appelle, 1969). Similarly, accuracy on a peripheral discrimination task is higher when a concurrent central task is low in perceptual load than when it is high (Williams, 1985). Even task-irrelevant stimuli presented at fixation can interfere with processing of peripheral visual targets (Beck & Lavie, 2005; Schwartz et al., 2005). Within a peripheral redundant-target paradigm with a simultaneous central-load task, such effects might limit processing resilience of peripheral targets, reducing the magnitude of the RSE. In addition, a prominent account of dual-task performance, multiple resource theory, argues that resource competition between tasks drawing on similar processing resources will decrease performance (Wickens, 2002; Wickens, 1981). According to this theory, within a dual tracking/target detection paradigm, the central tracking task may consume visual processing resources, limiting the attentional resources necessary for processing peripheral items. Based on such an effect, we would expect to see poorer efficiency when the detection task is accompanied by the central tracking task.

To test these possibilities, the current experiments assessed human performance within a dual-task paradigm pairing a central manual tracking task with a peripheral redundant-target task. We examined whether the detection of visual targets observed within a dual-task paradigm produces a redundancy gain, and if so, just how efficiently the processing compares to that of the UCIP model. In Experiments 1 and 2, we used a target detection task to assess processing resilience while performing under both single- and dual-task load. Finally, in Experiment 3, we designed stimuli to preclude parallel target processing to examine resilience within a serial model.

General Method

Here, we describe methods of stimuli and procedure common to all of the experiments that follow.

Apparatus and stimuli. Stimuli were presented on a 27” Samsung LED monitor, with a resolution of 1920 × 1080 pixels (1 pixel was equal to 0.33 mm) and a refresh rate of 100 Hz. Participants completed the experiment at a viewing distance of approximately 600 mm, although viewing distance was not fixed. The experimental program was created using Presentation software Version 16.5 Build 09.17.13 (Neurobehavioral Systems, 2018). Tracking task performance and responses to the concurrent target detection task were collected via a Logitech Attack 3 (Logitech, 2018) joystick.

Stimuli for the target detection task were black capitalised letters, with Ts as targets and Ls as distractors. Letters appeared in the upper left (location A) and right (location B) of the screen with polar coordinates $\theta = \pm 51.15°$ from the vertical midline and $r = 21.79°$ of visual angle from the screen centre point. The peripheral target/distractor stimuli were chosen randomly and with equal probability from among four combinations: redundant targets (TT), single target on left (TL), single target on right (LT), and redundant distractors (LL).

Peripheral stimuli appeared approximately 20 times per 60-second trial, and remained visible each time until the participant issued a joystick response or a timeout duration of 2000 ms was reached. To ensure that participants were unable to predict times at which a new target or distractor might appear in the periphery, the inter-stimulus interval between successive events in the peripheral channels was drawn from a delayed exponential distribution. The delayed exponential is the sum of a fixed delay value with a random value drawn from an exponential distribution. Here, the fixed delay was set to 1000 ms and the mean of the exponential component was set to 2000 ms. Because the exponential component of the distribution was memoryless, these parameters ensured that the interval between successive stimuli was at least 1000 ms, but was unpredictable beyond that.

Stimuli for the pursuit tracking task were a black cursor “+” in size 10 Arial font (0.76° × 0.76° of visual angle) and a red circular marker (subtending 0.95°). Both the cursor and the marker moved along a semicircle, extending into the upper visual field, with a radius of 9.93° centred along the horizontal midline of the display (see Figure 2-1). The pattern of target motion was created by summing sinusoids with frequencies of 0.07, 0.15, and 0.23 Hz (Strayer & Johnston, 2001). The centre point of the arc was 5.72° below the screen’s centre point. The component sinusoids were randomly phase-shifted to produce a different pattern of motion on each trial. The cursor moved along the same arc, at a maximum rate of 80° per second, but required manual control via the joystick to manoeuvre. To increase task difficulty, at the start of each trial the red target appeared at a randomly selected location along the semicircular path, whereas the cursor always began centred along the path. Thus, only the red marker was visible to participants. In all the experiments, the coordinates of both stimuli were recorded every 100 ms (every 3 frames) throughout each of the 20 tracking intervals. Figure 2-1a presents a schematic stimulus representation from a left single-target dual-task trial from Experiment 1b or Experiment 2.

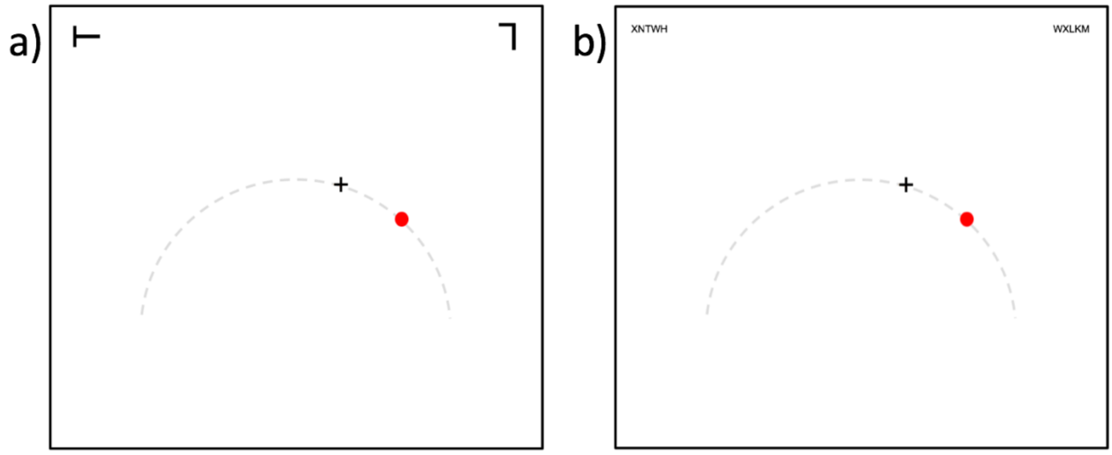

Figure 2-1. a. A single-target dual-task trial from either Experiment 1b or the dual-task condition of Experiment 2. *b*. A single-target dual-task trial from Experiment 3. The participant pressed a button when he/she detected the target (in the top left of these figures). The tracking task involved manually manoeuvring the black cursor (+) with the moving red circle. The black cursor and the red circle moved along an invisible arc (presented here as a dashed line). Stimuli for the single- and dual-task experiments/conditions were similar, except the black cursor was not visible in the single-task versions.

Procedure. Participants completed the task in a well-lit room. At the start of the session, participants were instructed to hold the joystick with two hands, allowing both thumbs to rest on the buttons on top of the joystick. To perform the detection task, participants were instructed to remain aware of targets appearing in the upper regions of the screen. Participants were required to respond as fast as possible if a letter T appeared in either one or both peripheral stimulus locations, but to refrain from responding if both peripheral letters were Ls. Responses were made by pressing the buttons on top of the joystick with both thumbs. Bimanual joystick button responses ensured that both hemispheres were activated during the task. As our aim was to understand the attentional processes involved in target detection, using bimanual responses reduced the likelihood of any stimulus-response compatibility effects (e.g., congruency between targets and response hand).

To enhance engagement, both tasks were framed within a driving scenario in which participants were asked to imagine they were driving a vehicle to the university. For the tracking task, participants aligned the cursor, representing their car, with the red marker, representing an in-vehicle navigation system. For the target-detection task, participants were told to imagine they were responding to traffic signals, where Ts represented red lights and Ls represented green lights. Thus, participants were required to brake by issuing a joystick button press as fast as possible if they encountered a red light (T), but to withhold responding if a pair of green lights (LL) appeared. Participants were encouraged to respond as fast as possible, whilst maintaining accuracy.

Each tracking interval lasted 60 seconds, after which participants were given the chance for a short break before starting the next interval. To begin a new interval, participants pulled the joystick trigger. Within each block, participants completed a total of one 60-second practice interval, followed by 20 experimental intervals (the number of blocks varied between experiments). In general, within each testing session participants completed approximately 72 trials for each of the four trial types (left, right, redundant, and target-absent).

After finishing the experiment, participants completed the FLANDERS questionnaire. Participants were then asked if they held a current valid driver's licence, and if so, approximately how many years of driving experience they had. Finally, participants were debriefed and thanked for their time.

Experiment 1a

Experiment 1a provided a baseline estimate of resilience for a parafoveal target detection task performed alone (i.e., in a single-task condition).

Method

Participants. Twenty-five Flinders University undergraduate students (21 female; M_{Age} = 23.08 years, *SD* = 5.12, *Range* = 18 – 40) were recruited as part of a course requirement. All participants had normal or corrected-to-normal visual acuity and normal colour vision, and were fluent in English. Participants were screened for right-hand dominance, with a minimum Flinders Handedness Survey (FLANDERS; Nicholls, Thomas, Loetscher, & Grimshaw, 2013) score of +5 (*M* = +9.76, *SD* = 0.66). Twenty participants held a current valid driver's licence, with between 0.5 and 15 years of driving experience (*M* = 4.69, *SD* = 3.61).

Apparatus and Stimuli. In Experiment 1a, stimuli for the target detection task were a black capital T (target) and L (distractor) presented in 16-point Arial font (1.58° × 1.14° of visual angle) on a white background. Stimuli letters were randomly and independently rotated between 0° and 270°, in steps of 90°. In addition, the black cursor was invisible to ensure participants did not attempt to perform the tracking task.

Procedure. In Experiment 1a, the participants' only task was to monitor and respond to peripheral targets. As such, participants were instructed to ignore the movements of the red target circle and were not instructed to perform the tracking task. Participants completed one block of 20 60-second tracking intervals. The entire process took approximately 30 minutes.

Analysis. For statistical analysis, raw resilience scores, $R(t)$, were converted to standardised resilience scores, *Rz*, (Houpt & Townsend, 2012) using the 'sft' package (Houpt, Blaha, McIntire, Havig, & Townsend, 2014) for R (R Core Team, 2016).

Analysis of RTs for correct responses, normalised resilience scores, and root mean squared error (RMSE) for tracking performance was performed through Bayesian parameter estimation using a Markov chain Monte Carlo (MCMC) sampling procedure (Kruschke, 2013, 2015; Lee & Wagenmakers, 2013). This approach begins by assuming a prior distribution on a parameter value of interest, then updates the prior through probabilistic sampling to approximate the posterior distribution on parameter values based on the observed data (Kruschke, 2015). Analyses were conducted using sampling functions from the JAGS package (Plummer, 2015) in R. RTs were analysed in a one-way, within-participant design, with additive effects of condition (first single-target, second single-target, redundant-targets) and participant. Effects were assumed to follow normal distributions with vague priors on their means and standard deviations. Following Kruschke (2015),

$$Y_{\text{participant, condition}} \sim N(a0 + a_{\text{participant}} + a_{\text{condition}}, \sigma_{\text{y}}^2)$$

$$\sigma_{\text{y}} \sim U(SD/1000, SD*1000)$$

$$a0 \sim N(M, [100 \times SD]^2)$$

$$a_{\text{participant}} \sim N(0, \sigma_{\text{participant}}^2)$$

$$a_{\text{condition}} \sim N(0, \sigma_{\text{condition}}^2)$$

$$\sigma_{\text{participant,}}\ \sigma_{\text{condition}} \sim \Gamma\ (\alpha, \beta)$$

$$\alpha = SD/2$$

$$\beta = 2 * SD$$

where $Y_{\text{participant, condition}}$ is the RT for a given participant in each condition, σ_y is the estimated standard deviation of the normal distribution of RTs, $a0$ is the estimated grand mean RT, $a_{\text{participant}}$ is the participant effect, $a_{\text{condition}}$ is the condition effect, M is the grand mean of the observed RT scores, and SD is the standard deviation of the observed RT scores. Deflections from the grand mean representing effect of condition were constrained to sum to zero across conditions. Using the data sample mean and standard deviation to set parameters of the prior ensured that the prior distribution was scaled appropriately to the data (Kruschke, 2015). To test for the possibility of lateral (left vs. right) attentional bias, along with redundancy gains, we estimated RTs in two different ways. In the first case, to check for the possibility of lateral asymmetries in performance, data were coded such that two single-target conditions represented the left single-target and right single-target trials. Thus, any difference in RTs in the first case would signal participants had tended to respond to targets in one location faster than the other. In the second case, to provide a conservative estimate of the redundancy gain, data were coded such that the two single-target conditions represented the faster and slower mean single-target condition for each participant. Redundancy gain was defined as the difference between the shorter of the two single-target RTs and the redundant-target RT. This method of measuring redundancy gains provides more conservative estimates than the alternative approach of comparing redundant-target RT to the mean of the single-target RTs (cf. Biederman & Checkosky, 1970).

Rz and RMSE scores were estimated in a one-sample design (Kruschke, 2013),

$Y_{\text{participant}} \sim N(u, \sigma^2)$

$u \sim N(M, [100 \times SD]^2)$

$\sigma \sim U(SD/1000, SD*1000)$

where $Y_{\text{participant}}$ is the score for a given participant, u is the estimated grand mean score, σ is the estimated standard deviation of the normal distribution of scores, M is the grand mean of the observed scores, and SD is the standard deviation of the observed scores.

Each parameter estimate was based on four MCMC chains, run for 1000 burn-in steps, followed by 250,000 steps each. Chains were thinned to every fifth step in to reduce sample autocorrelation, (number of effective samples [N_{eff}] > 4400). Visual inspection of the chains for different parameters indicated chains were visually mixing. All estimated parameters showed t-Rubin statistic values (Gelman & Rubin, 1992) of 1.01 or less, indicating satisfactory convergence of the MCMC chains (Kruschke, 2015).

Results

Error rates. Detection error rates were analysed to ensure participants had correctly followed instructions. As a general rule, the capacity coefficient is robust against error rates of up to 0.30 (Townsend & Wenger, 2004a). No participants in Experiment 1a produced false alarm rates that exceeded this value (*M* = 0.10, *Range* = 0.01 – 0.20). Miss rates in all target conditions—single target on left (*M* = 0.01, *Range* = 0.00 – 0.09), single target on right (*M* = 0.01, *Range* = 0.00 – 0.07), and redundant targets (*M* < 0.01, *Range* = 0.00 – 0.07)—were very low. On average, participants correctly responded to approximately 72 trials in each condition: *M* = 71.80 (*Range* = 67 – 75) for left-targets, *M* = 71.68 (*Range* = 67 – 75) for right-targets, and *M* = 71.56 (*Range* = 66 – 74) for redundant targets. Collapsed across target-present and target-absent trials, the mean accuracy rate was very high, *M* = 0.97 (*Range* = 0.93 – greater than 0.99).

RTs. In all experiments, RTs were only analysed for correct target-present trials (i.e., excluding false-positive responses). Inspection of the data suggested that participants generally complied with the instructions to respond to targets bimanually, making button presses with both thumbs in quick succession. Analyses were carried out using the RT for the faster of the two button presses for each trial.

Data showed no credible difference in RTs between single targets on the left (*M* = 577 ms, 95% Bayesian Credible Interval (BCI; Kruschke, 2015) = [536, 618]) and on the right (*M* = 568 ms, 95% BCI = [527, 610]), (left-right difference: M_{Diff} = 9 ms, 95% BCI = [-4, 22], *d* = 0.24). The mean single-target RT provides a measure of baseline response speed independent of any redundancy gain. Collapsed across the two single-target conditions, the mean single-target RT was 573 ms, 95% BCI = [532, 613]. Figure 2-2 shows the 95% BCIs for the mean single-target RT for Experiment 1a, along with those for the following experiments. As noted above, redundancy gains were calculated by subtracting RT for the redundant-target condition from RT for the faster single-target condition (left or right) for each participant. Even by this conservative measure, data gave clear evidence of a redundancy gain (redundant signals effect: M_{RSE} = 37 ms, 95% BCI = [25, 48], *d* = 1.86), with the redundant-target condition (*M* = 523 ms, 95% BCI = [482, 564]) producing shorter

RTs than the faster single-target condition (*M* = 560 ms, 95% BCI = [519, 601]). Figure 2-3 presents the mean and 95% BCI for the redundancy gain in each experiment.

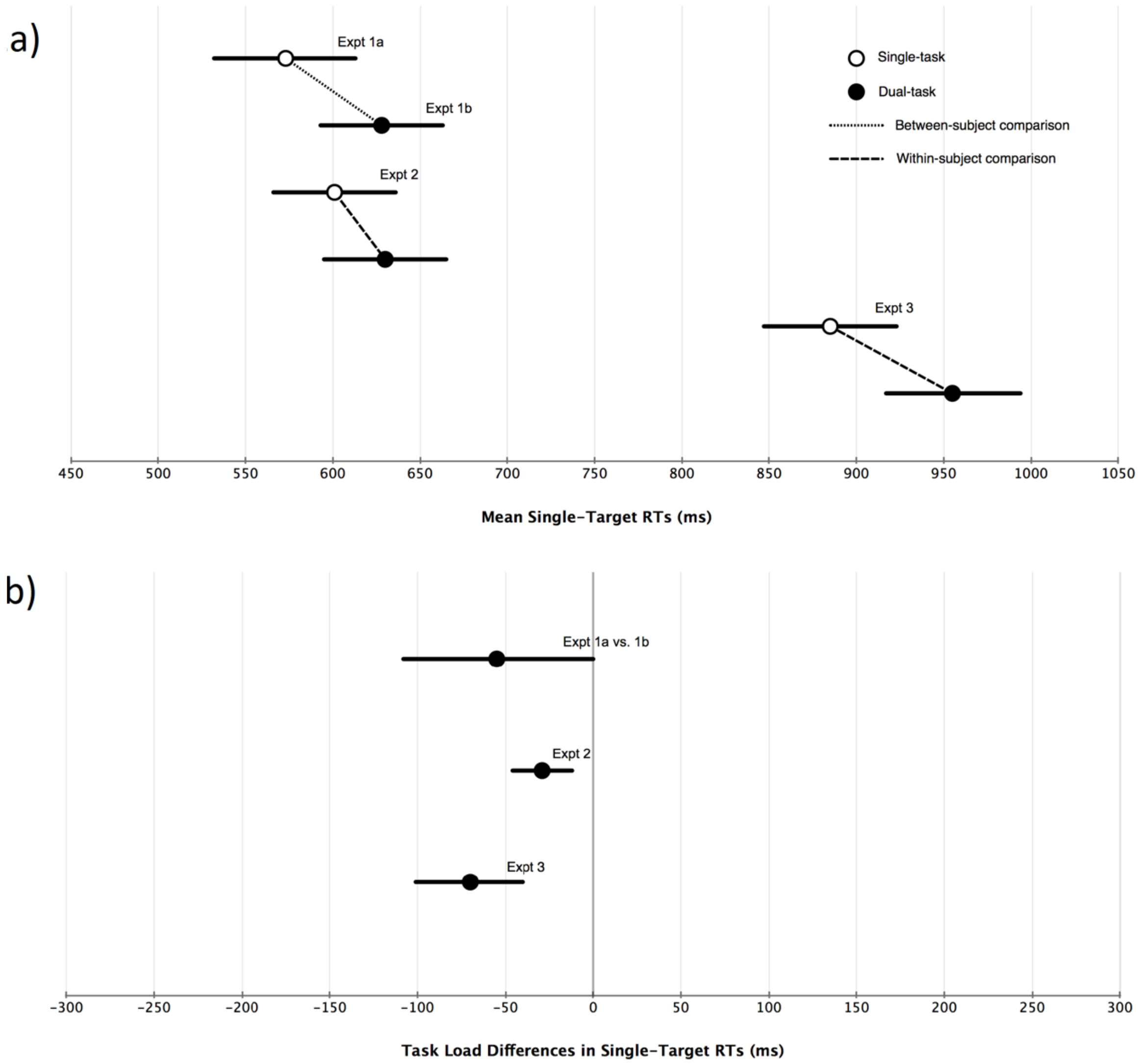

Figure 2-2. a. Means and 95% BCIs for single-target RTs (ms) in each experiment. *b.* Means and 95% BCIs on the task-load difference scores for single-target RTs in each experiment (single-task RT minus dual-task RT).

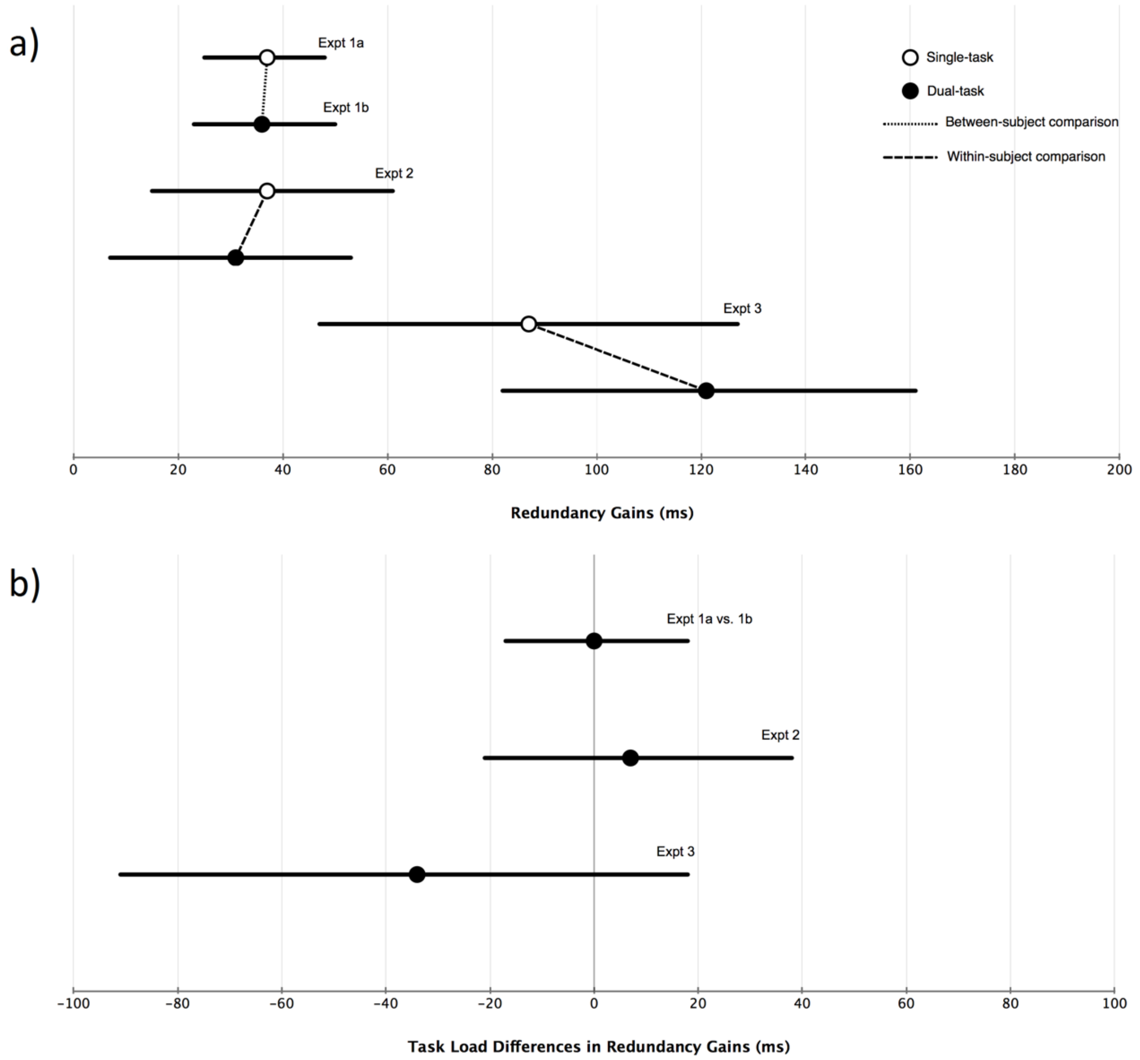

Figure 2-3. a. Means and 95% BCIs for redundancy gains (ms) by experiment. *b.* Means and 95% BCIs for task-load differences in redundancy gains (single-task RT minus dual-task RT) by experiment.

Resilience. As noted above, the standardised score *Rz* represents the normalised mean of $R(t)$ across values of t, weighted inversely by the variability of $R(t)$ at each time point (Houpt & Townsend, 2012). Values equivalent to zero represent UCIP processing, positive values indicate super-capacity, and negative values represent limited capacity. Mean *Rz* was credibly negative (M_{Rz} = -1.77, 95% BCI = [-2.35, -1.19]). See Figure 2-4 for the 95% BCIs for resilience scores for each experiment.

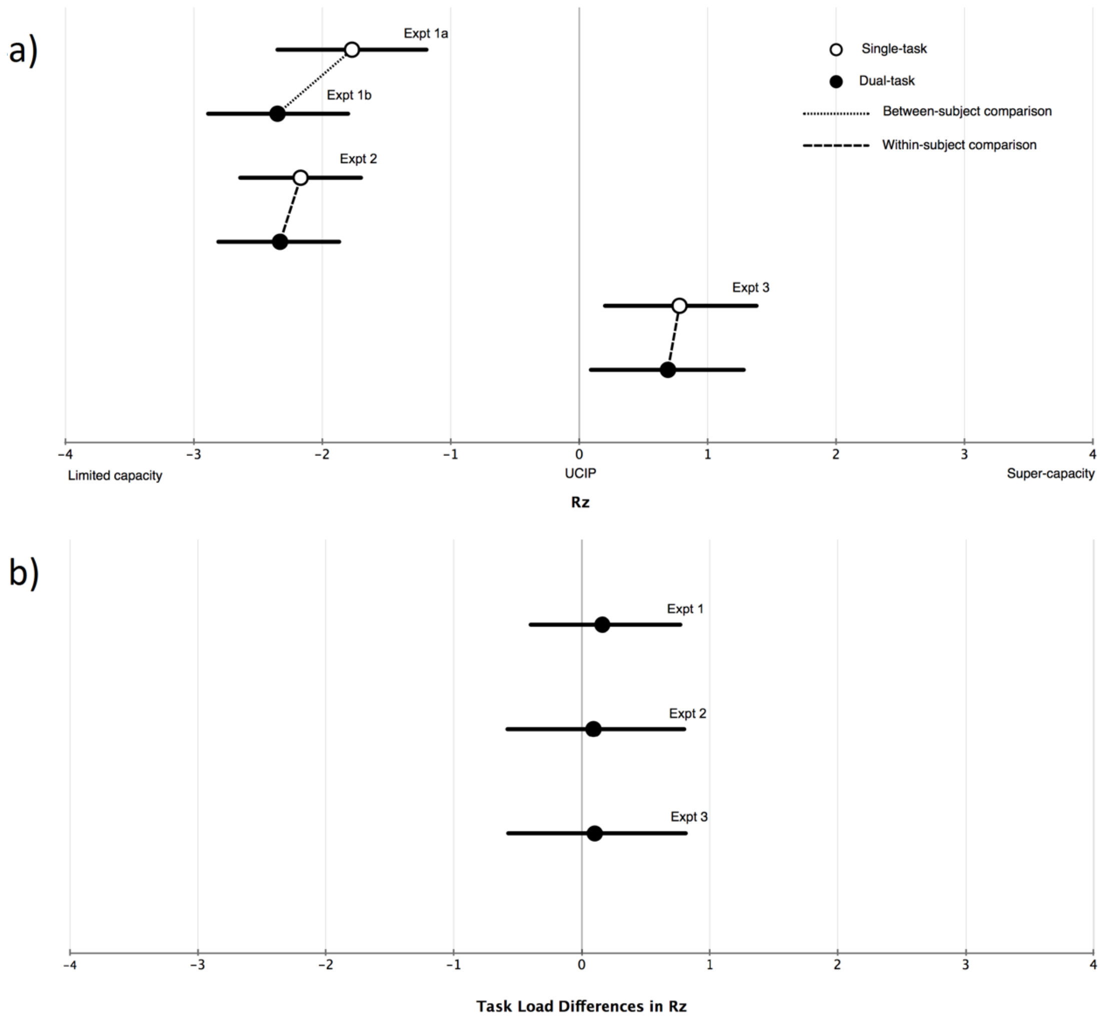

Figure 2-4. a. Means and 95% BCIs for standardised resilience/capacity scores for Experiments 1 to 3. *b.* Means and 95% BCIs for task-load differences in *Rz* (single-task minus dual-task) across experiments.

Tracking performance. In Experiment 1a, the participant-controlled cursor was invisible, and participants were told to ignore the movements of the red dot of the tracking task. However, joystick movements were recorded. These data provided an estimate of chance-level tracking accuracy, suitable as a baseline against which to compare active tracking performance in the subsequent dual-task experiments. Performance was measured by calculating the RMSE in angular distance of the cursor position relative to the target position. Mean RMSE was 31.34˚, 95% BCI = [26.01, 36.66]. If participants followed instructions to ignore the tracking task in Experiment 1a and perform it in the subsequent dual-task experiments, RMSE should be smaller in the later experiments.

Discussion

The goal of Experiment 1a was to provide a baseline measure of processing efficiency before any secondary task load was added. Resilience for redundant-target processing was highly limited, despite attention being wholly focused on the target detection task. Thus, within a standard distractor-present redundant-target task, the RT gains produced by redundant target presentation were smaller than predicted by statistical facilitation in a UCIP model.

Experiment 1b

Experiment 1b replicated the procedure of Experiment 1a but with the addition of a central manual tracking task, to test whether concurrent task load reduced processing resilience.

Method

Participants. As we aimed to match sample size from Experiment 1a, we ran participants until we had data for 25 participants who met the inclusion criteria for detection error rates. We achieved this goal after running 29 participants (see Error Rates section below for details on reasons for exclusions). All participants were undergraduate students (18 female, M_{Age} = 23.00 years, *SD* = 8.86, *Range* = 18 – 55), who received either AU$10 or course credit for their participation. None had participated in the previous experiment. All were right-hand dominant ($M_{FLANDERS}$ = +9.24, *SD* = 1.43), fluent in English, and had normal colour vision and normal or corrected-to-normal visual acuity. Twenty-three participants held current valid driver's licences, with driving experience ranging from 2 to 38 years (*M* = 6.19, *SD* = 8.68).

Apparatus and stimuli. The apparatus and stimuli were identical to those used in Experiment 1a, except that the cursor in the pursuit tracking task was made visible.

Procedure. In Experiment 1b, participants performed the peripheral target detection and manual tracking tasks concurrently. Participants were encouraged to maintain accuracy on both tasks, while also aiming to minimise RTs on the detection task. As in Experiment 1a, the task involved one block of tracking intervals, comprising one 60-second practice interval followed by 20 60-second experimental intervals. Lastly, participants completed the FLANDERS questionnaire, recorded their driving experience, and were debriefed.

Analysis. Analysis was identical to that of Experiment 1a.

Results

Error rates. As with Experiment 1a, participants with false alarm or miss rates greater than 0.30 in any of the three target conditions were excluded from analysis. Data for three participants with excessive false alarm rates (ranging 0.30 – 0.67) and for one participant with excessive miss rates (as high as 0.79 in the right-single target condition) were excluded. Mean false alarm rates for the remaining 25 participants were much lower (M = 0.09, *Range* = 0.01 – 0.22). Miss rates for the remaining participants were also very low (left single targets: M = 0.01, *Range* = 0.00 – 0.07; right single targets: M = 0.01, *Range* = 0.00 – 0.08; and redundant targets: M = 0.01, *Range* = 0.00 – 0.06). On average, participants correctly responded to approximately the same number of left-target trials (M = 70.88, *Range* = 65 – 74), right-target trials (M = 70.84, *Range* = 65 – 74), and redundant trials (M = 71.56, *Range* = 68 – 74) throughout the testing session. Collapsed across all trials, mean accuracy was very high (M = 0.97, *Range* = 0.93 – greater than 0.99).

RTs. Unlike Experiment 1a, RTs to left targets (M = 618 ms, 95% BCI = [583, 654]) were credibly shorter than those to right targets (M = 638 ms, 95% BCI = [602, 673]), (left -

right difference: M_{Diff} = -19 ms, 95% BCI = [-36, -3], d = 0.42). The addition of the manual tracking task in Experiment 1b produced a mean single-target RT (M = 628 ms, 95% BCI = [593, 663]) marginally longer than that of Experiment 1a, with the BCI on the difference between experiments just excluding 0, (single- minus dual-task difference: M_{Diff} = -55 ms, 95% BCI = [-108, -2], d = 0.57). Analysis confirmed that responses in the redundant-target condition (M = 574 ms, 95% BCI = [538, 610]) were faster than in the fastest single-target condition (M = 610 ms, 95% BCI = [575, 646]), (M_{RSE} = 36 ms, 95% BCI = [23, 50], d = 0.78). However, there was no credible difference between the size of the redundancy gain in Experiment 1b and that in Experiment 1a, (single- minus dual-task difference: M_{Diff} = 0 ms, 95% BCI = [-17, 18], d = 0.04).

Resilience Scores. Resilience was again limited (M_{Rz} = -2.35, 95% BCI = [-2.89, -1.80]), indicating redundancy gains were smaller than predicted by a UCIP model. As the number of correct trials was approximately consistent across Experiments 1a and 1b (approximately 71 correct target-present trials within each trial type), we can be confident that the variance in resilience does not differ substantially between experiments, and hence, we can compare resilience scores. A comparison between Rz scores in Experiments 1a and 1b found no credible difference, (single- minus dual-task difference: M_{Diff} = 0.58, 95% BCI = [-0.21, 1.37], d = 0.43).

Tracking performance. Mean RMSE was 15.16° (95% BCI = [13.04, 17.25]), credibly lower than in Experiment 1a, (single- minus dual-task difference: M_{Diff} = 16.18, 95% BCI = [10.47, 21.87], d = 1.79). Thus, data suggest that participants in Experiment 1b engaged in the tracking task as instructed.

To test the possibility of a trade-off in performance between the target detection and tracking tasks, bivariate correlations were calculated between Rz scores and RMSE. The credible interval on the correlation included a value of 0.0 but was wide, $r(23)$ = -.14, 95%

BCI = [-.58, .30], indicating that the data lacked resolution to strongly support or discredit the possibility of trade-offs between the two tasks.

Discussion

Experiments 1a and 1b tested whether a manual tracking task impairs processing efficiency for redundant visual targets. Consistent with previous findings (Eidels et al., 2014; Townsend & Nozawa, 1995), resilience was limited capacity. More surprisingly, resilience did not appear to suffer with the addition of a concurrent, central tracking task.

Experiment 2

Experiments 1a and 1b failed to find a clear difference in processing efficiency for redundant visual targets between single- and dual-task conditions. However, it is possible that the between-participants design of Experiment 1 simply was not sensitive enough to detect differences between the single- and dual-task conditions. To address this issue, Experiment 2 used a within-participants design to replicate Experiments 1a and 1b, providing a second test of the relationship between task load and target processing efficiency.

Method

Participants. Thirty-two Flinders University students (M_{Age} = 23.56 years, *SD* = 5.96, *Range* = 18 – 39) participated for AU$10. No participants had performed any of the previous experiments. Participants were all fluent in English, with normal colour vision, and normal or corrected-to-normal visual acuity. In addition, all participants were right-hand dominant ($M_{FLANDERS}$ = 9.56, *SD* = 0.23), and 28 had current valid driver's licences, with experience ranging from 1 to 20 years (*M* = 5.24, *SD* = 5.00).

Apparatus and stimuli. Apparatus and stimuli were the same as in Experiment 1.

Procedure. The tracking and discrimination tasks were performed in the same way as in Experiment 1. However, each participant completed two blocks of trials. In one block, the participant performed the target-detection task alone, following the same procedure as Experiment 1a (single-task condition). In the other block, the participant performed both tasks simultaneously, as in Experiment 1b (dual-task condition). Block order was counterbalanced across participants. To ensure Experiment 2 was consistent with Experiment 1 and due to time constraints within testing sessions, we did not include a separate condition to assess tracking performance on its own. At the beginning of each block, participants were given a 60-second practice session, before completing 20 60-second intervals. Participants were given a short break between blocks. As in the previous experiments, participants finished the testing session by completing the FLANDERS questionnaire and recording their driving experience. The entire session took approximately 50 minutes.

Analysis. Analysis was as in Experiment 1, but was adapted to account for the within-participant manipulation of task load. Analysis of RTs now included additive effects of task load and the interaction of target condition by load (Kruschke, 2015),

$$Y_{\text{participant, task load, condition}} \sim N(a0 + a_{\text{participant}} + a_{\text{task load}} + a_{\text{condition}} + a_{\text{task load} \times \text{condition}}, \sigma_{\text{y}}^2)$$

$$a_{\text{participant}} \sim N(0, \sigma_{\text{participant}}^2)$$

$$a_{\text{task load}} \sim N(0, \sigma_{\text{task load}}^2)$$

$$a_{\text{condition}} \sim N(0, \sigma_{\text{condition}}^2)$$

$$a_{\text{task load} \times \text{condition}} \sim N(0, \sigma_{\text{task load} \times \text{condition}}^2)$$

$$\sigma_{\text{participant,}}\, \sigma_{\text{task load}}, \sigma_{\text{condition}}, \sigma_{\text{task load} \times \text{condition}} \sim \Gamma\ (\alpha, \beta)$$

$$\alpha = SD/2$$

$$\beta = 2 * SD,$$

where deflections from the grand mean representing the effects of task load, condition, and their interaction were constrained to sum to zero across cells of the design. Likewise, analysis of *Rz* and RMSE included task load as an effect,

$$Y_{\text{participant, task load}} \sim N(a0\ + a_{\text{participant}} + a_{\text{task load}}, \sigma_{\text{y}}^2)$$

$\sigma_y \sim U(SD/1000, SD*1000)$

$a0 \sim N(M, [100 \times SD]^2)$

$a_{\text{participant}} \sim N(0, \sigma_{\text{participant}}{}^2)$

$a_{\text{task load}} \sim N(0, \sigma_{\text{task load}}{}^2)$

$\sigma_{\text{participant}}, \sigma_{\text{task load}} \sim \Gamma\ (\alpha, \beta)$

$\alpha = SD/2$

$\beta = 2 * SD,$

where deflections from the grand mean reflecting the effects of task load were constrained to sum to zero across conditions.

Results

Preliminary inspection found no effect of block order on any of the measures. As such, all analyses were carried out collapsed across block order. Analyses excluded data from three participants with excessive error rates (ranging 0.44 – 0.89 in any of the target conditions), one participant who appeared not to perform the tracking task in the dual-task condition (32.05° vs. 48.55° RMSE for the single- and dual-task, respectively), and one participant who failed to make enough button-press responses to be analysed. These exclusions left data from 27 participants for analysis.

Error rates. False alarm rates were reasonable in both the single- (M = 0.08, *Range* = 0.01 – 0.23) and the dual-task conditions (M = 0.08, *Range* = 0.01 – 0.21). Miss rates were low for each trial type in the single-task condition (left single: M < 0.01, *Range* = 0.00 – 0.06; right single: M < 0.01, *Range* = 0.00 – 0.03; redundant: M < 0.01, *Range* = 0.00 – 0.03) and in the dual-task condition (left single: M = 0.02, *Range* = 0.00 – 0.17; right single: M = 0.01, *Range* = 0.00 – 0.07; redundant: M = 0.01, *Range* = 0.00 – 0.08). The number of targets correctly detected in each of the three trial conditions was consistent across both the single- (left-targets: M = 71.41, *Range* = 67 – 75; right-targets: M = 71.62, *Range* = 69 – 75;

redundant-targets: *M* = 71.48, *Range* = 68 – 75) and dual-task conditions (left-targets: *M* = 70.25, *Range* = 59 – 74; right-targets: *M* = 71.33, *Range* = 66 – 75; redundant-targets: *M* = 70.71, *Range* = 67 – 74), meaning comparisons of *Rz* between conditions are appropriate. Collapsed across target-present and -absent trials, mean accuracy rate was extremely high within both the single- (*M* = 0.98, *Range* = 0.94 – 1.00) and dual-task conditions (*M* = 0.97, *Range* = 0.89 – 0.99).

RTs. Consistent with Experiment 1a, data showed no difference in mean RT for single targets presented on the left compared with single targets on the right for the single-task block (left: *M* = 601 ms, 95% BCI = [564, 639]; right: *M* = 601 ms, 95% BCI = [563, 637]; M_{Diff} = 0.79 ms, 95% BCI = [-22, 25], *d* = 0.08), and in contrast with the results of Experiment 1b, showed no difference in RTs for left versus right single targets in the dual-task block (left: *M* = 628 ms, 95% BCI = [591, 665]; right: *M* = 633 ms, 95% BCI = [596, 670]; M_{Diff} = -5 ms, 95% BCI = [-29, 18], *d* = 0.14). Mean single-target RT was credibly longer when the tracking task was performed concurrently (*M* = 630 ms, 95% BCI = [595, 665]) than when only the target-detection task was performed (*M* = 601 ms, 95% BCI = [566, 636]), (M_{Diff} = -29 ms, 95% BCI = [-47, -12], *d* = 0.42). Comparing the fastest single-target RTs (single-task: *M* = 587 ms, 95% BCI = [550, 624]; dual-task: *M* = 612 ms, 95% BCI = [575, 649]) with the redundant RTs (single-task: *M* = 550 ms, 95% BCI = [513, 587]; dual-task: *M* = 581 ms, 95% BCI = [544, 618]) revealed clear redundancy gains of roughly the same size in both the single- (M_{RSE} = 37 ms, 95% BCI = [15, 61], *d* = 1.47) and dual-task (M_{RSE} = 31 ms, 95% BCI = [7, 53], *d* = 0.90) conditions, (M_{Diff} = 7 ms, 95% BCI = [-21, 38], *d* = 0.26).

Resilience. As in the previous experiments, normalised resilience scores for both the single- (M_{Rz} = -2.17, 95% BCI [-2.64, -1.70]) and dual-task (M_{Rz} = -2.33, 95% BCI [-2.81, -1.87]) conditions were limited, well below the predictions of the UCIP model (see Figure 2-

4). Furthermore, comparisons of resilience between the dual- and single-task conditions again failed to find evidence of a difference (M_{Diff} = 0.16, 95% BCI = [-0.39, 0.76], *d* = 0.13). These results replicate the findings of Experiment 1, showing no credible effect of task load on dual-channel processing efficiency.

Tracking performance. RMSE was substantially smaller in the dual-task block (*M* = 16.87°, 95% BCI = [12.94, 20.78]) than in the single-task block (*M* = 32.97°, 95% BCI = [29.04, 36.86]) (M_{Diff} = 16.11, 95% BCI = [10.68, 21.46], *d* = 1.07), indicating that participants followed instructions to perform both tasks simultaneously during the dual-task block. Data from the dual-task condition found no evidence of a trade-off between RMSE and *Rz*, with higher *Rz* scores predicting smaller tracking error, *r*(25) = -.36, 95% BCI = [-.75, .04], although the BCI on this effect included 0.

Discussion

As in Experiments 1a and b, resilience was highly limited, but was not credibly smaller when participants performed a concurrent manual tracking task. Thus, the tracking and detection tasks did not appear to compete for processing resources (Wickens, 1981; Wickens, 2002), producing no performance trade-off between the tasks.

Experiment 3

The previous experiments found that processing efficiency for redundant visual targets, as measured by resilience, was similar across single- and dual-task conditions. In both cases, resilience was limited, producing mean *Rz* scores decisively below 0. Experiment 3 sought to generalise the results of Experiments 1 and 2 by testing the effects of dual-task load on *Rz* under conditions in which the baseline, single-task resilience scores were not highly limited.

Although neither of the first two experiments included a manipulation to diagnose system architecture, the observed resilience scores suggest that the left and right channels in the target detection task were processed in parallel. As noted above, a serial processing architecture can produce limited-resilience processing. This type of processing only occurs when the time needed to process a distractor is significantly lower than the time needed to process a target (Little et al., 2015). There is little reason to expect that this would have been the case in Experiments 1 and 2. Moreover, past work has shown that TL stimuli can be processed in parallel (Sung, 2008; Yamani, McCarley, Mounts, & Kramer, 2013), at least under conditions in which they are above the limits of sensory resolution and are not subject to visual crowding (Bouma, 1970) or attentional suppression (Yamani et al., 2013).

Experiment 3 measured resilience under single- and dual-task conditions using target and distractor stimuli designed to force serial processing and push resilience above the levels observed in the first two experiments. Targets and distractors were presented in a 4-pt font, and embedded in flanking characters intended to produce visual crowding (Bouma, 1970; Whitney & Levi, 2012) in the extrafoveal retina. This design meant that stimulus onsets could still be detected in the retinal periphery. However, to identify targets and distractors, participants had to foveate the stimuli, with little peripheral information to guide participants preferentially toward the target on single-target trials. Assuming that target and distractors required roughly the same amount of time to process, resilience should have reached super-capacity levels (Little et al., 2015), allowing us to test the generality of our findings from the first two experiments.

Method

The following experiment was preregistered on the Open Science Framework: https://osf.io/k4pz2/register/5771ca429ad5a1020de2872e.

Participants. We planned for a sample size of 30 participants who met the performance criteria for both the target detection and tracking tasks. To achieve this sample size, 34 undergraduate students from Flinders University (25 female; M_{Age} = 21.32, *SD* =

3.88, *Range* = 17 – 35) participated in the experiment either for course credit or for AU$10. No participants had participated in any of the previous experiments. Participants all exhibited normal or corrected-to-normal visual acuity, normal colour vision, and English fluency. Participants were required to be right-hand dominant ($M_{FLANDERS}$ = +9.48, *SD* = 1.93); one participant who failed this requirement was immediately excluded from the study prior to further analysis. Thirty-one participants reported holding a current valid driver's licence, and the mean years driving experience was 3.83 years (*SD* = 3.19; *Range* = 1 – 15 years).

Apparatus and stimuli. The apparatus was the same as above. Stimuli were similar except for the following changes. First, stimuli for the target detection task were reduced to 4-point font, with each letter subtending approximately 0.44° × 0.35° of visual angle. Second, targets and distractors were embedded within 5-item letter arrays. Target letters appeared in the same upper left and upper right locations as in Experiments 1-2, but were flanked on both sides by two letters randomly and independently selected from the set F, H, K, M, N, V, W, X, and Z. To avoid overlap between letters, target and distractor orientations were fixed at 0°. For an illustration of a dual-task single-target trial from Experiment 3, please return to Figure 2-1b.

Procedure and analysis. Procedure and data analysis were identical to Experiment 2.

Results

Data from one participant were removed from analysis for high false alarm rates in both the single- (0.53) and dual-task (0.61) conditions. Furthermore, data from two participants who produced roughly equal tracking error in both the single- and dual-task conditions (e.g., 27.58° vs. 29.64°, respectively) were also excluded.

Error rates. False alarm rates for the remaining 30 participants were acceptable within both the single- (*M* = 0.07, *Range* = 0.00 – 0.19) and dual-task (*M* = .08, *Range* = 0.00

– 0.26) conditions. Similarly, target miss rates were low in all trial types for both the single-task condition (left single: *M* = 0.01, *Range* = 0.00 – 0.16; right single: *M* = 0.02, *Range* = 0.00 – 0.20; redundant target: *M* = 0.01, *Range* = 0.00 – 0.18) and the dual-task condition (left single: *M* = 0.03, *Range* = 0.00 – 0.15; right single: *M* = 0.03, *Range* = 0.00 – 0.14; redundant target: *M* = 0.02, *Range* = 0.00 – 0.14). Collapsed across target-present and target-absent trials, mean accuracy rate was high and approximately equal in both the single (*M* = 0.97, *Range* = 0.84 – greater than 0.99) and dual-task (*M* = 0.96, *Range* = 0.87 – greater than 0.99) conditions. A similar number of targets were detected within each of the three trial types for both the single- (left single: *M* = 70.60, *Range* = 61 – 74; right single: *M* = 70.33, *Range* = 59 – 74; redundant target: *M* = 70.90, *Range* = 59 – 74) and dual-task conditions (left single: *M* = 69.77, *Range* = 58 – 74; right single: *M* = 69.70, *Range* = 60 – 73; redundant target: *M* = 70.13, *Range* = 62 – 73), allowing for comparisons of *Rz* between conditions.

RTs. Comparisons of RTs for left and right single targets revealed faster responses for targets on the left than those on the right for both the single- (left: *M* = 794 ms, 95% BCI = [749, 838]; right: *M* = 976 ms, 95% BCI = [932, 1019]; M_{Diff} = -182 ms, 95% BCI = [-227, -139], *d* = 1.11) and dual-task conditions (left: *M* = 880 ms, 95% BCI = [836, 924]; right: *M* = 1031 ms, 95% BCI = [987, 1074]), (M_{Diff} = -151 ms, 95% BCI = [-194, -105], *d* = 1.43), indicating that participants adopted a left-to-right scanning strategy under serial processing conditions. Mean single-target RT was credibly faster in the single-task condition (*M* = 885 ms, 95% BCI = [847, 923]) than the dual-task condition (*M* = 955 ms, 95% BCI = [917, 994]), (M_{Diff} = -70 ms, 95% BCI = [-101, -40], *d* = 0.50). We found clear evidence for redundancy gains when comparing the fastest single-target RTs (single-task: *M* = 776 ms, 95% BCI = [733, 818]; dual-task: *M* = 877 ms, 95% BCI = [835, 920]) with redundant-target RTs (single-task: *M* = 688 ms, 95% BCI = [646, 730]; dual-task: *M* = 756 ms, 95% BCI = [714, 798]) for both levels of task load (single-task: M_{RSE} = 87 ms, 95% BCI = [47, 127], *d* =

1.41; dual-task: M_{RSE} = 121 ms, 95% BCI = [82, 161], d = 2.21). Although there was a trend for larger redundancy gains in the dual-task condition, the BCI on the difference score contained 0 (M_{Diff} = -34, 95% BCI = [-91, 18], d = 0.50).

Resilience. As expected, and in contrast to the results of the first three experiments, normalised resilience scores for both the single- (M_{Rz} = 0.78, 95% BCI = [0.20, 1.38]) and dual-task conditions (M_{Rz} = 0.69, 95% BCI = [0.09, 1.28]) were credibly super-capacity. However, consistent with the previous experiments, we found no evidence that processing resilience varied credibly between load levels (single- minus dual-task difference: M_{Diff} = 0.10, 95% BCI = [-0.57, 0.81], d = 0.06).

Tracking Performance. RMSE was decisively smaller in the dual-task condition (M = 15.69°, 95% BCI = [11.91, 19.49]) than the single-task condition (M = 33.11°, 95% BCI = [29.29, 36.87]), (M_{Diff} = 17.41, 95% BCI = [12.47, 22.28], d = 1.39). As in Experiment 2, data trended in the opposite direction to a trade-off between RMSE and Rz scores, $r(28)$ = -.35, 95% BCI = [-.72, .02], with the credible interval just overlapping 0.

Discussion

Experiment 3 assessed target processing efficiency within a forced serial process paradigm. As expected, serial scanning produced super-capacity processing of redundant targets (Little et al., 2015). Notably, the large difference in resilience scores found in the current experiment versus those in the earlier experiments supports the idea that, when stimuli were above sensory thresholds and not compromised by crowding, target processing was parallel with limited-capacity. But, despite the difference in processing architecture between experiments, none of the experiments found an effect of task load on processing efficiency. Resilience remained largely unaffected by variations in task load, despite large variations in baseline resilience values and changes to processing architecture.

General Discussion

The current studies examined redundant-target processing within a dual-task paradigm. As expected, a concurrent manual tracking task increased RTs for target detection in the periphery. But despite this difference in baseline target detection times, the efficiency with which redundant targets were processed did not vary credibly between task loads. In other words, a central task slowed responses to peripheral targets, but did not change the rate at which multiple targets were processed relative to single targets. This effect was true regardless of whether targets were processed in parallel with limited resilience (Experiments 1-2), or in serial with super-capacity resilience (Experiment 3).

One interpretation is that the central manual tracking task and peripheral target detection task tapped into partially-independent pools of information-processing resources (Wickens, 2002). Although multiple resource theory includes visual attention as one form of processing resource, it posits separate pools of processing resources for both focal and ambient vision, linking focal processing to the central visual field and ambient to the peripheral visual field. The theory thus allows that the task-load manipulation might not have affected processing efficiency because the tracking task engaged central resources and the target detection task engaged ambient resources. Contrary to this hypothesis, though, mean single-target RTs for dual-task conditions were credibly longer than those for single-task conditions in across all experiments. These results suggest the central tracking and peripheral detection tasks likely tapped common processing resources, presumably at the stages Wickens (2002) labels perception or cognition; the target and distractor stimuli of Experiment 3 were in fact designed to be indiscriminable in ambient vision, ensuring competition for focal attention between the central and peripheral tasks. Moreover, Wickens' (2002) model proposes that focal processes are specialised for detailed object perception and recognition, whereas ambient processes are specialised for spatial processing. Assuming that participants fixated near the display centre to perform the tracking task, the central and peripheral processing demands in the current experiments therefore would not have aligned well with the attentional pools hypothesised by multiple resource theory. To optimise the distribution of resources under the model, participants would have had to fixate near the boundary of the display while tracking the moving target with peripheral vision. Eye movement data might test whether any participants adopted such a strategy, or to estimate more generally how often eye movements occurred between the central and peripheral tasks. At best, though, the data indicate that distributing task load over different resource pools would have attenuated dual-tasks costs, not eliminated them.

An alternative explanation for the present results could be that even when redundant peripheral targets were themselves processed in parallel, attention shifted between the central and peripheral tasks in serial (Wickens & Gopher, 1977). By this account, participants would have performed the central tracking task while using a diffuse attentional window to monitor the display periphery for targets and distractors (Steelman et al., 2013; Van der Stigchel et al., 2009). The visual transients produced by peripheral stimulus onsets would have interrupted the central tracking task (Yantis & Jonides, 1990), drawing attention towards the target and distractor stimuli for identification. In Experiments 1-2, attention in this interval would have been spread broadly over the left and right stimuli, processing them in parallel. By contrast, the design of the stimuli in Experiment 3 would have demanded that attention focus on the stimuli in serial, through a series of saccadic eye movements. In both cases, after detecting a target or confirming that both peripheral items were distractors, attention would have returned to the tracking task. Resilience would have been similar across the single- and dual-task blocks, because, in both cases, attention would have been disengaged from the central task while peripheral items were being processed.

One caveat of this attention-switching account is that such a theory predicts a positive association between tracking error and resilience for the redundant targets, whereas our data trended in the opposite direction. The tendency toward better tracking among participants with higher resilience hints at individual differences in effort or ability, differences that might have masked any trade-offs between tracking and resilience. To better understand how attention is divided between the two tasks, future experiments might employ eye-tracking to identify participants' attentional strategies, and to test for evidence of discrete attention shifts between the centre and periphery.

In application, our results indicate that redundant visual signals are likely to be as effective at aiding visual detection under multiple-task conditions as under single-task conditions. This means both that redundant coding will be useful within multi-task workspaces, and that the results of single-task pilot testing can be used to predict the magnitude of RT gain that redundant signals will purchase in a multi-task environment. Thus, design guidelines for complex visual workspaces, such as pilot cockpits or vehicle dashboards, should encourage the use of redundant coding of visual alerts for enhancing detection.

The data also imply a trade-off between redundancy gains and display complexity. We find that redundant visual targets in peripheral visual displays are of greatest value for low-salience stimuli, those that demand focused attention for detection or recognition, such as when monitoring a large set of gauges or meters. Stimuli of higher salience, discriminable enough to be processed in parallel, are more likely to be processed with limited resilience and with far more modest redundancy gains. This pattern suggests that as a general guideline, display designers might trade redundant target presentation against target salience, reserving highly salient display modes for the most critical signals and presenting information that is less urgent but still time-sensitive in lower salience, redundant signals. By using redundant presentation as a substitute for high conspicuity, this strategy would reduce the risk of a salience-saturated environment in which high-contrast signals compete for attention or overwhelm the operator.

Notably, our findings only consider identical redundant visual signals. Thus, additional work will be necessary to generalise the results to environments in which redundant signals are non-identical (Ben-David & Algom, 2009) or to environments involving auditory or multimodal stimuli (Diederich & Colonius, 2004; Fox et al., 2014). As many warning technologies and displays employ multimodal signals (Rowe & Halpin, 2013; Selcon et al., 1995), further research should examine whether redundant non-identical or multimodal signals also produce equally-efficient processing benefits within single- and multi-task environments.

Conclusions

Within a peripheral redundant-target paradigm, data give no evidence for poorer target processing efficiency while under the load of a secondary tracking task. However, in line with previous findings, (e.g., Little et al., 2015), data do show variations in processing efficiency as a function of display characteristics. Findings suggest there is a modest benefit to employing redundant targets in peripheral visual displays (e.g., on a vehicle dashboard) for situations in which targets are processed in parallel. However, we find redundant displays have more substantial benefits for target items that demand serial processing.

Availability of data

The datasets supporting the conclusions of this article are available in the Figshare repository, [https://figshare.com/s/be3a9ccbcf358569a80e (Experiments 1a & 1b); https://figshare.com/s/c8f3fad139c9b5afc01b (Experiment 2);

https://figshare.com/s/acb5b737ebf9325889d1 (Experiment 3);

https://figshare.com/s/68a01641c01b78e1a675 (Excluded Data)].

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CHAPTER 3: STUDY 2

Dual-Task Redundant-Target Processing:

The Case of the Limited Capacity Parallel Model

The following chapter is a version of a published conference proceedings paper from the 62nd International Meeting of the Human Factors and Ergonomics Society in Philadelphia, NJ, September 2018. The paper involves a follow-up experiment to the experiments in Chapter 2. In contrast to the experiments in the previous chapter, here I explore dual-task effects on redundant-target processing in distractor-absent displays.

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Author Contributions:

All three authors formulated the design of the study. SAM collected the data and wrote the first draft of the manuscript. Both SAM and JSM carried out the data analysis. JSM and NAT provided revisions on the manuscript.

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Abstract

We examined the effect of a central tracking task on visual target processing efficiency in a combined target detection/manual tracking paradigm. Participants performed a redundant-target task by itself, and concurrently with the tracking task. A measure of workload capacity gauged target processing efficiency. Processing was less efficient than predicted by a standard parallel race model under both levels of task load. However, data suggested no difference in processing efficiency between the single- and dual-task conditions. Our findings provide further evidence that processing capacity for peripheral visual targets is consistently limited but robust against changes to concurrent task load.

Dual-Task Redundant-Target Processing:
The Case of the Limited Capacity Parallel Model

The capacity of the human information processing system is limited (Moray, 1967), forcing operators to divide resources between concurrent tasks (Navon & Gopher, 1979). Resource competition between tasks can produce mutual interference, increasing response times (RTs) to critical events and decreasing response accuracy (Wickens, 2002; 2008). In addition, a demanding central visual task performed with a peripheral visual task may produce a tunnel vision effect, diverting attention away from peripheral information (Crundall & Underwood, 1998; Crundall, Underwood, & Chapman, 1998; Williams, 1985). For example, drivers under cognitive load detect critical events more slowly (Strayer & Johnston, 2001), check their mirrors and speedometer less often (Recarte & Nunes, 2003), and scan the forward field of view more narrowly (Recarte & Nunes, 2000) than undistracted drivers.

When attending to a central task, the amount of capacity available for processing peripheral visual signals is reduced. However, although dividing attention between tasks lengthens detection RTs, it is less clear whether this effect results from a decrease in target processing capacity (see also Morey, Thomas, & McCarley, 2018b). Thus, our current study tested the effect of a central visuo-manual tracking task on workload capacity (i.e., processing efficiency) for visual target detection. In other words, we explored whether dividing attention between two visually demanding tasks reduces how efficiently the cognitive system processes visual signals.

Measuring Processing Capacity for Visual Signals

A common method for assessing processing capacity is to use a *redundant-signals task* (Miller, 1982). A *redundancy gain* or *redundant signals effect* (*RSE*) is the speed-up in response times associated with presenting two or more signals with the same meaning at the same time.

Within a standard redundant signals paradigm, the participant is asked to attend to two channels (i.e., possible target locations) and issue a positive response if a target appears on either. The task is said to employ a *first-terminating stopping rule* (Colonius & Vorberg, 1994), as a response occurs after the first target detection on either channel.

Although a robust effect, the RSE may be small or even absent in some contexts. It can vary due to the cognitive system's *architecture*—the arrangement of processing channels (i.e., in parallel or serial); due to changes to the system's *workload capacity*, the efficiency at which the channels operate as the number of channels increases (Townsend & Ashby, 1983; Townsend & Nozawa, 1995); and due to dependencies between different channels (Townsend & Wenger, 2004a). For the present study, our primary interest was workload capacity, and understanding how processing efficiency varies as a function of task load.

The simplest account of the RSE is the *unlimited capacity independent processing* (*UCIP*) model (Townsend & Eidels, 2011). Within this model, two or more channels operate simultaneously and with stochastic independence, and the rate of each individual channel is unaffected by the number of channels operating (Townsend & Eidels, 2011). Under a first-terminating stopping rule, the UCIP produces an RSE purely because the RT for the whole system is based on the fastest channel's finishing time for each separate trial, known as *statistical facilitation* (Raab, 1962). The UCIP provides a benchmark of unlimited capacity performance. *Super-capacity* obtains when an RSE is larger than predicted by the UCIP model. Finally, when an RSE is smaller than predicted by the UCIP, performance is *limited capacity*. Under extreme capacity limitations, a system may show no RSE.

Although mean RTs can demonstrate an RSE, they cannot distinguish between moderately limited, unlimited, and super-capacity processing. Miller (1982) and Grice, Canham, and Gwynne (1984) established upper and lower bounds on UCIP performance. However, these bounds provide highly conservative tests and are insensitive to modest differences in capacity.

An alternative approach to studying capacity is to use the normalised *capacity coefficient, Cz* (Houpt & Townsend, 2012). *Cz* provides a fine-grained measure of channel processing and can detect differences in capacity between the two bounds (see also Townsend & Nozawa, 1995, or Townsend & Eidels, 2011, for a variant of the capacity coefficient that plots capacity as a function of time). *Cz* scores follow a standard normal distribution, with a mean of 0 and a standard deviation of 1. A value of 0 indicates UCIP performance, and values higher and lower than 0 indicate super-capacity and limited capacity processing, respectively.

Notably, two variants of the redundant-targets task are possible. In the no-distractor variant, a target only ever appears on its own or with a redundant target; a distractor never accompanies a target. In this case, the task is purely a detection task rather than a discrimination task, and as such, the participant responds the moment an item appears on either channel. In the with-distractor variant, on the other hand, on single-target trials a distractor occupies the channel that does not contain a target. The task thus demands a discrimination decision: *is either of the items a target?* Responses are generally slower to distractor-present single-target displays than distractor-absent single-target displays, as the distractor can divert processing resources from the target (Houpt & Little, 2017; Little et al., 2015). The RSE in the distractor-present paradigm conflates the release from interference that occurs when a distractor is removed with the RT facilitation that results when two copies of a target item are present (Houpt & Little, 2017).

Our research question was whether processing efficiency for peripheral targets decreases when attention is divided between tasks. More specifically, we compared target processing efficiency—*Cz*—for peripheral targets in a divided-attention, dual-task condition with *Cz* in a full-attention, single-task condition. A recent study (Morey et al., 2018b) found no dual-task costs to processing efficiency when targets were accompanied by distractors. In the redundant-targets task with a distractor, though, the effects of removing the distractor are generally larger than those of adding a second target (e.g., Allen et al., 1992). Therefore, any effects of concurrent task load on redundant-target processing facilitation could have been masked by variability caused by release-from-distractor interference. Thus, here we examined the effect of concurrent task load on peripheral target processing efficiency in a no-distractor redundant-targets paradigm.

Method

Participants

Thirty undergraduate students from Flinders University (19 female; *M* = 22.47, *SD* = 6.92, *Range* = 17 to 48 years) completed the study either for course credit or for AU$10. Participants were fluent in English, had either normal or corrected-to-normal visual acuity, and had normal colour vision. To control for any effects of hand dominance, only participants with a right hand dominance of at least +5 (*M* = +9.63, *SD* = 1.00) on the Flinders Handedness Survey (FLANDERS) (Nicholls et al., 2013) were eligible to participate. Twenty-two participants held current valid driver's licences, with driving experience ranging from 0.5 to 30 years (*M* = 3.86, *SD* = 6.00).

Apparatus and Stimuli

Apparatus and stimuli were identical to those used in a recent study (Morey et al., 2018b; Experiment 2); however, all distractors were removed entirely from the design. The experiment was performed on a 27" Samsung monitor with a screen resolution of 1920 x 1080 pixels (each pixel = 0.33mm) and a refresh rate of 100 Hz. Participants sat approximately 600mm in front of the monitor. The experiment was programmed using

Presentation Software Version 16.5 Build 09.17.13 (Neurobehavioral Systems, 2018). A Logitech Attack 3 joystick (Logitech, 2018) collected responses to both the target detection task and the manual tracking task.

The tracking task involved a small black cursor in 10-point Arial font (subtending 0.76° × 0.76° visual angle) and a red circular target (subtending 0.95°). The target moved along an unmarked semi-circular path with a radius of 9.93° and a midpoint offset 5.72° visual angle below the screen centre. The tracking target's movements were based on a combination of three sine waves (0.07, 0.15, and 0.23), making target motion effectively unpredictable (Strayer & Johnston, 2001). The cursor moved along the same semi-circular path as the target, but with a maximum speed of 80° per second.

The target for the detection task was a black capitalised 'T' appearing on a white background. Targets appeared in 16-point Arial font, each subtending a visual angle of 1.58° × 1.14°. Targets appeared in the top left (Location A) and/or top right (Location B) locations of the monitor, with polar coordinates $\theta = \pm 51.15°$ from the vertical midline and $r = 21.79°$ from the screen centre point. Every target appeared randomly rotated in 90° steps for 2000 ms or until a button press was made; whichever came first. Figure 3-1 shows an example of the trial process within each 60-second tracking interval.

On left single-target trials, a T appeared in Location A but Location B was empty; on right single-target trials, a T appeared in Location B but Location A was empty; and on redundant-target trials, both locations were occupied with a T. On target-absent trials, no targets were present, and as such, the trials appeared no different to a blank screen. The four trial conditions occurred with equal probability throughout the task and appeared in a random order.

To respond to targets, participants pressed the buttons on the top of the joystick using both thumbs at the same time. To reduce temporal certainty, the inter-stimulus interval between a target offset and the next onset was determined by an exponential distribution with a fixed delay of 1000 ms and an exponential component with a mean of 2000 ms.

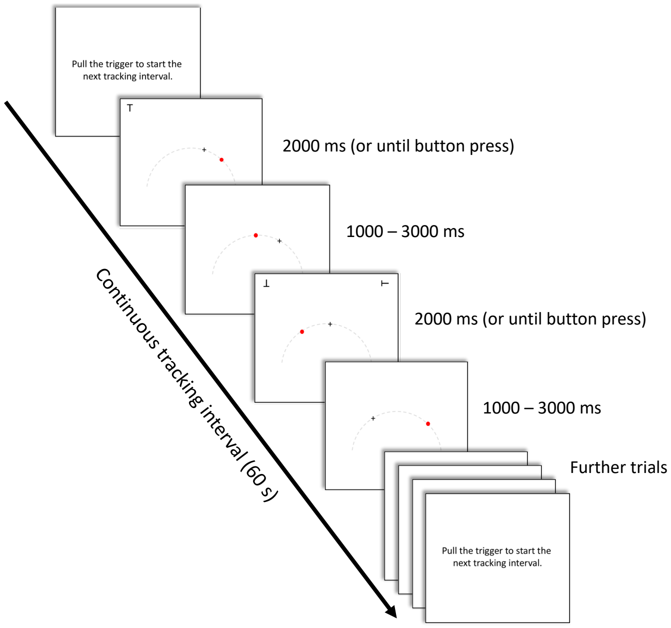

Figure 3-1. A left single-target trial (Slide 2) and redundant-target trial (Slide 4) within a 60-sec dual-task tracking interval. While responding to targets in the top corners of the screen, participants used a joystick to manually manoeuvre a black cursor (+) to align with a moving red circle. The cursor and circle both moved along an imaginary semi-circle (shown here as a grey dashed line). In the single-task block, stimuli were identical except that the black cursor for the tracking task was made invisible.

Procedure

After providing informed consent, participants were tested for normal visual acuity and colour vision. We carried out the experiment in a single testing station in a quiet room. Participants were informed that they would perform two blocks of trials, and that in one block they would only perform the target detection task, whereas in the other block they would perform both the tracking and detection tasks. At the start of each block, the participant performed a 60-second practice trial, then 20 experimental trials of 60 seconds each. Peripheral targets appeared approximately 20 times within each tracking interval.

To enhance participants' engagement with the tasks, we framed the experiment with a driving scenario. Participants were instructed to imagine the task simulated their drive to university. Holding the joystick with both hands, they were asked to align their vehicle (the black cursor) as best as possible with the navigator (red circular target). The target Ts were described as being red traffic signals. The participants' task was to use both thumbs to press the two buttons on top of the joystick as soon as a stop signal (target) appeared. Both speed and accuracy were emphasised on the detection task.

In the single-task block, participants performed the target detection task by itself. The red moving target was visible, but the black cursor was hidden. Participants were told to ignore the movements of the red dot and to focus on the targets. In the dual-task block, participants performed the detection and tracking tasks concurrently. Neither task was assigned a higher priority. Block order was counter-balanced across participants.

After completing the experiment, participants filled in the FLANDERS questionnaire and verbally answered whether they held a current valid driver's licence, and if so, how many years of driving experience they had accrued.

Analysis

We analysed capacity, mean RTs, and tracking error using a Bayesian parameter estimation based on a Markov chain Monte Carlo (MCMC) sampling procedure (Kruschke, 2015; Lee & Wagenmakers, 2013). For complete details about the parameter estimations, please see Morey et al. (2018b; Experiment 2).

Results

Error Rates

Workload capacity analyses are robust against the effect of errors up to a value of about 0.30 (Townsend & Wenger, 2004a). False alarm rates were well below this value for all participants in both the single- (*M* = 0.02, *Range* = 0.00 – 0.09) and dual-task (*M* = 0.03, *Range* = 0.00 – 0.25) conditions. Miss rates were low in the single-task condition (single-target on left: *M* = 0.01, *Range* = 0.00 – 0.16; single-target on right: *M* = 0.01, *Range* = 0.00 – 0.15; redundant targets: *M* < 0.01, *Range* = 0.00 – 0.08), as well as the dual-task condition (single-target on left: *M* = 0.01, *Range* = 0.00 – 0.04; single-target on right: *M* = 0.01, *Range* = 0.00 – 0.06; and redundant targets: *M* = 0.01, *Range* = 0.00 – 0.08). Participants, on average, responded to approximately 71 trials within each target-present condition, regardless of task load (single-task condition: single-target on left: *M* = 70.64, *Range* = 59 – 74; single-target on right: *M* = 71.07, *Range* = 69 – 74; and redundant targets: *M* = 71.54, *Range* = 64 – 74; dual-task condition: single-target on left: *M* = 71.11, *Range* = 67 – 74; single-target on right: *M* = 71.14, *Range* = 67 – 74; and redundant targets: *M* = 71.18, *Range* = 68 – 73). Thus, the variance of *Cz* did not differ substantially between conditions. Collapsing across trials produced a very high mean accuracy rate in both the single- (*M* = 0.99, *Range* = 0.88 – 1.00) and dual-task conditions (*M* = 0.99, *Range* = 0.93 – 1.00).

Analyses excluded data from two participants who displayed excessively poor tracking performance in the dual-task condition, leaving an *N* of 28.

RTs

RTs were examined only for correct target-present trials (i.e., all false-positive responses were removed). Visual inspection of the data suggested that participants followed instructions to respond bimanually. We used the faster of the two button press responses on each trial for analysis.

Mean single-target RT served as a measure of baseline response speed independent of any redundancy gain. As expected, mean RT was credibly shorter in the single-task condition

(*M* = 475, 95% BCI = [450, 500]) than the dual-task condition (*M* = 523, 95% BCI = [498, 548]), (M_{Diff} = -47 ms, 95% BCI = [-66, -28], *d* = 1.45). See Figure 3-2.

To assess the size of redundancy gains, we compared the mean of the faster single-target RT (left or right target) from each observer to the mean redundant-target RT. This method provides a more conservative estimate of redundancy gain than simply comparing the mean single-target RT with the redundant-target RT (cf. Biederman & Checkosky, 1970). Both task-load conditions had shorter RTs for redundant-target trials (single-task: *M* = 409, 95% BCI = [382, 437]; dual-task: *M* = 484, 95% BCI = [456, 512]) than for the fastest single-target trials (single-task: *M* = 423, 95% BCI = [396, 450]; dual-task: *M* = 507, 95% BCI = [480, 535]). However, redundancy gains were approximately equal in the single (*M* = 13, 95% BCI = [-13, 39]) and dual-task (*M* = 23, 95% BCI = [-2, 50]) conditions, (M_{Diff} = -10 ms, 95% BCI = [-46, 13], *d* = 0.67) (see Figure 3-3).

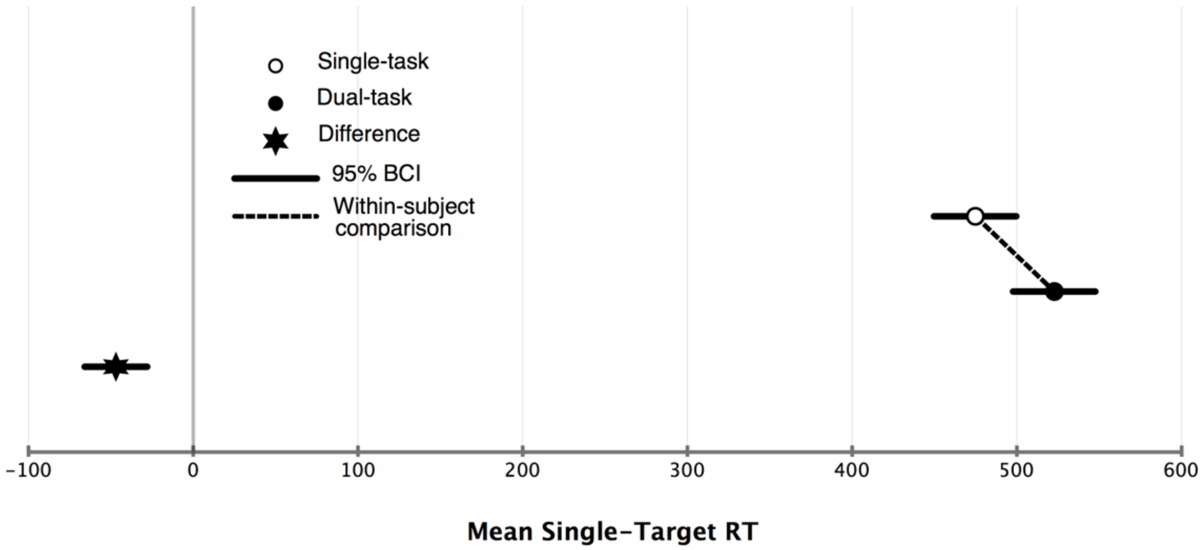

Figure 3-2. Mean single-target RTs (ms) and the task-load difference (with 95% BCIs).

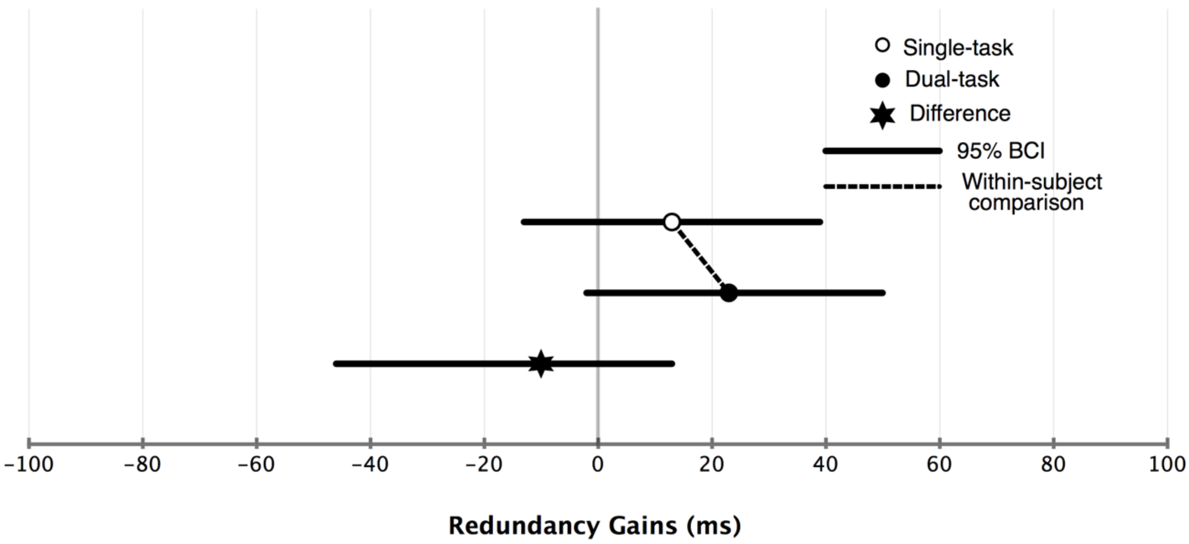

Figure 3-3. Mean redundancy gains and the associated task-load difference. Error bars are 95% BCIs.

Target Processing Capacity

To quickly reiterate, $Cz = 0$ denotes unlimited capacity, $Cz < 0$ denotes limited capacity, and $Cz > 0$ denotes super-capacity. Here, processing capacity was credibly limited for both the single-task ($M_{Cz} = -3.15$, 95% BCI = [-3.66, -2.65]) and dual-task conditions ($M_{Cz} = -2.92$, 95% BCI = [-3.40, -2.43]). More critically, as shown by the difference score (star) in Figure 3-4, the data showed no difference in Cz due to the dual-task manipulation ($M_{Diff} = -0.23$, 95% BCI = [-0.77, 0.25], $d = 0.33$).

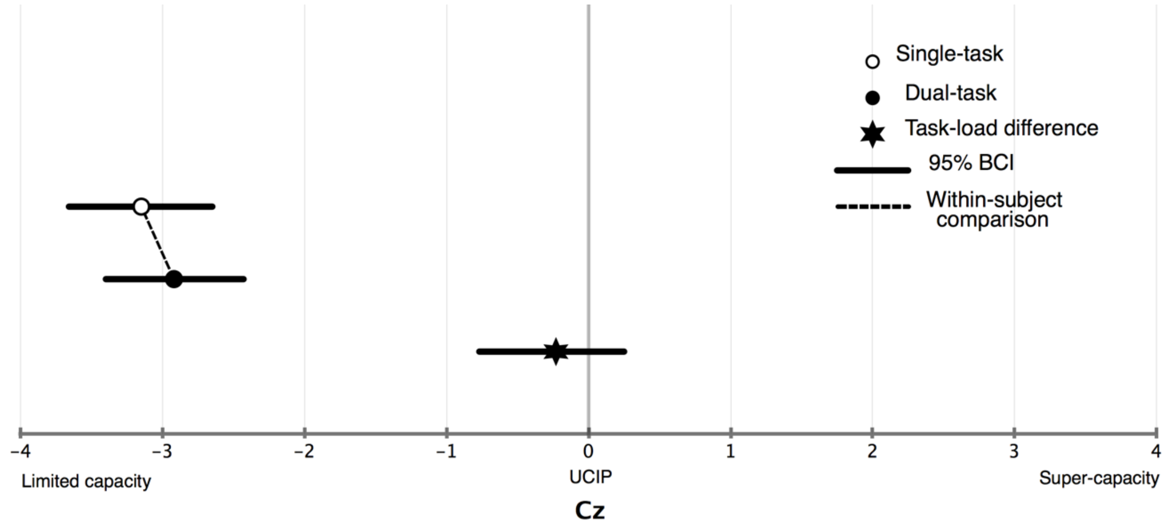

Figure 3-4. Single- and dual-task *Cz* scores, along with the task-load difference. Error bars are 95% BCIs.

Tracking Performance

Though tracking performance was not our primary focus, we analysed tracking error to check that participants had followed instructions in the dual-task condition. To assess tracking performance, we used the cursor and red tracking target coordinates to calculate root mean squared error (RMSE). The RSME provides a measure of how far the cursor deviates from the target's path. Because we needed a comparison condition against which we could compare tracking performance in the dual-task block, we created a baseline control RMSE based on how participants would have performed had they not moved the cursor at all throughout the dual-task block. Thus, the control RMSE represents baseline performance had participants failed to perform the task entirely. Assuming participants had performed the tracking task as instructed, actual RMSE should be smaller than control RMSE. Actual RMSE for the dual-task condition (M_{RMSE} = 16.67 ms, 95% BCI = [14.68, 18.69]) was credibly smaller than that of the control condition (M_{RMSE} = 25.70 ms, 95% BCI = [23.71, 27.70]), (M_{Diff} = 9.03 ms, 95% BCI = [6.34, 11.70], d = 1.27), indicating that participants followed instructions to perform the tracking task.

Discussion

Building on from previous findings, the current study investigated task-load effects on workload capacity for distractor-absent displays. Consistent with previous findings using uncluttered distractor-present displays (Morey et al., 2018; Experiment 1 & 2), processing efficiency was extremely limited capacity within both task-load conditions. Taken together, these studies suggest processing capacity for large, uncluttered targets is limited capacity, regardless of distractor presence.

Further consistent with Morey et al.'s (2018b) study, we found no effect of task load on redundant-target processing efficiency. Although mean single-target RTs were shorter under single-task load, this difference did not translate to a difference in processing efficiency between load conditions. In other words, the task-load difference in the speed of individual detections did not correspond with the rate with which multiple targets could be processed at any one time.

This effect contradicts the expectation that concurrent tasks competing for processing resources should interfere with one another (Gopher & Navon, 1980; Navon & Gopher, 1979; Wickens, 2002; Wickens, 2008). What made peripheral visual efficiency robust against dual-task load? We can dismiss two potential explanations that might have seemed *a priori* reasonable. One plausible possibility might be that peripheral target detection, because it involved no distractors, required little or no attention. Contrary to this hypothesis, though, capacity for the peripheral task was decisively limited. Another possibility is that the two tasks tapped into different resource pools, linked to central and peripheral visual fields (Wickens, 2002), allowing them to be performed concurrently without interference. However, this hypothesis falters on the finding that mean single-target RTs were substantially longer in the dual-task condition than in the single-task condition. This result suggests that the tracking and target-detection tasks indeed tapped common resources at some stage of processing.

Alternatively, an attention-switching model may explain attention within the dual-task condition (Wickens & Gopher, 1977). Unlike the single-task, where attention was focused wholly on the targets, in the dual-task condition participants may have shifted attention between both tasks with the on- and offset of targets. The time cost associated with switching between tasks could explain why mean RTs were longer in the dual-task condition than the single-task condition, despite processing efficiency remaining consistent across both conditions. Future studies using similar paradigms may benefit from tracking eye gaze to examine more directly how individuals divide attention between tasks.

Overall, our findings suggest that the divided resource allocation when performing dual visual tasks does not influence processing capacity for visual targets.

Acknowledgements

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CHAPTER 4: STUDY 3

Attentional Capacity

is Constant Across the Visual Field

The following chapter is an unpublished manuscript comprising two experiments examining target location effects on redundant-target processing capacity under load. Thus, here I manipulated both target eccentricity (Experiment 1) and visual field (Experiment 2) to assess whether capacity under dual-task load varies in response to the location of information in the visual field.

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Author Contributions:

All three authors formulated the design of the study. SAM collected the data and wrote the first draft of the manuscript. Both SAM and JSM carried out the data analysis. JSM and NAT provided numerous revisions on the manuscript.

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Abstract

Target detection response times are typically shorter for targets at lower eccentricities than for those at higher eccentricities, and for targets in the lower visual field rather than for the upper visual field. The current experiments asked whether target location might also affect target processing efficiency within a dual-task paradigm. We manipulated the location of visual targets within a combined redundant-target detection/manual tracking task paradigm in two experiments. In Experiment 1, targets appeared intermixed at either high or low eccentricities. In Experiment 2, targets appeared intermixed between the upper and lower visual fields. Workload resilience (Little et al., 2015) provided a measure of redundant-target processing efficiency. In both experiments, processing efficiency was limited capacity (i.e., less efficient than predicted by an unlimited capacity parallel model) but did not vary as a function of target position. Our findings support the notion that redundant-target processing under dual-task load is generally inefficient, but robust against changes to target location within the visual field.

Attentional Capacity
is Constant Across the Visual Field

What we notice in everyday scenes depends on a range of factors. Highly salient objects or events can attract our attention (Itti & Koch, 2000; Wolfe & Horowitz, 2017), and knowledge can guide attention toward particular objects of interest (Theeuwes, 2010). But our focus may also be directed to particular regions within our visual field. Typically, targets at higher retinal eccentricities are detected more slowly, and are more likely to go undetected, than targets further in the retinal periphery (Carrasco & Yeshurun, 1998; Carrasco, Evert, Chang, & Katz, 1995; Carrasco, McLean, Katz, & Frieder, 1998; Nikolic, Orr, & Sarter, 2004; Wolfe et al., 1998). This has been termed the *eccentricity effect* (Carrasco et al., 1995). It is caused, in part, by differences in spatial resolution across the retina (Carrasco & Yeshurun, 1998), but is exacerbated by a tendency to bias our attention towards the central visual field, prioritising items near fixation over more peripheral stimuli (Wolfe et al., 1998).

The eccentricity effect is robust, appearing in tasks such as visual search (Carrasco et al., 1995; Wolfe et al., 1998) and target detection (Nikolic etal., 2004; Steelman, McCarley, & Wickens, 2013), through to driving (Crundall, Underwood, & Chapman, 1999; Recarte & Nunes, 2003) and pilot flight-deck tasks (Wickens, Muthard, Alexander, Van Olffen, & Podczerwinski, 2003; Wickens, Sebok, McCormick, & Walters, 2016; Williams, 1995). Critically, the costs of eccentricity might become even stronger under dual-task load, an effect known as *cognitive tunnelling* (Williams, 1985). Dividing attention between multiple visual tasks has been argued to narrow attention towards the centre of the display (Williams, 1985, 1995), reducing the size of the observer’s effective visual field (Rantanen & Goldberg, 1999) and compromising detection of peripheral targets (Ikeda & Takeuchi, 1975; Leibowitz & Appelle, 1969; Reimer, 2010).

Surprisingly, neither cognitive tunnelling nor eccentricity losses have been demonstrated in measures of *target processing efficiency*. In other words, it remains unclear what effect target eccentricity, when combined with a demanding central task, has on the efficiency of a cognitive system to process multiple visual items concurrently (Houpt & Townsend, 2012; Wenger & Townsend, 2000). Recent findings indicate a central loading task does not affect processing efficiency for peripheral redundant visual targets (Morey et al., 2018a; 2018b). Morey et al. (2018a; 2018b) measured processing efficiency for redundant visual targets appearing in the upper periphery of a visual display while participants performed a manual tracking task in the display centre. Average processing efficiency was limited capacity. More interestingly, in neither studies did processing efficiency vary in response to changes in task load. However, Morey et al.'s studies only used stimuli appearing at one level of visual eccentricity. Thus, any potential tunnelling effect would not have been detected.

Moreover, some evidence from a single-task target identification paradigm has hinted at processing efficiency benefits associated with increasing eccentricity (Yamani, McCarley, & Kramer, 2015). Yamani et al. (2015) measured processing efficiency for redundant visual targets appearing on the vertical midline, at equal distances above and below fixation. In contrast to a typical eccentricity effect, processing efficiency for redundant visual targets increased as a function of eccentricity. Thus, higher eccentricity target pairs were processed more efficiently than lower eccentricity target pairs.

In the current study, we tested for an effect of target eccentricity on target processing efficiency consistent with a standard eccentricity effect in response time data: that low eccentricity targets should be processed faster than high eccentricity targets (Carrasco et al., 1995; Wolfe et al., 1998). To amplify any effect of eccentricity and to simulate a situation where a cognitive system is overloaded with a concurrent cognitive task, we included a visuo-manual tracking task within the target-detection paradigm.

An effective method for measuring processing efficiency is the redundant-targets paradigm (Todd, 1912; Townsend & Ashby, 1983). On each trial, an item appears on one or both of two potential stimulus channels. Each item can be either a target or distractor. The participant is asked to make a speeded response if either of the two items is a target, but to withhold if both items are known distractors. For example, a participant may be asked to respond if at least one of two items presented within a display is a puppy (i.e., target), but to withhold if both items are kittens (i.e., distractors). This type of paradigm is described as using a *first-terminating stopping rule* because a response can be made the moment a prescribed target is first detected on either channel, regardless of the presence of information on other channels (Colonius & Vorberg, 1994). Typically, when two or more targets with same meaning are presented simultaneously, response times (RTs) are faster than when a single target is presented alone (Miller, 1982). This phenomenon is known as a *redundant signals effect* (RSE) or *redundancy gain* (Miller, 1982; Todd, 1912).

The magnitude of the redundancy gain depends on a constellation of factors. The first is the cognitive system's *workload capacity*. Here, *workload* represents the number of items to be processed, and *capacity* is the efficiency with which the channels operate as workload increases (Townsend & Eidels, 2011; Townsend & Nozawa, 1995). The second factor that can affect the size of the RSE is the cognitive system's *architecture*, or arrangement of processing channels (Townsend & Eidels, 2011; Townsend & Nozawa, 1995). Architecture can be either a serial, parallel, or co-active process. Finally, the RSE may also vary in response to the *stochastic independence* or *dependence* of channels, which refers to the statistical relationships between channels (Townsend & Wenger, 2004a). If a system operates with complete stochastic independence, the finishing times for different channels on a single trial are uncorrelated.

The simplest account of the redundancy gain is the *unlimited capacity independent parallel* (*UCIP*) model (Townsend & Eidels, 2011). In this model, channels operate simultaneously and with stochastic independence, and the processing rates of the individual channels remain constant regardless of the number of channels operating at any time. A UCIP model under a first-terminating stopping rule produces a redundancy gain because the processing time of the system as a whole is based on the RT of the first channel to finish processing (Raab, 1962). This effect is known as *statistical facilitation* (Raab, 1962). A system that produces redundancy gains larger than expected from the UCIP model—because of inverse dependencies between channels, or because an increase in workload produces a speed-up in channel processing (Townsend & Wenger, 2004a)—is said to operate with *super-capacity*. Thus, added workload facilitates target processing. Alternatively, an increase in workload may produce gains smaller than expected from the UCIP model, either because of dependencies between channels or because processing rates decline as workload increases (Townsend & Wenger, 2004a). In this case, the system is said to operate with *limited capacity*.

Using the UCIP model as a basis for standard parallel processing, Miller (1982) identified an upper bound on UCIP performance. Known as the *race model inequality*, this bound stipulates that, within the UCIP model, the cumulative distribution function (CDF) of the redundant-target condition cannot be greater than the combined CDFs of the two single-target conditions. Violations of the race model inequality provide evidence for a super-capacity model. In a similar fashion, Grice, Canham, and Gwynne (1984) identified a lower bound on UCIP performance that implies a limited-capacity model. However, both bounds provide conservative estimates of processing efficiency, and provide no way of discriminating between moderate deviations from unlimited capacity. A statistic known as the *capacity coefficient* (Townsend & Eidels, 2011; Townsend & Nozawa, 1995) provides a more fine-grained measure, quantifying variations of redundant-target processing efficiency between and beyond the Miller and Grice bounds.

The concept of workload capacity refers to processing efficiency for redundant-target trials as measured against single-target trials where the second potential target location is left empty, that is, does not contain a distractor. The presence of a distractor on a single-target trial tends to interfere with target processing, slowing responses (Ben-David et al., 2014; Little et al., 2015). Thus, redundancy gains tend to be larger when using distractor-present trials as the single-target baselines are greater than when using distractor-absent trials. A measure of processing efficiency related to the capacity coefficient, known as *workload resilience*, $R(t)$ assesses processing efficiency taking into account the costs of single-target distractors (Little et al., 2015). $R(t)$ can be converted to a normalised version of resilience, denoted Rz (Houpt & Little, 2017). Rz scores represent normalised measures of $R(t)$ for all time points of t, inversely weighted depending on the variability of $R(t)$ at each time point. Positive values of Rz indicate super-capacity processing, a value of zero indicates unlimited capacity, and negative values indicate limited capacity. Here, we used Rz to measure target processing efficiency.

The current experiment examined whether redundant-target processing resilience decreases as a function of eccentricity. Using a similar paradigm to Morey et al. (2018a, 2018b), we assessed target processing resilience at two levels of eccentricity. As reaction times are faster and more accurate for targets closer to fixation (e.g., Carrasco et al., 1995, 1998; Wolfe et al., 1998), we expected processing efficiency to be greater for targets appearing closer to fixation than for those at higher eccentricities. Moreover, as eccentricity effects amplify under conditions of additional central load (e.g., Williams, 1985, 1995), including a secondary tracking task should enhance differences in capacity between task loads. As such, we included a central loading task in the paradigm that ensured participants primarily fixated the screen centre. Thus, in Experiment 1, participants carried out a redundant-targets task with targets intermixed between low and high eccentricity locations, while also performing a concurrent joystick tracking task.

Experiment 1

The current experiment was preregistered online on the Open Science Framework: https://osf.io/bm87v/register/5771ca429ad5a1020de2872e.

Method

Participants. Our preregistration stated that we would collect data until we had 30 participants who met the inclusion criteria. We recruited 33 Flinders University undergraduate students (18 female; *M* = 23.62 years, *SD* = 10.66, *Range* = 17 – 73 years) to achieve this goal. All participants were compensated with course credit. Eligibility requirements were normal or corrected-to-normal visual acuity, normal colour vision, and English fluency. Data for two participants, one who failed the visual acuity test and one who left the study early, were immediately excluded. All participants were screened for right-hand dominance, defined as a minimum Flinders Handedness Survey (FLANDERS; Nicholls et al., 2013) score of +5 (*M* = +9.84, *SD* = 0.09). Twenty-seven participants held a current, valid driver's licence, with the mean years of driving experience being 6.87 years (*SD* = 10.75, *Range* = 0.5–55 years).

Apparatus and stimuli. Stimuli were presented on a 27" inch Samsung SyncMaster SA950 Full HD 3D LED monitor with a screen resolution of 1920 × 1080 (pixel size = 0.33 mm). The task was presented using Presentation Experiment Software (Neurobehavioral Systems, 2018). Participants sat approximately 600 mm from the monitor, though viewing distance was unconstrained. Inputs from the participant were collected with a Logitech Attack 3 joystick (Logitech, 2018).

Stimuli for the tracking task were a red circular target (subtending 0.95°) and a black cursor "+" (0.76° × 0.76° of visual angle) in size 10 Arial font. The two stimuli moved left to right along a horizontal path, 19.85° in length, centred within the display. A horizontal tracking path was used to ensure fixation remained central within the display, and hence, to maintain the fidelity of the target eccentricities. A combination of three sine waves with frequencies of 0.07, 0.15, and 0.23 Hz (Strayer & Johnston, 2001) determined the red target's movement. To ensure the movement differed during each tracking interval and remained unpredictable to the participant, the three component sinusoids were randomly phase-shifted on each tracking interval. The black cursor could be manoeuvred using the joystick.

Stimuli for the target detection task were black letters "T" and "L", drawn in 16-point Arial font (1.6° × 1.1° of visual angle onscreen). Letters appeared in four combinations: two single-target combinations (TL and LT), a redundant-target combination (TT), and a redundant distractor combination (LL). On each trial, two stimulus letters appeared simultaneously in the upper half of the screen, at polar coordinates of $\theta\pm = 51.50^{o}$ from the vertical midline and with an r of either 11.00° (low eccentricity) or 21.79° (high eccentricity) of visual angle from the screen centre point. Figure 4-1 presents a schematic illustration of the stimulus.

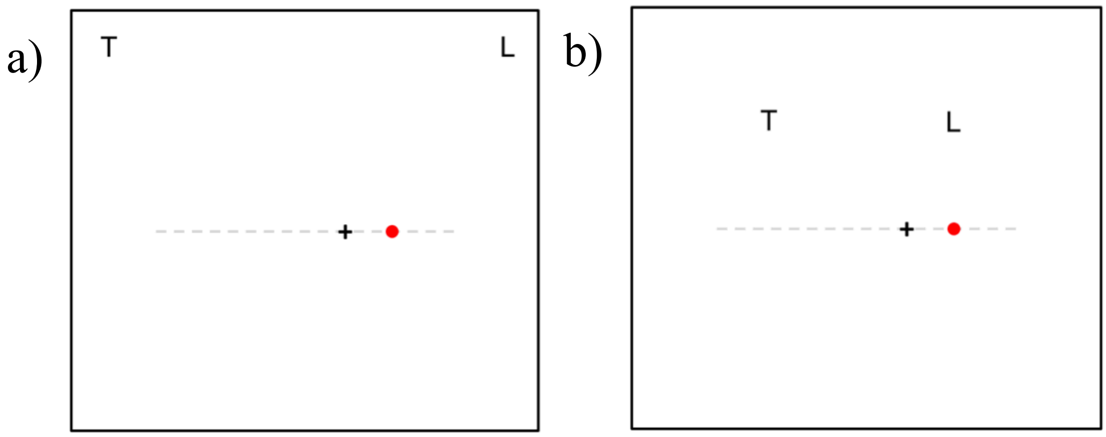

Figure 4-1. On each trial, stimuli appeared at either *a*. a high eccentricity, or *b.* a lower eccentricity, closer to the centre of the screen. Throughout the experiment, participants matched up a black cursor (+) with a red circular target that moved along an invisible horizontal axis (shown here as a grey dashed line).

Procedure. The task was carried out in a small, well-lit room. At the beginning of the testing session, participants were seated in front of the monitor with the joystick on the table in front of them. After providing informed consent, participants were provided with instructions for the tasks, then completed a 60-second practice interval to familiarise themselves with the procedure.

Participants were instructed to hold the joystick with both hands, with thumbs resting on the two buttons atop the joystick. The tracking task required participants to align the black cursor with the moving red target, manoeuvring the joystick back and forth to control the cursor. To encourage engagement with the task, participants were asked to imagine they were driving to their university and were required to use the joystick to direct their vehicle along a route designated by a navigation system (the red target). The participants' goal was to keep the cursor as closely aligned with the moving target as possible.

The target detection task required participants to respond to target letters that appeared in the display periphery. The letter T was designated as the target, and L as the distractor. In line with the driving scenario mentioned above, we explained that the stimuli represented traffic signals. Participants were told the onset of any T required them to issue a brake response as quickly as possible by depressing the left and right buttons on top of the joystick with both thumbs at the same time. Bimanual responses were requested in order to minimise stimulus-response compatibility effects (e.g., Simon, 1969) and lateral attentional asymmetries related to response activation. Participants were instructed that Ls, on the other hand, represented green lights and therefore required no response. Participants were told to respond if either or both stimuli were targets, and to withhold a response only if both stimuli were distractors. They were also asked to aim for speed, whilst maintaining accuracy.

To allow for both strategic effects as well as inherent biases in attention, in the current experiment low and high eccentricity trials were randomly intermixed throughout each tracking interval. Any effect could then later be tested using a blocked paradigm to rule out the effects being due to strategic influences. Peripheral stimuli occurred at inter-trial intervals drawn from a delayed exponential distribution with a fixed delay component of 1 second and an exponential component with a mean of 2 seconds. The delayed exponential distribution ensured that the time delay between one stimulus' offset and the next one's onset was no less than 1 second but was otherwise unpredictable to participants. Stimuli offsets were triggered by a button press by the participant, or if no response was made, a timeout of 2 seconds. Approximately 40 stimulus onsets (including both targets and distractors) occurred throughout each 60-second interval.

Participants were asked to perform the tasks concurrently and were not asked to prioritise one task over the other. Following a practice interval of 60 seconds, each participant completed 20 60-second experimental intervals. After each interval, participants were allowed a short break. After completing the experiment, participants were debriefed and thanked for their time. The entire process took approximately 45 minutes.

Statistical analyses. We used the 'sft' (Houpt, Blaha, McIntire, Havig, & Townsend, 2014) package for R (R Core Team, 2016) to calculate standardised resilience scores (*Rz*) for participants at each level of target eccentricity. Tracking error was calculated as the root mean squared error (RMSE) in lateral and vertical position between the moving red target object and the participant's cursor. Thus, a value of 0 indicated perfect tracking and larger values represented poorer performance. Tracking error was only calculated during periods in which targets were not present on screen to rule out any effect of the targets diverting attention away from the tracking task.

We then analysed RTs, *Rz*, and tracking error using Bayesian parameter estimation through Markov chain Monte Carlo (MCMC) sampling (Kruschke, 2013, 2015; Lee & Wagenmakers, 2013). This process begins with a prior distribution on a parameter of interest, then uses a probabilistic sampling method to update parameter estimates based on the observed data, producing an estimated posterior distribution of parameter values (Kruschke, 2015). Parameter estimation was carried out using the R package, ‘JAGS’ (Plummer, 2015). As in Morey et al. (2018a, 2018b), we employed a one-way within-subjects design. We included the additive effects of target condition (single target 1, single target 2, redundant targets) and participant, as well as the additive effects of eccentricity and the target condition by eccentricity interaction. We assumed a normal likelihood distribution, and used vague priors on all parameters to avoid committing the data a priori to any strong conclusion:

$Y_{\text{participant, eccentricity, condition}} \sim N(a0 + a_{\text{participant}} + a_{\text{eccentricity}} + a_{\text{condition}} + a_{\text{eccentricity} \times \text{condition}}, \sigma_y^2)$

$a_{\text{participant}} \sim N(0, \sigma_{\text{participant}}^2)$

$a_{\text{eccentricity}} \sim N(0, \sigma_{\text{eccentricity}})$

$a_{\text{condition}} \sim N(0, \sigma_{\text{condition}}^2)$

$a_{\text{eccentricity} \times \text{condition}} \sim N(0, \sigma_{\text{eccentricity} \times \text{condition}}^2)$

$\sigma_{\text{participant}}, \sigma_{\text{eccentricity}}, \sigma_{\text{condition}}, \sigma_{\text{eccentricity} \times \text{condition}} \sim \Gamma\ (\alpha, \beta)$

$\alpha = SD/2$

$\beta = 2 * SD$

Deflections from the grand mean were constrained to sum to zero for each of the effects of eccentricity, target condition, and their interaction. Likewise, analysis of RTs, *Rz* and RMSE for the tracking task included eccentricity as an effect,

$Y_{\text{participant, eccentricity}} \sim N(a0 + a_{\text{participant}} + a_{\text{eccentricity}}, \sigma_y^2)$

$\sigma_y \sim U(SD/1000, SD*1000)$

$a0 \sim N(M, [100 \times SD]^2)$

$a_{\text{participant}} \sim N(0, \sigma_{\text{participant}}^2)$

$a_{\text{eccentricity}} \sim N(0, \sigma_{\text{eccentricity}})$

$\sigma_{\text{participant}}, \sigma_{\text{eccentricity}} \sim \Gamma\ (\alpha, \beta)$

$\alpha = SD/2$

$\beta = 2 * SD,$

with the deflections from the grand mean for the effect of eccentricity constrained to sum to zero across conditions.

Results

Error rates. Prior to the main analyses, we calculated error rates to ensure that participants performed the target detection as instructed. The capacity coefficient is considered robust against error rates up to 0.30 (Townsend & Wenger, 2004a). Hence, participants who exceeded this value were removed from analyses. These exclusions led to the removal of data from one participant who produced excessive left- (0.98) and right- (0.98) target miss rates. This left data from 30 participants for analysis. For the remaining participants, false alarm rates were low-to-moderate (M = 0.10, *Range* = 0.00 – 0.23 and M = 0.10, *Range* = 0.00 – 0.27 for low and high eccentricity, respectively). Within each trial condition, miss rates were low, and participants correctly responded to approximately 73 targets within each trial condition, confirming that the variance of Rz scores was comparable across conditions (see Appendix B for details). The total proportion of correct trials was approximately equal in both the low (M = 0.96, *Range* = 0.80 – greater than 0.99) and high (M = 0.96, *Range* = 0.80 – 1.00) eccentricity conditions.

RTs. False-positive RTs were excluded from analysis. After preliminary inspection of the data suggested that participants had correctly responded to target-present trials bimanually, we examined RT data using the faster of the two button-press responses for each target trial.

There was no difference between RTs for left and right single-target trials in either the low eccentricity condition (left target: M = 594 ms, 95% BCI = [559, 630]; right target: M = 603 ms, 95% BCI = [564, 636], left minus right difference: M_{Diff} = -5 ms, 95% BCI = [-21, 10], d = 0.12), or the high eccentricity condition (left target: M = 624 ms, 95% BCI = [588, 660]; right target: *M* = 630 ms, 95% BCI = [594, 666]), (M_{Diff} = -7 ms, 95% BCI = [-22, 9], *d* = 0.14). To provide a measure of baseline response speed for single targets, we calculated the mean single-target RT. Figure 4-2 shows estimated mean single-target RTs, collapsed across left and right locations. Data showed a clear effect of eccentricity, with shorter RTs for low eccentricity targets (*M* = 598 ms, 95% BCI = [562, 633]) than for high eccentricity targets (*M* = 627 ms, 95% BCI = [592, 662]), (M_{Diff} = -30 ms, 95% BCI = [-41, -18], *d* = 0.85). In Figure 4-2, error bars for the difference score (star) do not cross zero, indicating a credible effect of eccentricity on mean single-target RTs.

To measure redundancy gain, RTs for the redundant-target condition were subtracted from the faster of the two single-target conditions (i.e., left and right single-target conditions). This method produces a more conservative measure of redundancy gain than simply comparing the mean of the two single-target conditions with the redundant-target condition (cf. Biederman & Checkosky, 1970). Figure 4-3 shows estimated mean redundancy gains. Comparisons between the fastest single-target trials and redundant-target trials found evidence of small redundancy gains at both low (M_{RSE} = 15 ms, 95% BCI = [1, 28]) and high (M_{RSE} = 17 ms, 95% BCI = [3, 31]) target eccentricities. Redundancy gains did not vary as a function of eccentricity, (M_{Diff} = -2 ms, 95% BCI = [-21, 15], *d* = 0.07).

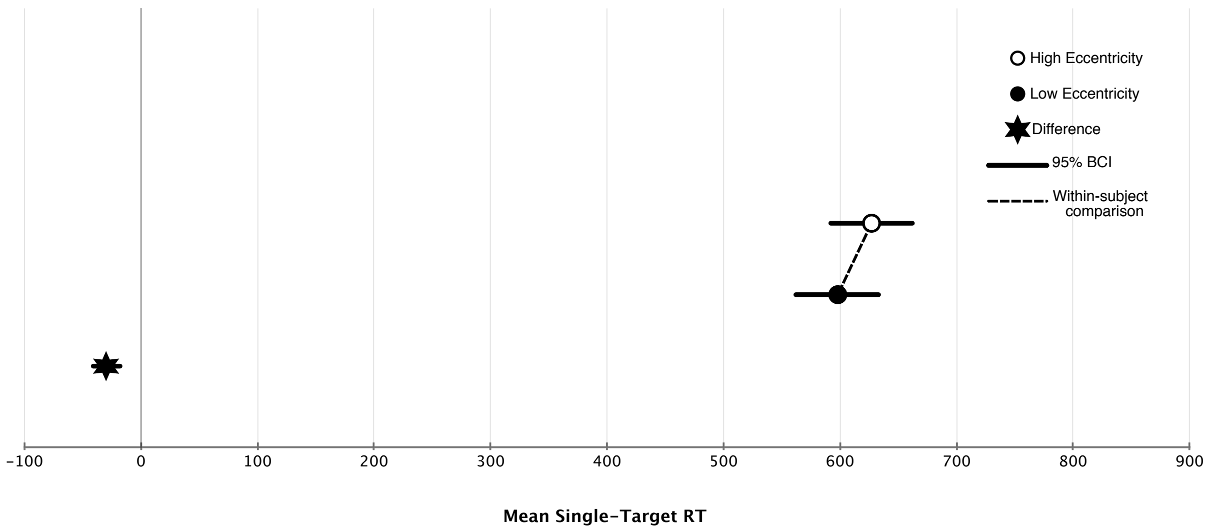

Figure 4-2. Mean single-target RTs and difference scores (low – high eccentricity) for each level of eccentricity. Error bars are 95% BCIs.

Figure 4-3. Mean redundancy gains and difference score (low – high eccentricity), along with corresponding 95% BCIs, for both levels of eccentricity.

Resilience. Figure 4-4 presents estimated mean *Rz* scores. Resilience was decisively limited in both the low eccentricity (M_{Rz} = -3.22, 95% BCI = [-3.82, -2.64]) and high eccentricity (M_{Rz} = -3.01, 95% BCI = [-3.59, -2.42]) conditions. More interestingly, resilience scores did not differ credibly between the two levels of eccentricity, (M_{Diff} = -0.22, 95% BCI = [-0.93, 0.43], d = 0.14). Thus, contrary to predictions, presenting targets closer to fixation did not engender greater processing efficiency.

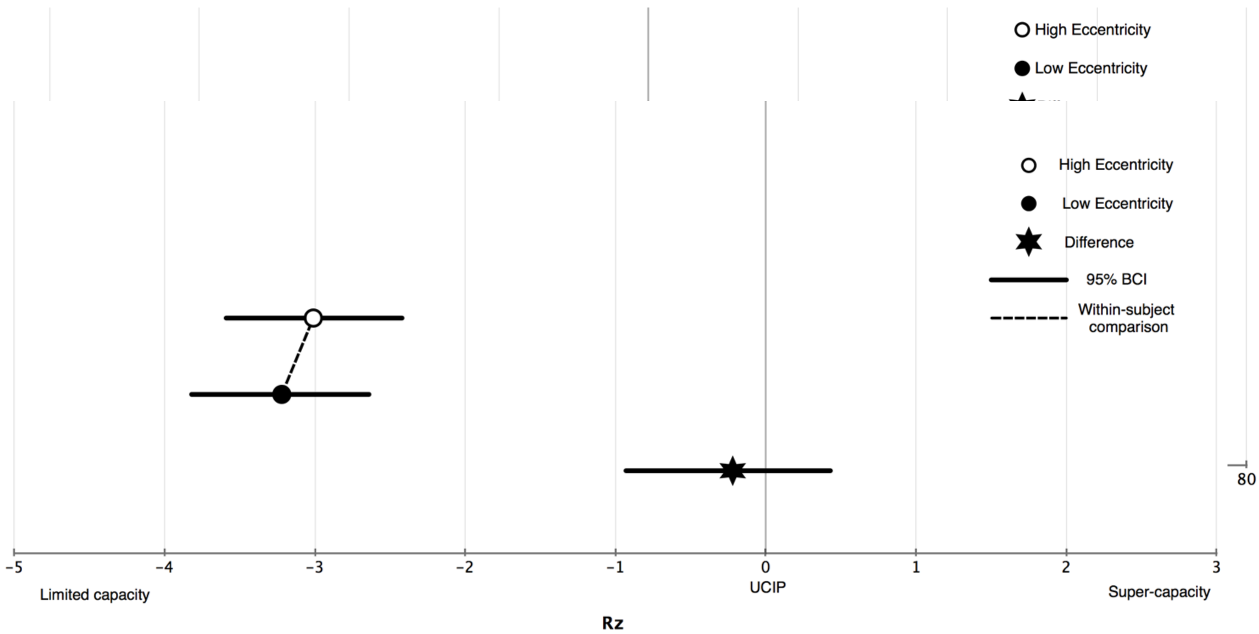

Figure 4-4. Mean *Rz* and difference score (low – high eccentricity) for the target-detection task for each level of eccentricity. Error bars are 95% BCIs.

Tracking Performance. We measured tracking performance to ensure participants had performed the central loading task as instructed. As high and low eccentricity stimuli appeared intermixed during the task, we calculated an overall RMSE for the duration of the testing session. To provide a way of assessing whether participants had successfully performed the task, we compared participants' true RMSE with a control RMSE calculated under the assumption that participants had left the cursor in the starting position throughout the entire task. To keep the method consistent with the true RMSE, the control RMSE was only calculated based on moments when targets were not present. Results suggested participants had successfully followed instructions, as the true RMSE (M_{RMSE} = 16.29º, 95% BCI = [14.40, 18.18]) was credibly smaller than the control RMSE (M_{RMSE} = 25.71º, 95% BCI = [23.82, 27.58]), M_{Diff} = 9.42º, 95% BCI = [6.88, 11.96], d = 1.35. To test whether a trade-off in performance occurred between the tracking and detection tasks, *Rz* scores were correlated with RMSE. Given that higher scores on the tracking task represent poorer performance, a positive correlation between the two tasks indicates that higher performance on one task was associated with poorer performance on the other task (i.e., a dual-task trade-off). Our analyses gave no credible evidence of a correlation, $r(28) = -0.14$, 95% BCI = [-0.40, 0.12], suggesting that participants did not trade off performance on one task against the other.

Discussion

Our aim for the current study was to test whether target processing under dual-task load is greater for targets that appear closer to fixation. By loading participants with a concurrent tracking task, we aimed to drive attention towards the centre of the display, increasing any eccentricity effect. Contrary to predictions, we found no evidence in support of a difference in processing resilience based on eccentricity. Rather, processing resilience was equally limited in both eccentricity conditions. Thus, despite including a concurrent central tracking task aimed at narrowing the visual field and driving attention towards the centre of the screen, target processing resilience was no more efficient for targets low in eccentricity than for target high in eccentricity. As with previous research (e.g., Carrasco et al., 1995; Carrasco & Yeshurun, 1998; Williams, 1985; Wolfe et al., 1998), we found an eccentricity effect on raw RTs, with mean single-target RTs approximately 30 ms faster for targets low in eccentricity than for those high in eccentricity. However, this effect did not translate to a difference in redundancy gains, and more importantly, did not affect redundant-target processing resilience.

Experiment 2

In Experiment 1, the eccentricity manipulation was unsuccessful at influencing target processing efficiency. However, stimuli only ever appeared within the upper regions of the screen in Experiment 1. Visual search is also influenced by changes in visual field location, with biases existing between stimuli appearing in upper visual field (UVF) and the lower visual field (LVF) (Levine & McAnany, 2005; Qu, Song, & Ding, 2006; Skrandies, 1987; Thomas & Elias, 2011). Although we found no effect of target eccentricity in Experiment 1, a difference in processing efficiency could depend on whether targets appear in the UVF or LVF.

Processing differences between upper and lower visual field stimuli are dependent on context and task type. A wide range of perceptual tasks show processing differences between the UVF and LVF, from word recognition (Mishkin & Forgays, 1952), to visually guided pointing tasks (Danckert & Goodale, 2001). The UVF is associated with faster visual search performance (Fecteau, Enns, & Kingstone, 2000), as well as better spatial resolution (Talgar & Carrasco, 2002), depth discrimination (Levine & McAnany, 2005), and greater performance on higher-level perceptual processing tasks, such as categorising the sex of human faces (Quek & Finkbeiner, 2014a) or hands (Quek & Finkbeiner, 2014b). The LVF, on the other hand, is associated with better contrast sensitivity (Skrandies, 1987), hue discrimination (Levine & McAnany, 2005), distractor-present target detection (Rezec & Dobkins, 2004), and processing of basic perceptual shapes, such as illusory contours (Rubin, Nakayama, & Shapley, 1996).

Functional differences between the LVF and UVF are explained by differences in visual cortical networks (Previc, 1990). Information in the UVF is predominantly processed via the ventral visual pathway (in conjunction with the parvocellular pathway). The ventral pathway is responsible for local processing and assists with object identification and processes information in extrapersonal space. In contrast, information in the LVF passes through the dorsal visual pathway (in conjunction with the magnocellular pathway). The dorsal pathway is responsible for global processing, focuses on coordinating spatial or motion information, and is biased toward peripersonal space (Milner & Goodale, 2008; Previc, 1990; Thomas & Elias, 2011). Unlike the ventral stream, which is associated with slower RTs, the dorsal stream has a temporal processing advantage (Nieuwenhuis, Jepma, Fors, & Olivers, 2008).

Target detection is generally better for stimuli in the LVF over those in the UVF, both in terms of response time and accuracy (Intriligator & Cavanagh, 2001; Rezec & Dobkins, 2004). One explanation for superior performance on visual search and tracking tasks in the LVF is that attentional resolution is greater in the lower field (He, Cavanagh, & Intriligator, 1996). Alternatively, detection advantages for LVF targets accompanied by distractors could reflect an uneven 'attentional weighting' across the visual field, which biases information in the LVF over information in the UVF (Rezec & Dobkins, 2004).

The asymmetry in visual processing between the upper and lower visual fields could affect the efficiency of peripheral visual target processing. Faster and more accurate target processing in the LVF could imply more efficient processing of multiple concurrent targets than within the UVF. As mentioned above, the dorsal stream is linked to information processing in the LVF and is associated with faster temporal processing (Nieuwenhuis et al., 2008). Thus, a logical extension is that processing efficiency for visual stimuli should be greater in the LVF compared to the UVF. Consequently, we would expect higher values of processing resilience (*Rz*) for targets in the LVF than in the UVF.

In Experiment 2 we assessed whether processing capacity is greater for targets in the LVF than the UVF under dual-task load. Our methodology was identical to Experiment 1, with the exception that we intermixed high eccentricity targets between the UVF and the

LVF. To keep the design directly comparable to Experiment 1, participants performed the central visuo-manual tracking task while performing the redundant-targets task.

Method

Participants. As in Experiment 1, we aimed to collect 30 participants who passed the eligibility criteria and successfully completed the experiment. We tested 37 undergraduate students (30 female; $M = 21.59$ years, $SD = 5.44$ years, *Range* 18 – 50) in exchange for payment (AU$10). No participants had taken part in Experiment 1. Right-hand dominant participants, with a mean FLANDERS score (Nicholls et al., 2013) of +9.72 ($SD = 0.78$), were maintained for data analysis; one participant was removed. In addition, all participants had normal or corrected-to-normal visual acuity, normal colour vision, and were fluent in English. Twenty-eight participants held current, valid driver's licences, with the number of years of driving experience ranging from less than 1 to 34 years ($M = 4.10$, $SD = 6.04$).

Apparatus and stimuli. The same experimental setup and apparatus used in Experiment 1 were used in Experiment 2. Stimuli for the tracking task were identical to those of Experiment 1.

Stimuli for the target-detection task were identical to Experiment 1, with letters appearing either in the previous upper locations (UVF trials) or else in the mirror-reversed locations within the lower half of the screen (LVF trials). Here, letters appeared at polar coordinates $\theta\pm = 51.50°$ from the vertical midline (i.e., to the left and right) and $r = 21.79°$ visual angle from the screen centre point, with both targets appearing in the UVF or the LVF (refer to Figure 4-5 below). To allow for both strategic and non-strategic influences on performance, UVF and LVF stimuli were intermixed throughout the task.

Procedure. The procedure was consistent with Experiment 1, except that participants were instructed to respond to targets appearing at high eccentricities in either the UVF or the

LVF. Once again, participants completed a single 60-second practice interval before carrying out the 40 experimental trials. Following completion of the task, participants filled out the FLANDERS questionnaire, recorded their driving experience, and were debriefed. The entire procedure took approximately 45 minutes.

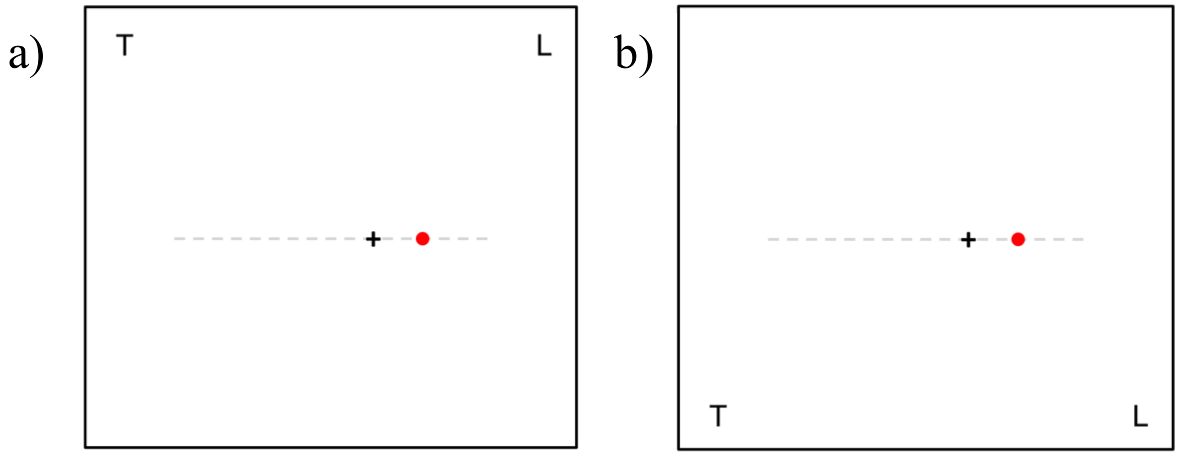

Figure 4-5. In Experiment 2, targets appeared in the high eccentricity locations from Experiment 1; however, on half of the trials, stimuli appeared in the UVF (*a.*), whereas on the other half of trials stimuli appeared in the LVF (*b.*).

Statistical analyses. We employed the same Bayesian parameter estimation MCMC sampling method as in Experiment 1, but replaced the effect of eccentricity with the effect of visual field.

Results

Error rates. Five participants were removed from analyses for excessive false-go (e.g., 0.58) rates, leaving data for 31 participants for the main analyses (UVF: $M = 0.09$, *Range* = 0.00 – 0.20; LVF: $M = 0.08$, *Range* = 0.00 – 0.19). Miss rates were low in all conditions for both UVF and LVF trials; Appendix C shows in detail miss rates and the number of targets correctly detected in each trial condition. The number of targets correctly detected did not differ greatly between conditions, and hence, the variance of *Rz* was similar between the UVF and LVF. The proportion of overall correct responses was high for both UVF (*M* = 0.95, *Range* = 0.81 – greater than 0.99) and LVF (*M* = 0.96, *Range* = 0.88 – greater than 0.99) targets.

RTs. Single-target RTs did not differ between left and right locations for either the UVF (left: *M* = 632 ms, 95% BCI = [590, 673]; right: *M* = 638 ms, 95% BCI = [597, 680]; M_{Diff} = -7 ms, 95% BCI = [-22, 9], *d* = 0.15) or the LVF trials (left: *M* = 644 ms, 95% BCI = [602, 685]; right: *M* = 649 ms, 95% BCI = [607, 690]; M_{Diff} = -5 ms, 95% BCI = [-21, 12], *d* = 0.07). As shown in Figure 4-6, mean single-target RTs, calculated by averaging the RTs of the two single-target trials, trended toward being faster in the UVF than in the LVF, though the BCI on the RT difference between hemifields just included 0 (UVF trials: *M* = 635 ms, 95% BCI = [595, 676]; LVF trials: *M* = 646 ms, 95% BCI = [606, 687]; M_{Diff} = -11 ms, 95% BCI = [-23, 1], *d* = 0.23).

Data showed similar redundancy gains for UVF trials (*M* = 19 ms, 95% BCI = [4, 33]) and LVF trials (*M* = 16 ms, 95% BCI = [1, 30]), (M_{Diff} = 3 ms, 95% BCI = [-15, 22], *d* = 0.07) (see Figure 4-7 below).

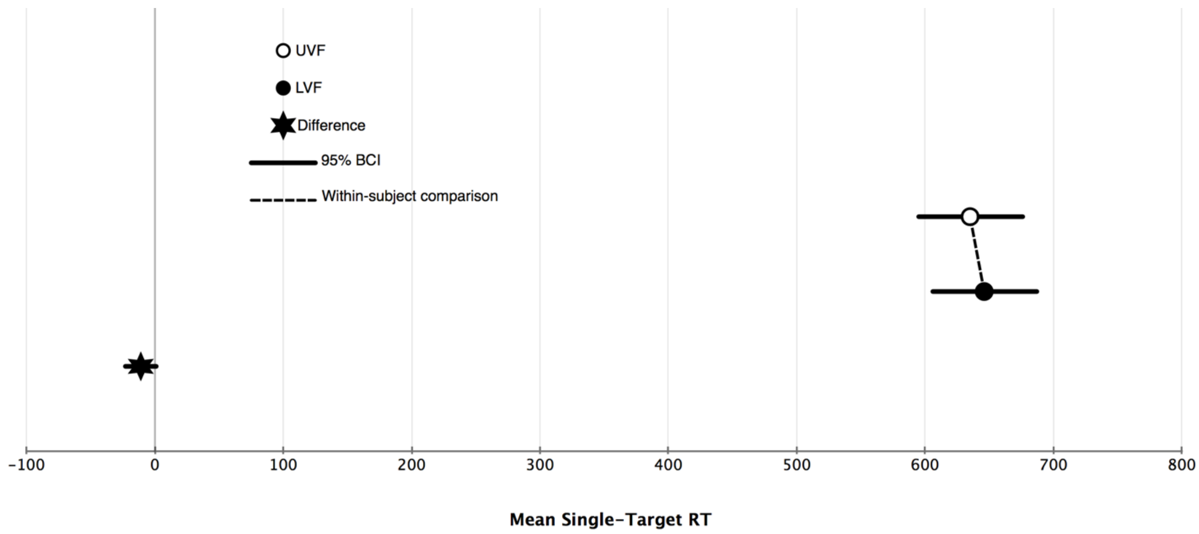

Figure 4-6. Means and difference scores (UVF – LVF) 95% BCIs for single-target RTs (collapsed across left and right locations).

Resilience. Figure 4-8 shows mean *Rz* values and 95% BCIs for both visual fields. *Rz* scores were limited, both for UVF trials (M_{Rz} = -3.04, 95% BCI = [-3.58, -2.52]), and LVF trials (M_{Rz} = -3.11, 95% BCI = [-3.63, -2.60]). Furthermore, there was no credible difference in resilience between the UVF and LVF, (UVF minus LVF difference: M_{Diff} = 0.01, 95% BCI = [-0.58, 0.75], *d* = 0.04).

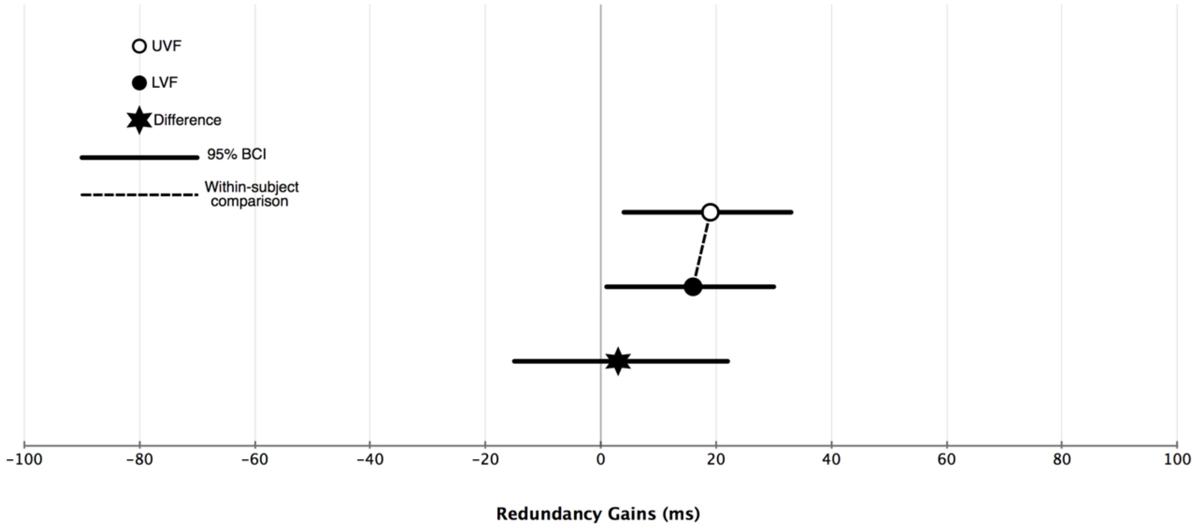

Figure 4-7. Redundancy gains and mean difference score (UVF – LVF) (and corresponding 95% BCIs) for UVF and LVF targets.

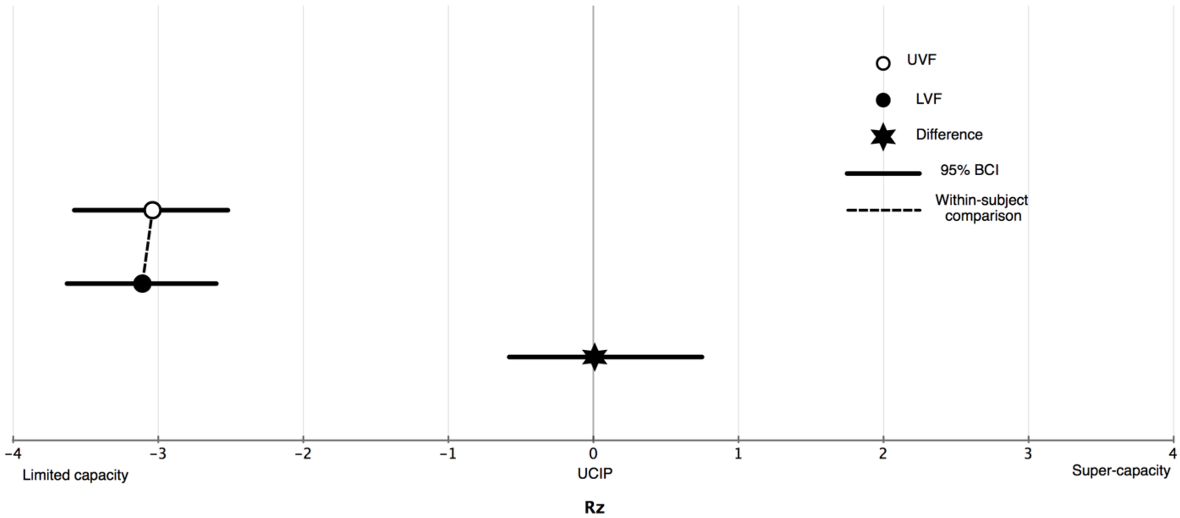

Figure 4-8. Mean *Rz* and difference (UVF – LVF) scores by visual field. Error bars are 95% BCIs.

Tracking Performance. As in Experiment 1, we compared observed RMSE in the tracking task with a control RMSE value that assumed the cursor had not been moved at all throughout the task. Observed RMSE (M = 16.27°, 95% BCI = [15.16, 17.38]) was credibly smaller than the control RMSE (M = 25.68°, 95% BCI = [24.55, 26.81]), (M_{Diff} = 9.41°, 95% BCI = [7.93, 10.90], d = 2.26), indicating that participants performed the central tracking task as instructed. Correlating true RMSE with overall *Rz* found no evidence of a trade-off in performance between the two tasks, $r(29) = .04$, 95% BCI = [-.22, .30].

Discussion

Experiment 2 tested whether workload resilience for peripheral visual targets varies as a function of visual field. Specifically, we had predicted faster RTs, and hence, more efficient redundant-target processing, for targets appearing in the LVF than the UVF. For mean RTs, we found a trend toward faster detections for targets appearing in the UVF than in the LVF. Critically, despite a small difference in RTs between the two visual fields, we found no credible difference in processing resilience as a function of visual field.

General Discussion

A target's distance from fixation (e.g., Carrasco et al., 1995, 1998; Wolfe et al., 1998) and its location within either the upper or lower visual field (e.g., Intriligator & Cavanagh, 2001; Levine & McAnany, 2005; Rezec & Dobkins, 2004), can influence detection. Based on these findings, we tested whether eccentricity and visual field differences influence redundant-target processing efficiency while under load from a secondary central tracking task. Overall, we found little evidence to suggest that a target's location within the visual field directly affects processing efficiency under load. Across all conditions, processing resilience was limited, providing evidence for inefficient processing of multiple targets.

In Experiment 1, we found no evidence to support an effect of eccentricity on processing resilience. Despite a 30 ms advantage for low eccentricity targets, redundancy gains and resilience scores between high and low eccentricity targets did not differ credibly. One explanation for finding no effect of eccentricity relates to the spatial separation between targets. Previous findings suggest that attended items very near one another in the visual field compete for perceptual resources, producing mutual interference that gets smaller as the separation between targets increases (McCarley, Yamani, Kramer, & Mounts, 2012; Yamani et al., 2013). This introduces the risk that gains in efficiency at smaller eccentricities may have been offset by interference produced when targets moved nearer one another. However, this seems an unlikely explanation for the current findings, as spatial attentional interference tends to be modest when displays are uncluttered (Yamani et al., 2013) and when attended items are in different lateral hemifields (Mounts & Gavett, 2004). Here, targets appeared in the left and right visual fields even when they were at the smaller eccentricity, and displays included no clutter beyond the moving target and cursor. Spatial attentional interference between the targets is therefore likely to have been weak at best.

The absence of display clutter may also explain why capacity did not increase with eccentricity, as reported by Yamani et al. (2015). In that study, processing efficiency increased as redundant targets moved farther from the centre of the visual field, in directions along the vertical midline. However, when displays were uncluttered, this effect was only evident for older adults; younger adults showed no change in capacity with increases in eccentricity unless displays were cluttered. Given that the displays in the current study were uncluttered and our participant sample primarily comprised young adults, potential benefits to processing efficiency at large eccentricities may have been small. Further experiments exploring this relationship may clarify the interactions of clutter, target discriminability, and target eccentricity that modulate processing efficiency, and may delineate the boundary conditions under which capacity and resilience remain robust across the visual field.

In addition to finding no effect of target eccentricity, we also found no evidence for an effect of upper versus lower visual hemifield on resilience. Processing in both the UVF and the LVF, despite a trend toward shorter RTs in the UVF, was limited capacity. Thus, together, these two experiments find consistent evidence that redundant-target processing across the visual field is, by and large, limited capacity, and is not affected by a target’s position in space. Our findings corroborate recent research showing that large targets appearing on uncluttered backgrounds are processed in parallel, even under the load of a visuo-manual loading task (Morey et al., 2018a, 2018b), with below-UCIP processing.

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CHAPTER 5: STUDY 4

Benefits of the 'Pop-Out' Target:

Salience Attracts Attention under Task Load

The following chapter is an unpublished manuscript of an experiment exploring the relationship between task load and target salience in driving processing capacity for single visual targets.

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Author Contributions:

SAM and JSM formulated the design of the study. SAM collected the data and wrote the first draft of the manuscript. Both SAM and JSM performed the data analysis. JSM and NAT provided revisions on the manuscript.

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Abstract

Increasing signal salience is a common method for improving target detection in high-stress, multi-operational environments. It remains unclear, however, whether dividing attention between concurrent tasks reduces an operator's ability to detect a high salience target. Thus, the current experiment tested whether performing a concurrent tracking task reduces the benefit of salience on a target-detection task. Thirty-four participants performed a combined target-detection/manual tracking dual-task paradigm. Targets were either high in salience (highly discriminable from non-targets) or low in salience (poorly discriminable from non-targets). Workload capacity (Blaha & Houpt, n.d.; Townsend & Eidels, 2011) was used to measure target processing efficiency. Despite a trend toward more limited capacity in the dual-task condition, capacity was not credibly affected by task load, and overall, processing was capacity-limited. However, there was a main effect of salience, with higher salience targets engendering more efficient processing than their low salience counterparts. Our findings suggest increasing target salience may be a valuable method for increasing processing of critical signals or events within both single-task, full-attention contexts, as well as within dual-task, divided-attention environments.

Benefits of the 'Pop-Out' Target:

Salience Captures Attention under Task Load

On a quiet Friday night, an air traffic controller works in the control room of a small city airport. Every so often, the controller coordinates with local radar centres and informs ground control of upcoming departures, while intermittently updating awaiting aircrafts of route clearances before taxiing. While attention is divided between tasks, a light starts flashing, indicating a possible system error. The alert is highly noticeable, rapidly capturing her attention and allowing the controller to immediately defuse the situation. But, what if it had been a much busier night at the airport, increasing operator task demand in the air traffic control room? Would the benefits of a salient signal be enough to protect against interference from concurrent tasks?

Every day, different factors drive us to notice specific items within our visual environment (Theeuwes, 2010; Wolfe & Horowitz, 2017). *Attention capture* occurs when stimuli attract attention automatically (Most, Scholl, Clifford, & Simons, 2005). Stimulus-driven, bottom-up processing contributes heavily to attention capture (Theeuwes, 1994). Bottom-up processing refers to instances where the physical properties of a stimulus allow it to stand out from its surrounding environment, capturing attention (Itti & Koch, 2000; Nothdurft, 1992; Theeuwes, 1994). Properties of an object, such as its shape, colour, size, or luminance, increase the object's *salience*, or the feature contrast between the object and its background (Itti & Koch, 2000; Parkhurst, Law, & Niebur, 2002; Theeuwes, 1994; Treisman & Gelade, 1980). The greater the difference between competing stimulus properties—in other words, the greater a level of salience—the more likely a property will 'pop-out' and be noticed. Conversely, the more similar a stimulus attribute is to other competing information, the lower the object's salience, and hence, the poorer the search efficiency (Duncan & Humphreys, 1989).

Although much research on attention guidance has been done using highly abstracted laboratory tasks, the value of stimulus salience has also been demonstrated in more naturalistic tasks. For example, pilots are faster and more accurate at detecting changes in a visual surveillance task when the critical information is highlighted (Wickens, Muthard, Alexander, Van Olffen, & Podczerwinski, 2003), and when the contrast between target symbology and background is high (Ververs & Wickens, 1998). Guidelines for visual display design, therefore, recommend manipulations of salience to improve noticeability of critical signals in high-stress operational environments (e.g., Federal Aviation Administration, 2011; General Aviation Manufacturers Association, 2000; Wickens, Sebok, McCormick, & Walters, 2016).

High salience does not guarantee rapid target detection, however. Some data have suggested that purely bottom-up capture is impossible, and that the tendency for salient stimuli to attract attention is contingent on the observer's attentional set for a particular feature (Folk, Remington, & Johnston, 1992). Other work, analogously, has suggested that a salient stimulus can capture attention only if it lies within a window of spatial attention (Belopolsky, Zwaan, Theeuwes, & Kramer, 2007). An easily visible stimulus can therefore be overlooked if an observer's attention is 'tuned' to a different set of visual features (Most et al., 2001; Most et al., 2005; Simons & Chabris, 1999) or is focused on another visual stimulus (Cartwright-Finch & Lavie, 2007; Mack & Rock, 1998). A visual stimulus can also fail to capture awareness if the observer is engaged in a non-visual task (Boot, Brockmole, & Simons, 2005; Fougnie & Marois, 2007; Strayer, Drews, & Johnston, 2003), though in other circumstances, cognitive load can interfere with an observer's ability to suppress attention capture by a salient stimulus (Boot et al., 2005; Lavie & De Fockert, 2005).

The finding that concurrent load modulates attention capture is pertinent to the design of visual workspaces and displays, as operators rarely perform a visual monitoring task in isolation. In many circumstances, rather, they perform several demanding tasks concurrently, including multiple visually-demanding tasks. Studies of visual monitoring have found that some salience benefit is preserved under multi-task load. For instance, Nikolic, Orr, and Sarter (2004) asked participants to detect critical signals in a peripheral visual display while concurrently playing a videogame in a central channel. Data confirmed that peripheral stimuli with high feature contrast were easier to detect than low-contrast stimuli. Similarly, an experiment measuring detection rates for peripheral visual signals in a simulated flight task found that distinctive targets were more readily detected than non-distinctive ones; however, this effect was more pronounced when attention was biased away from the target locations (Steelman et al., 2013).

However, neither Nikolic et al. nor Steelman et al. compared the effects of salience under task-load to those under a single-task baseline condition. Instead, both paradigms focused on the benefits of salience when loaded by a concurrent visuo-manual task. Therefore, it is still unclear whether high salience is equally effective for enhancing detections when attention is directed entirely at the monitoring task and when divided between tasks. Thus, the goal of the current study was to explore whether increased salience assists processing, despite changes to the level of task-load. More specifically, we tested whether dual-tasking reduces the benefits of salience. To address this question, we adopted a paradigm similar to that used in previous studies of processing efficiency under task-load (Morey et al., 2018a, 2018b), pairing a peripheral target detection task in conjunction with a visuo-manual tracking task. By manipulating the salience of target stimuli in this paradigm, we were not only able to measure the effect of salience on response times (RTs), but also the effect of salience on target processing efficiency.

Measuring Processing Efficiency

We assessed whether target salience enhances processing both when a person is performing a detection task alone and when dividing attention with a concurrent visuomotor task. To do this, we measured *workload capacity*, an element of Townsend and Nozawa's (1995) *Systems Factorial Technology* (*SFT*) (Houpt, Blaha, McIntire, Havig, & Townsend, 2013; Houpt, Blaha, Base, & Burns, 2013). Workload capacity refers to the efficiency for processing visual targets as the number of items processing on different channels (i.e., *workload*) increases (Townsend & Eidels, 2011; Townsend & Nozawa, 1995). Thus, the greater a person's workload capacity, the faster that person can process multiple items, and, consequently, identify a target, at any moment in time. For highly cluttered displays containing multiple competing items, a greater processing capacity is required to process all items simultaneously. Although differences in processing capacity may change in response to perceptual and cognitive load (Fitousi & Wenger, 2011), whether salience can protect against task-load interference on workload capacity has not yet been tested.

Workload capacity is calculated using the *capacity coefficient*, $C(t)$, (Townsend & Nozawa, 1995; Townsend & Wenger, 2004a). $C(t)$ provides a measure of a cognitive system's energy throughput expenditure for each moment in time and is calculated by comparing the cumulative hazard functions for targets on different channels. The hazard function $h(t)$ in a speeded response task represents the instantaneous probability that a process will end (i.e., the participant will make a response) at time t, given that the participant has not yet made a response (Townsend & Ashby, 1983). The cumulative hazard function, $H(t)$, is thus the integral of the hazard function up to time t. $C(t)$ compares multiple-channel processing with channel processing for each channel independently. The benchmarks for these predictions stem from the conceptualisation of the standard parallel model, also known as the *unlimited capacity independent processing* (*UCIP*) model. As the name implies, the model carries three critical premises: parallel processing, stochastic independence, and unlimited capacity. The premise of parallel processing stipulates that multiple channels operate concurrently, each with its own evidence accumulator. The premise of stochastic independence stipulates that finishing times for the multiple channels are uncorrelated. Finally, the premise of unlimited capacity stipulates that individual channels operate at the same rate as the total number of channels in operation increases. $C(t)$ gauges the performance of a system relative to the predictions of the UCIP model.

$C(t)$ was originally developed for use with the redundant-target paradigm (Todd, 1912) and was later extended for application to tasks requiring exhaustive processing of multiple stimuli (Townsend & Wenger, 2004a). Recent work has developed a variant of the capacity coefficient for the *single-target self-terminating* (*ST-ST*) visual search task (Blaha, 2011; Blaha & Houpt, n.d.; see also Houpt et al., 2013). In the ST-ST paradigm, a target appears either alone or in the company of n distractors and the observer responds when they detect the target. Hence, the search process ends when the observer detects a target, regardless of the presence of distractors. $C(t)$ is then,

$$C_{\text{ST-ST}}(t) = K_{k,1}(t)/K_{k,n}(t) \tag{5.1}$$

where $K_{k,1}(t)$ is the cumulative reverse hazard function for the condition in which a target is present on channel k and the display contains no distractors, and $K_{k,n}(t)$ is the cumulative reverse hazard function for the condition in which a target is present on channel k and the display contains n distractors. Within an ST-ST model, if the processing rate of the target on channel k is unaffected by the number of n channels also processing, and hence, $K_{k,1}(t) = K_{k,n}(t)$, we find evidence for the UCIP model. Thus, an ST-ST paradigm relies on the prediction that a UCIP model will produce a $C_{\text{ST-ST}}(t) = 1.0$. When processing within an ST-ST system is more efficient than the UCIP (i.e., super-capacity), $C_{\text{ST-ST}}(t) > 1.0$. Finally, when ST-ST processing is poorer than predicted by the UCIP, we find evidence of limited capacity processing and $C_{\text{ST-ST}}(t) < 1.0$.

The *standardized capacity coefficient, Cz*, (Houpt & Townsend, 2012) is a transformation of $C(t)$ that provides a summary measure of processing efficiency, averaged over time. Under the assumption of UCIP processing, *Cz* is distributed with a mean of 0 and standard deviation of 1. Therefore, reliable deviations from 0 imply limited capacity ($Cz < 0$) or super-capacity ($Cz > 0$). The main advantage of using a normalised measure of capacity is that we can compare processing efficiency from different paradigms or experiments, making *Cz* a valuable tool for assessing processing efficiency for two different types of target stimuli. Thus, *Cz* allows us to compare processing for targets that are poorly discriminable from their distractors (i.e., low in salience) with targets that are more highly discriminable from their distractors (i.e., high in salience).

Few studies have examined task-load effects on ST-ST capacity (though, see Fox & Houpt, 2018, for a model of multi-tasking performance); however, recent findings suggest that redundant-target paradigms with peripheral target displays elicit limited capacity processing that is resistant to changes in task load (Morey et al., 2018a, 2018b). Hence, processing efficiency for redundant targets does not appear to change with an increase in task load. Together, these findings suggest redundant-target processing efficiency is highly robust against changes in task load. Critically, the speed-up in responding associated with presenting targets redundantly (i.e., the *redundancy gain*) may simply be too strong to be sensitive to changes in the level of task load. In other words, the benefit from employing redundant targets may be enough to shield against any fluctuations in the person's cognitive capacity resulting from changes in task load. Single-target paradigms, on the other hand, may be more sensitive to increases in task load, as there is no second target to boost processing when loaded by a secondary task. Thus, it is entirely plausible that dual-task effects, though absent from redundant-target paradigms, occur for single-target displays.

Our main aim was to assess processing capacity as a function of task load and target salience, and to determine whether increasing target salience is beneficial to target detections despite changes to the level of task load. More specifically, we predicted that increasing target salience, by enhancing discriminability between targets and distractors, would increase processing efficiency for single peripheral, visual targets. We also expected that increasing salience would improve processing efficiency for both single- and dual-task conditions, but increased salience would produce a greater benefit for the single-task condition.

Method

The current study was preregistered and is currently available online on the Open Science Framework. To access the preregistration information please visit: https://osf.io/278ba/register/5771ca429ad5a1020de2872e.

Participants

As preregistered, we planned to collect data for 30 participants who met the eligibility criteria and completed the experiment successfully. We achieved this *N* after testing a total of 34 participants (26 female; M_{Age} = 20.62, *SD* = 5.57, *Range* = 17 – 48 years). The final sample excluded three participants who failed to follow instructions (e.g., responded to no-go stimuli) and one who experienced a computer error during the experiment. All participants were Flinders University undergraduate students, compensated with either course credit or AU$10. Participants were screened for normal or corrected-to-normal visual acuity and normal colour vision. All participants were fluent in English and had a minimum Flinders Handedness Survey (FLANDERS) (Nicholls et al., 2013) score of +5 (*M* = +9.82, *SD* = 0.72). Twenty-seven of the 34 participants held current valid driver's licences, with driving experience ranging from 0.5 to 32 years (M_{Years} = 3.31, *SD* = 6.14). The study was approved by Flinders University's Social and Behavioural Research Ethics Committee.

Apparatus and Stimuli

Stimuli were presented on a 27" Samsung LED monitor with a screen resolution of 1920 x 1080 pixels, 0.33 mm per pixel, and a screen refresh rate of 100 Hz. We developed the experimental program and stimuli using Presentation software Version 16.5 Build 09.17.13, (Neurobehavioral Systems, 2018). Participants viewed the display from a distance of approximately 60 cm. A Logitech Attack 3 joystick (Logitech, 2018) collected tracking and target detection inputs.

The participants performed a combination target-detection and visuo-manual tracking task similar to that used in earlier studies (Morey et al., 2018a, 2018b). On each trial, either one or two stimulus letters appeared in the upper hemifield of the screen, 13.81° above the horizontal midline and ± 1.53° to the left and/or right of the vertical midline. We presented peripheral letters in close proximity to one another to strengthen the interference between them (Bouma, 1970; Yamani et al., 2013). Stimuli were capital letters in 16-point Arial font, each subtending 1.58° × 1.14° visual angle, and appearing randomly rotated in 90° steps from 0° to 270°. To manipulate target salience, we employed two target letters that differed in their discriminability from the distractor letter, L. The low salience target was a letter T, distinguished from the distractor by the arrangement of constituent features (Wolfe, 1998). The high-salience target was a letter O, distinguished from distractor by curvature, a low-level visual feature (Treisman & Gormican, 1988; Wolfe & Horowitz, 2004). On target-present trials, a target could be either paired with a distractor or presented alone. This produced 11 different trial letter combinations including eight target-present trial types (T_; _T; TL; LT; O_; _O; OL; LO, where the underscores represent the absence of a stimulus) and three target-absent trial types (LL; L_; _L). Salience trials were intermixed throughout each tracking interval to allow for strategic effects of attention.

Values of inter-trial intervals were sampled from a delayed exponential distribution with a fixed delay of 1000 ms and an exponential component with a mean of 1000 ms. Thus, onsets appeared no earlier than 1000 ms after the offset of the previous trial but were unpredictable after that. Stimuli remained onscreen until a joystick button press response from the participant, or until a timeout limit of 2000 ms.

Stimuli for the tracking task were a red circular target (subtending 0.95° of visual angle) and a black cursor (+) in 10-point Arial font (0.76° × 0.76° of visual angle). The target moved along an imaginary semi-circular arc (19.85° in diameter and offset 5.72° below the screen's centre point) that was centred horizontally within the display, and that arched into the upper visual field with its base on the horizontal midline. To ensure the movements of the red circle were unpredictable to the participant, the target followed a path determined by a combination of the sine waves 0.07, 0.15, and 0.23 Hz (Morey et al., 2018a, 2018b; Strayer & Johnston, 2001). For each tracking interval, the sinusoids were randomly phase-shifted. The cursor moved along the same semi-circular path as the target but was controlled by participants using the joystick and moved at a maximum velocity of 80° per second. Although only one block involved the tracking task, the red circular target and black cursor were visible on screen throughout every tracking interval during both the dual- and single-task blocks. Figure 5-1 shows a sample series of stimulus events.

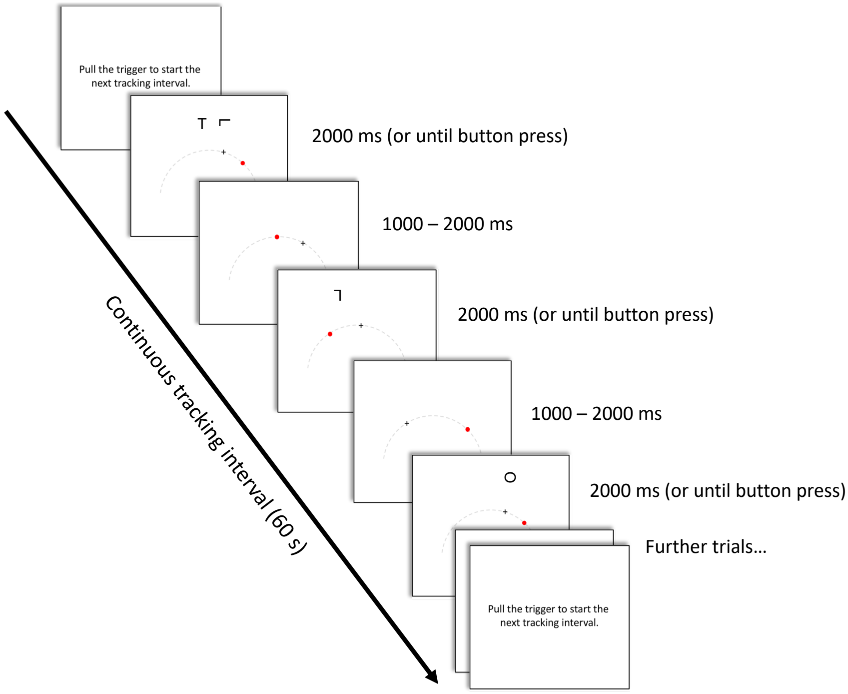


Figure 5-1. A series of sample trials within a 60-sec dual-task tracking interval. Here, after starting the interval, a low salience target (T) accompanied by a distractor (L) appear for a maximum of 2000 ms, followed by an inter-stimulus interval between 1000 and 2000 ms. This is followed by a distractor-only (L) trial, and later with a high salience target-only (O) trial.

Procedure

After providing informed consent and completing the visual tests, participants completed the primary experimental task in a private testing station. Participants were told they would perform two separate tasks. The first was to monitor for visual targets in two adjacent positions in the upper periphery of the display. Participants were told that the letters 'T' and 'O' were both targets, and that the appearance of a target required a button press response. Participants were instructed to hold the joystick with both hands, with their two thumbs on the buttons on top of the joystick, and to respond to targets bimanually. Bimanual responses were intended to minimise stimulus-response compatibility effects in RTs (e.g., Simon, 1969) and reduce the risk of lateral attentional biases resulting from greater response-related activation in one hemisphere. Participants were told to respond as quickly and as accurately as possible whenever a target appeared on screen, regardless of whether the target was accompanied by a distractor. The appearance of only a distractor, on the other hand, required no response.

The second task was a visuo-manual tracking task. This required the participant to manoeuvre the joystick to align the cursor with the red moving target, simulating visuo-manual tasks such as driving a car or steering a remote-controlled device. Because the target's motion was largely unpredictable to the participants, the task required attention to perform successfully.

Participants were told they would perform two blocks of 22 60 second tracking intervals each. They were also told that in one block they would only perform the target-detection task (single-task condition) whereas in the other they would perform both tasks (dual-task condition). In the dual-task, participants were asked to monitor for targets whilst maintaining tracking performance. Single-task instructions asked participants to focus entirely on the target detection task and to ignore the cursor and moving red target of the tracking task. The order of single- and dual-task blocks was counterbalanced across participants. Each block began with a 60 second practice interval for the first block. After completing the experimental task, participants filled out the FLANDERS questionnaire, and verbally reported whether they held a valid driver's licence, and if so, the number of years of driving experience they had accrued. They were then debriefed. The study took approximately 55 minutes to complete.

Analysis

To assess performance on the manual tracking task, we calculated the root mean squared error (RMSE) between the position of the participant's cursor and the moving red tracker. Though the tracking task was only performed by participants during the dual-task condition, we measured RMSE within the single-task condition as well. This provided a baseline measure of tracking performance to ensure participants had performed the task as instructed in the dual-task blocks.

For all calculations of capacity scores, we used the 'sft' package (Houpt, Blaha, McIntire, Havig, & Townsend, 2013; Houpt, Blaha, Base, & Burns, 2013) within R (R Core Team, 2016). Standardised capacity scores, *Cz*, was calculated separately for each participant, in each experimental condition.

Inferential analyses were performed using Bayesian parameter estimation with the 'JAGS' (Plummer, 2015) R package. Bayesian parameter estimation works by initially assuming a prior distribution for parameters of interest, then sampling values from that distribution using a Markov chain Monte Carlo procedure to generate an estimated posterior distribution of parameter values in light of the observed data. RTs were analysed in a 2 (task load: single, dual) x 2 (salience: low, high) x 2 (distractor condition: absent, present) within-subjects design, with an additive effect of participant (Kruschke, 2015). We assumed normal likelihood distributions and vague priors on all means and standard deviations. Following Kruschke (2015),

$$Y_{\text{participant, task load, salience, distractor condition}} \sim N(a0 + a_{\text{participant}} + a_{\text{task load}} + a_{\text{salience}} + a_{\text{distractor condition}} + a_{\text{task load} \times \text{salience} \times \text{distractor condition}}, \sigma_y^2)$$

$$a0 \sim N(M, [100 \times SD]^2)$$

$$a_{\text{participant}} \sim N(0, \sigma_{\text{participant}}^2)$$

$$a_{\text{task load}} \sim N(0, \sigma_{\text{task load}}^2)$$

$$a_{\text{salience}} \sim N(0, \sigma_{\text{salience}}^2)$$

$$a_{\text{distractor condition}} \sim N(0, \sigma_{\text{distractor condition}}^2)$$

$$a_{\text{task load} \times \text{salience} \times \text{distractor condition}} \sim N(0, \sigma_{\text{task load} \times \text{salience} \times \text{distractor condition}}^2)$$

$$\sigma_{\text{participant}}, \sigma_{\text{task load}}, \sigma_{\text{salience}}, \sigma_{\text{distractor condition}}, \sigma_{\text{task load} \times \text{salience} \times \text{distractor condition}} \sim \Gamma\ (\alpha, \beta)$$

$\alpha = SD/2$

$\beta = 2 * SD,$

where *M* and *SD* denote the mean and standard deviation, respectively, of the observed RT values. Use of the observed values in the parameter prior distributions ensured that distributions were appropriate to the scale of the data. Deflections from the grand mean were constrained to sum to zero for each of the effects of task load, salience, distractor condition, and their interaction. Analysis of *Cz* was similar, but did not include the effect of distractor condition (which is accounted for in the calculation of *Cz*),

$Y_{\text{participant, task load, salience}} \sim N(a0 + a_{\text{participant}} + a_{\text{task load}} + a_{\text{salience}}, \sigma_{\text{y}}^2)$

$\sigma_{\text{y}} \sim U(SD/1000, SD*1000)$

$a0 \sim N(M, [100 \times SD]^2)$

$a_{\text{participant}} \sim N(0, \sigma_{\text{participant}}^2)$

$a_{\text{task load}} \sim N(0, \sigma_{\text{task load}}^2)$

$a_{\text{salience}} \sim N(0, \sigma_{\text{salience}}^2)$

$\sigma_{\text{participant}}, \sigma_{\text{task load}}, \sigma_{\text{task load}} \sim \Gamma\ (\alpha, \beta)$

$\alpha = SD/2$

$\beta = 2 * SD,$

where *M* and *SD* denote the mean and standard deviation, respectively, of the observed *Cz* values. Deflections from the grand mean for the effects of task load and salience were again constrained to sum to zero across conditions.

Results

Error Rates

All 30 of the included participants produced false alarm rates below a preregistered cut-off value of 30% (Townsend & Wenger, 2004b) in both the single ($M = 0.07$, $Range = 0$ –

0.27) and dual-task blocks (*M* = 0.07, *Range* = 0.01 – 0.28). Collapsing across all trials (including target absent trials) produced very high overall mean accuracy rates in both the single- (*M* = 0.96, *Range* = 0.88 – 1.0) and dual-task conditions (*M* = 0.95, *Range* = 0.85 – greater than 0.99). Miss rates were very low across conditions and are reported, along with the mean number of correct target present trials within each condition, in Appendix D. As the number of correct target trials did not differ greatly between conditions, the variance of the *Cz* statistic reported below should be similar across conditions.

RTs

RTs for false-positive responses (i.e., responses to distractor-only trials) were excluded from analysis. The experimental program recorded participants' RTs for both hands (bimanual button presses). The faster of the two RTs for each trial was selected for analysis.

Data showed the expected main effects of distractor presence, target salience, and task load (see Figure 5-2 below). First, RTs for distractor-present trials (*M* = 559 ms, 95% Bayesian Credible Interval [BCI; Kruschke, 2015] = [553, 564]) were credibly longer than those for distractor-absent trials (*M* = 527 ms, 95% BCI = [521, 533]), (M_{Diff} = 31 ms, 95% BCI = [20, 43], *d* = 0.83). Second, responses to high salience targets (*M* = 534 ms, 95% BCI = [528, 539]) were credibly faster than those to low salience targets (*M* = 552 ms, 95% BCI = [546, 557]), (M_{Diff} = 18 ms, 95% BCI = [6, 29], *d* = 0.42). Finally, RTs in the single-task block (*M* = 512 ms, 95% BCI = [507, 518]) were credibly shorter than RTs in the dual-task block (*M* = 573 ms, 95% BCI = [568, 579]), (M_{Diff} = 61 ms, 95% BCI = [50, 72], *d* = 0.87).

To test for a 3-way interaction between task load, target salience, and distractor presence, we assessed the *interaction contrast* (*IC*; Keppel, 1991) between target salience and distractor presence for each level of task load. The interaction contrast was calculated as follows:

$$IC = RT_{LP} - RT_{HP} - RT_{LA} + RT_{HA}, \quad (5.2)$$

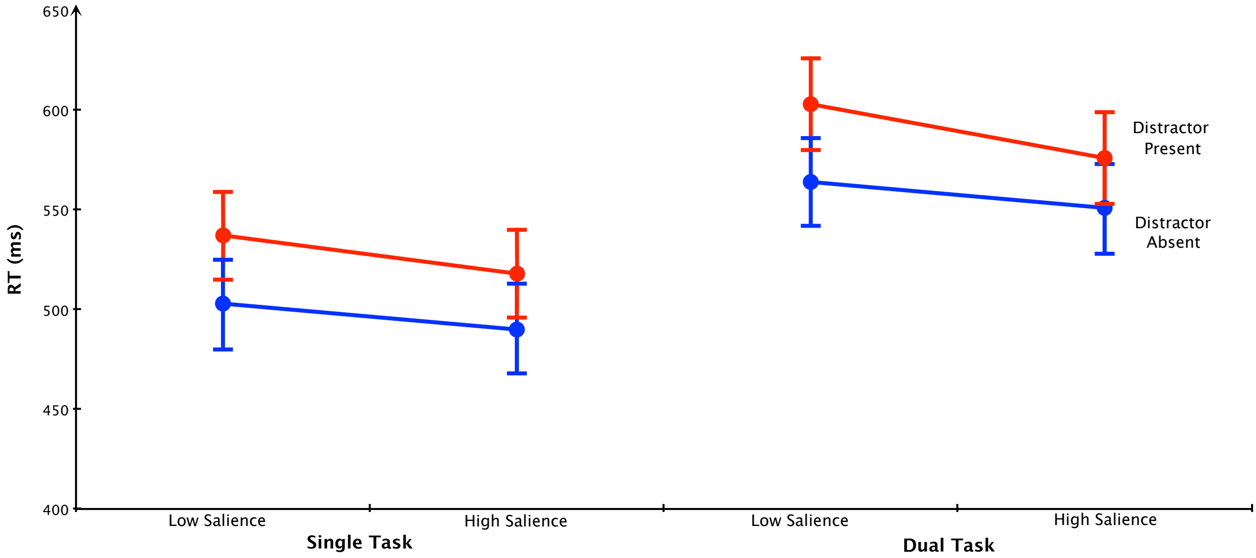
where the subscripts L (low) and H (high) denote the level of target salience, and the subscripts P (present) and A (absent) denote the level of distractor presence. A value of IC = 0 would indicate additive effects of salience and target distractor, a value greater than 0 would indicate superadditive effects, and a value less than 0 would indicate subadditive effects. The IC was calculated separately for the single-task condition (IC_{Single}) and the dual-task condition (IC_{Dual}). Though both were nominally positive, neither IC_{Single} (M = 7.00, 95% BCI = [-13.81, 33.73]) nor IC_{Dual} (M = 12.93, 95% BCI = [-7.81, 43.66]) were credibly different from 0. Furthermore, the two values of IC did not differ from one another, (M_{Diff} = -5.78, 95% BCI = [-41.78, 25.07], d = 0.16).

Workload Capacity

To reiterate, Cz values below 0 represent limited capacity processing, values greater than 0 represent super-capacity processing, and values of 0 represent UCIP-equivalent processing.

Within both the single- and dual-task conditions, Cz scores were negative, indicating limited capacity. In line with expectations, high salience targets (M_{Cz} = -0.81, 95% BCI = [-1.17, -0.44]) produced higher values of Cz than low salience targets (M_{Cz} = -1.80, 95% BCI = [-2.17, -1.44]), (M_{Diff} = -1.00, 95% BCI = [-1.36, -0.63], d = 0.81). However, despite a trend towards more efficient processing in the dual-task condition (M_{Cz} = -1.18, 95% BCI = [-1.54, -0.82]) than single-task condition (M_{Cz} = -1.43, 95% BCI = [-1.80, -1.08]), there was no credible main effect of task load on Cz, (M_{Diff} = -0.26, 95% BCI = [-0.62, 0.10], d = 0.18).

a)



b)

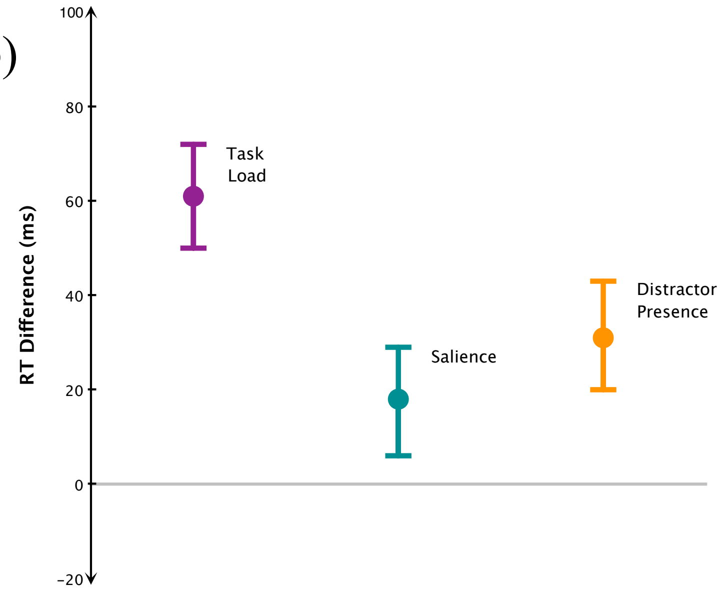


Figure 5-2. a. Estimated mean RT as a function of task load, salience, and distractor presence. *b*. Estimated mean difference scores reflecting the main effects of task load (dual-task – single-task), salience (low – high), and distractor presence (present – absent) on mean RTs. Error bars are 95% BCIs. In *b*, error bars not overlapping zero indicate credible effects.

The central hypothesis for the current study was that target salience would enhance target processing efficiency in both conditions, but to a greater extent for the single-task condition. Contrary to this prediction and as presented in Figure 5-3, data showed no credible interaction between salience, task load, and processing efficiency. Under single-task load, high salience targets (M_{Cz} = -0.91, 95% BCI = [-1.35, -0.48]) were processed more efficiently than low salience targets (M_{Cz} = -1.96, 95% BCI = [-2.39, -1.52]), (M_{Diff} = -1.04, 95% BCI = [-1.54, -0.55], d = 0.80). Similarly, under dual-task load, high salience targets (M_{Cz} = -0.70, 95% BCI = [-1.14, -0.27]) were processed more efficiently than low salience targets (M_{Cz} = -1.65, 95% BCI = [-2.09, -1.22]), (M_{Diff} = -0.95, 95% BCI = [-1.44, -0.46], d = 0.81). The IC_{Cz} was very close to 0 (IC_{Cz} = 0.09, 95% BCI = [-0.55, 0.76], d = 0.07), implying additive effects of task load and salience.

Tracking Performance

We measured tracking performance to check that participants had followed instructions to track the cursor in the dual-task but not the single-task condition. We calculated RMSE of the participant's cursor from the red moving target. Higher scores indicate poorer tracking performance. To check participants followed instructions to only track during the dual-task block, we compared RMSE between both levels of task load. As expected, dual-task RMSE (M_{RMSE} = 14.28º, 95% BCI = [13.22, 15.34]) was credibly smaller than single-task RMSE (M_{RMSE} = 26.07º, 95% BCI = [25.04, 27.13]), (M_{Diff} = 11.80º, 95% BCI = [10.49, 13.11], d = 3.46), indicating that participants performed the tracking task during the dual-task block as instructed.

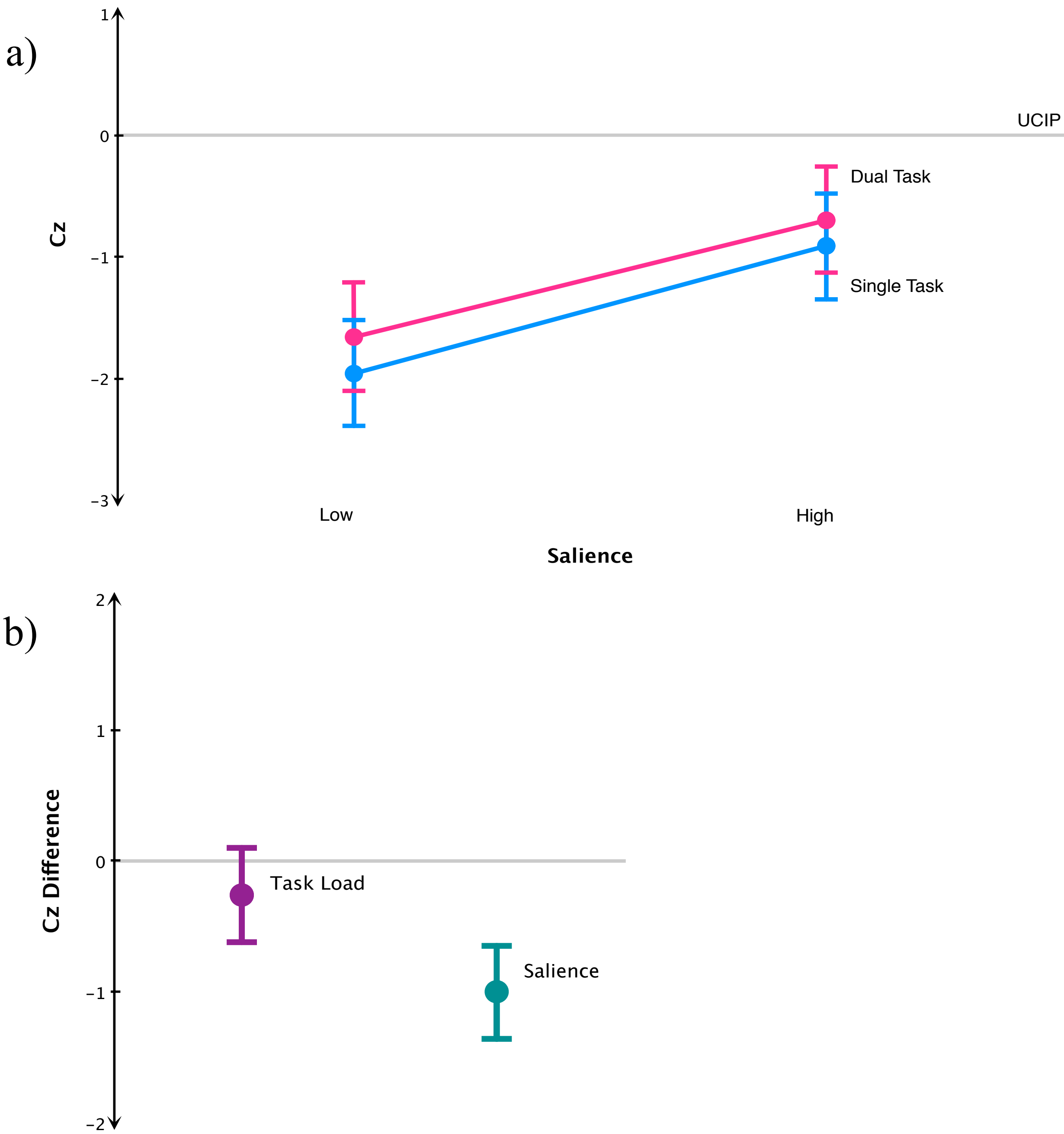


Figure 5-3. a. Estimated mean normalised capacity scores as a function of salience and task load. The grey zero line represents UCIP model performance. *b.* Estimated difference scores of the main effects for salience (low – high) and task load (dual-task – single-task). Error bars are 95% BCIs.

Discussion

In the current study, we tested whether a concurrent visuo-manual task reduces the value of target salience for boosting visual processing efficiency. As expected, high salience targets were processed with greater efficiency than low salience targets. To reiterate, within the ST-ST paradigm (Blaha, 2011; Blaha & Houpt, n.d.; see also Houpt et al., 2013), $C(t)$, or its normalised version, *Cz*, is calculated by comparing the processing rates of a target alone versus a target appearing with one or more distractors. The observed negative values of *Cz* indicate that the addition of a distractor slowed the processing of a target. This finding was true both for low and high salience targets, indicating that salience did not make the target fully immune to distractor interference. *Cz* was higher for high-salience targets, indicating that salience reduced the difference in processing rates between distractor-present and distractor-absent target trials. More critically, dual-tasking did not reduce the benefits of the salience effect. Even under high task load, high salience targets were detected more efficiently than low salience targets.

Our current findings are consistent with our previous studies showing no dual-task cost on peripheral target processing (Morey et al., 2018a, 2018b). Our earlier studies showed that performing a visuo-manual tracking task had no effect on processing capacity for redundant peripheral visual targets (Morey et al., 2018a, 2018b). Here, we show these findings extend to single-target visual displays. In other words, target processing efficiency is not affected by changes to task load for redundant-target displays, nor is capacity influenced by task load for single-target displays. Thus, regardless of display type, task load does not affect visual processing capacity.

The current findings lend support to existing guidelines (e.g., Federal Aviation Administration, 2011; General Aviation Manufacturers Association, 2000) encouraging designers to increase stimulus salience to improve visual processing, both in simple, single-task contexts and in more complex, operational environments. Increasing feature contrast between target information and irrelevant or distractor information may be especially valuable for increasing the noticeability of critical information in complex operational displays, such as those used in air traffic control and in military command and control.

One argument for the lack of a dual-task cost to capacity may be that the tracking task was insufficient at increasing resource demand. However, this explanation seems unlikely. Although the tracking task did not reduce processing capacity, it was difficult enough to increase RT for target detection. Thus, our results provide evidence of interference between the target-detection and tracking tasks. Alternatively, the findings here may reflect an attention-switching model (e.g., Morey et al., 2018b; Wickens & Gopher, 1977). While directing attention toward the moving tracker, a stimulus onset may have interrupted performance on the tracking task (Yantis & Jonides, 1990), temporarily diverting attention towards the stimuli and allowing rapid stimulus identifications. Thus, the visual targets could be processed in parallel during the dual-task block, despite attention switching serially between the tracking and detection tasks. Such a model could explain the lack of any credible difference between the single- and dual-task conditions.

The current study used a novel method to assess visual processing capacity under task load while manipulating salience. This is the first time the ST-ST measure of workload capacity has been used to assess the effects of salience on processing within a dual-task design. The clear effect of salience, along with the trend towards an effect of task load, suggests that the ST-ST method may be a useful measure for assessing processing capacity under load.

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CHAPTER 6: STUDY 5

Visual Detection under Load in a Simulated Military Dual-Task

The following chapter is an unpublished manuscript prepared in collaboration with researchers at Defence Science and Technology Group, Edinburgh, South Australia.

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Author Contributions:

All three authors formulated the design of the study. SAM developed the simulation scenario, collected the data, and wrote the first draft of the manuscript. Both SAM and JSM carried out the data analysis. DEP and JSM provided revisions on the manuscript.

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Preface

The previous studies in this thesis examined task-load effects on visual target processing in highly-controlled laboratory environments. To test whether these findings extend to more real-world domains, the following study assessed visual monitoring under dual-task load in a high-fidelity operational scenario. The study was a collaborative project with researchers at Defence Science and Technology Group in Edinburgh, South Australia. Here, we conducted a study to measure detection performance of a commander either manually operating or supervising the movements of a semi-autonomous ground vehicle using a high-fidelity driving simulator. A vehicle operating autonomously, requiring little manual input (i.e., requiring only supervisory control), is expected to produce low operator workload. We therefore liken the supervisory control mode to the single-task condition in our earlier experiments. Conversely, the higher level of cognitive demand and the extra tasks of steering and accelerating/braking in the manual control (i.e., teleoperation) condition is akin to the dual-task condition in our laboratory experiments. Thus, the current study implemented a dual-task paradigm in an ecologically valid, complex military environment.

Given the constraints of a high-fidelity simulation (e.g., less controlled target onset and offsets, greater variability between participants), we infer changes of processing capacity directly from response times (RTs) and from signal detection theory (SDT; Green & Swets, 1966; Stanislaw & Todorov, 1999) measures of sensitivity and bias, rather than using the more sophisticated measures in the previous chapters. Though, as mentioned previously, RTs and accuracy/sensitivity provide an imperfect means of assessing capacity, we used them here as a crude measure of visual processing performance that is most feasible given limitations of the simulation software and other methodological constraints. As a manipulation check to confirm that operator workload differed across vehicle autonomy mode, we also measured subjective workload between conditions.

Abstract

Increasing automation in high-stress environments can reduce operator task load and workload. As such, it may be valuable for improving concurrent task performance. Here, we tested whether higher levels of unmanned vehicle autonomy improved operators' performance on a primary visual monitoring task within a simulated humanitarian aid task. Twenty-one participants performed a target monitoring task while operating a vehicle under a low (teleoperation) or high (supervisory control) level of vehicle autonomy. SDT measures of sensitivity (*d'*) and bias (*c*) were accumulated over time to assess changes in monitoring following target onset. Performance on the control task was assessed using vehicle speed and the number of critical incidents within the scenario. Despite higher levels of subjective workload in teleoperation than supervisory control, *d*' and *c* did not vary between vehicle control conditions. The current findings suggest the reduced workload resulting from increased system autonomy might not improve monitoring performance on a visual detection task.

Visual Detection Under Load

in a Simulated Military Dual-Task

Automation is technology that carries out tasks, or parts of tasks, that were previously performed by humans (Parasuraman, Sheridan, & Wickens, 2000). By reducing the number and complexity of tasks performed by human operators, automation provides a possible solution for freeing up human cognitive capacity. Autonomous vehicles, in particular, are increasingly being used in the high-risk operational settings, such as mining (e.g., Komatsu Australia, 2018; Rio Tinto, 2018), to improve efficiency and safety by minimising the opportunity for human error. An increase in vehicle autonomy may allow operators to improve performance on other, non-driving tasks. In future military command and control environments, for instance, increasing vehicle autonomy has the potential to increase the operator's capacity to plan a route or monitor the environment for hazards (e.g., Ivanova, Gallasch, & Jordans, 2016). Thus, performance on other non-driving, yet still important tasks, may improve as the level of vehicle autonomy increases.

In general, humans are not well-equipped to perform multiple tasks simultaneously (e.g., Wickens, 2002; Wickens, 2008). Many prominent theories of multiple task performance argue that task performance depend on the cognitive resources required by each task; when concurrent tasks tap into similar resource pools, exceeding the maximum available capacity, performance declines (e.g., Gopher & Navon, 1980; Navon & Gopher, 1979; Wickens, 1981; Wickens, 2008). Given the risks associated with overloading an operator, autonomous systems provide a potential option for increasing task efficiency by reducing the number of tasks an operator performs concurrently, freeing up cognitive capacity necessary for other, non-driving tasks (Manzey, Reichenbach, & Onnasch, 2012; Sethumadhavan, 2009; Young & Stanton, 2007).

Several studies support the notion that fully or partially automating one task can reduce operator workload and increase cognitive resources available for a concurrent task (e.g., Griffiths & Gillespie, 2005; Kaber & Endsley, 2004; Parasuraman, Cosenzo, & De Visser, 2009; Young & Stanton, 2002a; Young & Stanton, 2004; Young & Stanton, 2007). For example, Griffiths and Gillespie (2005, Experiment 3) found that automation in a driving task reduced RTs to tones in a secondary tone localisation task, without compromising performance to the primary task. Moreover, increased automation has also often been linked to decreased operator workload (Parasuraman et al., 2009; Young & Stanton, 2002a). Young and Stanton (2002a, 2002b, 2007) showed that an increase in automation on a simulated driving task decreases workload, and furthermore, frees up capacity for a concurrent visuo-spatial task. However, they also found a potential cost to automation: that attentional resources may shrink in situations when workload is low. Young and Stanton argued that if automation reduced workload too much, the mental resources necessary to carry out tasks decrease, limiting performance. Thus, their findings suggest automation may increase available resources for a secondary task, so long as the automation does not also reduce mental workload too far.

In addition to causing mental underload, highly reliable automation can reduce operator attentiveness (e.g., Kessel & Wickens, 1982; Wickens & Kessel, 1979). In particular, highly reliable automation can make operators less prepared to respond to critical events within the environment (such as an impending hazard on the road) or to changes in a system's status. In system fault-detection tasks, for example, operators are faster and more accurate at detecting errors when manually controlling the system than when supervising a system operating in autonomous mode (Kessel & Wickens, 1982; Wickens & Kessel, 1979).

Automation may also be problematic for tasks requiring operators to maintain an awareness of their surrounding situation (Endsley, 1995; Endsley & Garland, 2000). Chen et al. (2017) compared different levels of automation on performance on a simulated submarine track management triple-task. The automation was designed to assist performance on a contact classification task and a contact tracking task, but not on a concurrent dive task. Compared with no automation, static automation, in other words, automation that was on throughout the duration of the task, led to faster and more accurate target classifications in the classification task, increased the number of accurate decisions on the contact tracking task, and also reduced subjective workload. However, despite these improvements in performance on the automated tasks, compared with the no automation condition, static automation severely impaired situation awareness and reduced performance on the non-automated concurrent dive task (Chen et al., 2017). In fact, even when automation was switched on and off manually by the operator (adaptable automation) or automatically based on task load (adaptive automation), situation awareness was poorer than the no automation control condition. Thus, in some situations, automated systems may lead operators to have a poorer awareness of their surroundings than those requiring manual control. This reduced awareness could lead to poorer performance on a concurrent task, especially if the task requires monitoring or detecting events within the environment.

Here, we examined how increasing vehicle automation on a driving task affects performance on a concurrent target monitoring task. Participants either supervised a simulated unmanned ground vehicle in an autonomous control mode (supervisory control) or a manual control mode (teleoperation), while completing a target detection task. In line with theories that suggest automation may reduce operator task load and thereby enhance operator performance (e.g., Griffiths & Gillespie, 2005; Wickens, 1981; Wickens, 2008), we expected the supervisory control mode would allow greater target detection than the teleoperation mode.

Method

The study was approved by Defence Science and Technology Group's Ethics Review Panel and the Flinders University Social and Behavioural Research Ethics Committee. The study was also preregistered on the Open Science Framework. A link to the preregistration information can be found at: https://osf.io/hb98p/register/5771ca429ad5a1020de2872e?view_only=4c1fed94e84249e4962cf6810de5ac52.

Participants

Twenty-one participants (9 female; M_{Age} = 36.81, *SD* = 18.59, *Range* = 21 - 80), including nine Defence Science and Technology Group current and former staff, five Flinders University students, and seven other individuals recruited from the general public, volunteered to take part in the current study. Though our preregistered goal was to run 30 participants if possible, time constraints and difficulty recruiting prevented that.

All participants reported normal or corrected-to-normal visual acuity and normal colour vision. All participants were regular drivers holding a current valid driver's licence, with an average of 20.05 years of driving experience (*SD* = 18.61, *Range* = 2 – 63 years). Three participants reported having personal military experience. All participants were fluent in English. Most participants reported having only basic experience using driving simulators or the Virtual Battlespace 3 software, and eight participants reported working within the area of simulation technology. Eleven participants reported having at least an intermediate level of videogaming experience. After excluding data for one participant who terminated the session early due to simulator sickness (who showed an increase in pre- to post-session SSQ scores of 37.4), we were left with 20 complete data sets for analysis.

Apparatus and Stimuli

Participants completed the study in an individual testing station within a simulation laboratory onsite at DST Edinburgh, South Australia. Participants sat in a vehicle simulator throughout the duration of the task. The simulator consisted of a driver's seat fixed to a motion base that could be adjusted in three degrees of motion, a steering wheel, and three pedals (accelerator, brake, and reverse). To minimise the risk of simulator sickness, motion and vibration settings for the motion base remained switched off throughout the duration of the study. Participants used the steering wheel to perform the teleoperation task. All participants wore Sennheiser over-ear headsets throughout the testing session. The headsets played sounds within the scenario such as the vehicle accelerating. Visual stimuli were displayed on a 26" flat screen monitor with a screen resolution of 1920 × 1080 pixels (1 pixel was equal to 0.03 cm), mounted to the wall in front of the participant. Participants completed the task at a viewing distance of approximately 1000 mm, though viewing distance was not held fixed and could vary depending on each participant's seat position. The monitor provided the participants with a forward view of the scenario, giving the impression that a camera was fixed to the front of the vehicle being operated.

A battlefield management system (BMS) was presented on a Windows Surface Pro tablet on a table in front of the participant. The BMS showed a map view of the scenario and tracked the position of the vehicle at it moved along the prescribed route, identified by a black line.

The simulation scenario was created using Virtual Battlespace 3 (VBS 3; Bohemia Interactive Simulations, 2015, Version 3.7.0.127787) software. The scenario involved participants partaking in a simulated military reconnaissance mission on a fictitious island, Sahrani. The scenario involved either remotely controlling or supervising an unmanned reconnaissance vehicle carrying aid supplies along a predetermined route. The terrain in the scenario varied between rural and urban landscapes.

The scenario was split into two blocks: in one block participants manually controlled the vehicle (teleoperation condition), and in the other block, the vehicle operated in a driverless mode in which participants could not control the vehicle's movements (supervisory control condition). During the teleoperation block, participants used the steering wheel and foot pedals to control the movements of the vehicle along the prescribed route. In the supervisory control block, a confederate located in a separate testing station manually operated the vehicle. The confederate was thoroughly practiced on the task to ensure performance across participants was as consistent as possible. The same trained research assistant acted as the confederate for every session. Block order was counterbalanced between participants. Due to time constraints within each testing session, and as we were primarily interested in visual processing rather than vehicle control, we did not include a third condition to measure vehicle control performance on its own.

Throughout each scenario, participants completed a concurrent target-detection task in a go/no-go design. Targets were human threats (armed persons) and non-targets were human non-threats (unarmed persons). Both targets and non-targets appeared intermixed throughout the scenario and appeared intermittently along the predetermined route, in locations both on and off the road. Targets and non-targets could be stationary (e.g., person standing still on the side of the road) or dynamic (e.g., running out from behind a tree and across the road). Participants were asked to respond to targets with a speeded button press on a response panel attached to the front of the steering wheel. Response times were recorded from the moment a target became visible onscreen, as determined during scenario development. A response was counted as a hit if it occurred within 5 seconds of the time a target became visible. A response was counted as a false alarm if it occurred within 5 seconds of the time a non-target became visible. Button presses made outside of the 5 second period following the appearance of the target were not recorded. Although a target's distance from the vehicle and its location varied throughout the scenario, in general, the 5 second time period was long enough that a target was no longer visible on screen by the time the response period ended (i.e., due to the vehicle having driven past the target). To avoid confounding target responses, no more than one target was ever visible at any moment throughout the task. In total, there were 35 targets and 18 non-targets per block.

Vehicle speeds were recorded with a sampling rate of 2 Hz, and were timestamped to allow comparison of the teleoperation and supervisory control blocks.

Materials & Measures

Demographics Questionnaire. We recorded general participant information via a demographics questionnaire (e.g., age, gender, highest level of education). The questionnaire also asked for participants' gaming knowledge and experience (e.g., *How would you rate your knowledge of video gaming (i.e. how it works)? None? Basic? Intermediate? Expert?*), and whether participants were experienced with simulation technology. In addition, the questionnaire measured participants' previous experience with using the Virtual Battlespace 3 software and with driving simulators.

Simulator Sickness Questionnaire. A Simulator Sickness Questionnaire (SSQ; Kennedy, Lane, Berbaum, & Lilienthal, 1993) was administered to identify any participants at risk of experiencing simulator sickness. Participants first completed the SSQ on arrival at the testing session, and then after each practice and experimental block.

NASA-TLX. The NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988) was administered to participants to assess workload at each level of vehicle control. Measures were taken immediately after completing each block. The NASA-TLX displays high validity and reliability and is regularly used in studies measuring operator workload.

Number of critical incidents. To provide a crude measure of participants' performance on the vehicle control task, we recorded the number of critical incidents in each session. A critical incident was defined as any situation that violated the 'mission instructions' to ensure the vehicle arrived as safely as possible at the destination. Critical incidents included any instances in which the vehicle collided with a pedestrian (either target or non-target) or with a stationary object (e.g., wall, street sign), and instances in which the participant either rolled the vehicle or required assistance to return to the prescribed route. Critical incidents were recorded in both the teleoperation and supervisory control block.

Procedure

After providing informed consent, participants completed the basic demographic questionnaire and completed the SSQ as a baseline measure of simulator sickness. Next, participants were introduced to the driving simulator and scenario. We asked participants to imagine they were the commander of a reconnaissance mission on the fictitious island of Sahrani. Their role was to remotely supervise or teleoperate an unmanned vehicle between two locations to deliver aid supplies. Participants were told that, due to dangerous conditions around the island, they would need to either remotely supervise or remotely operate the vehicle from a command centre at the base camp. Thus, rather than driving a vehicle and risking human life, their task was to supervise the vehicle remotely, relying on the cameras fixed to the front of the vehicle.

Participants were also instructed that the vehicle could operate in two different control modes. The first was a supervisory control mode in which the vehicle operated autonomously, without the need for direct input from the participant. The second was a teleoperation mode, in which the vehicle required direct manual control from the participant. Participants were not informed that a confederate was driving the vehicle in the supervisory control condition, but were told that the vehicle was operating in a mode in which the participant was not the driver. As noted, we trained the confederate thoroughly to ensure the supervisory control drive was similar across participants. Nonetheless, to alleviate any participant concern over apparent mistakes or imperfections in the performance of the self-driving vehicle, we informed participants that the supervisory control mode was not perfect, and thus, on some occasions the vehicle could erroneously veer off track or have difficulty navigating tight corners. Participants were informed that they would undergo one block in each control mode. A cover story explained that the control mode depended on the conditions of the environment the vehicle was driving through.

Participants were also informed that they would need to watch out for and respond to threats appearing throughout the scenario. They were instructed to respond to armed human threats via a speeded button press on a key located on the steering wheel, and to make no response if an unarmed human non-threat appeared. Participants were informed that they should only press the button for threatening targets (armed persons) and to withhold responses for all non-threatening targets (unarmed persons). We told participants that armed targets posed a threat to the aid mission and, therefore, targets identified throughout the scenario needed to be reported as soon as possible back to the base camp via a button press. Participants performed the target-detection task throughout the full experimental session. They were required to perform the detection task during supervisory control and teleoperation. We instructed participants to keep their left index finger or thumb on the response board attached to the steering wheel at all times to encourage rapid responses. This meant that in the teleoperation condition, participants primarily controlled the vehicle using their right hand on the steering wheel. We encouraged both speed and accuracy on the detection task. We told participants to continue performing the detection task, regardless of the performance of the self-driving vehicle in the SC condition.

To familiarise themselves with the task, all participants performed a practice block before starting the experimental block. During the practice, participants were introduced to the vehicle simulator and audio headsets. They were introduced to the accelerator, brake, and reverse pedals and were given five minutes to practice manoeuvring the vehicle. Participants were asked to obey normal road rules and to obey the speeds limits of 50-kilometres per hour (kph) in urban or built-up settings and 80-kph in rural environments. These were the same speeds that the experimental confederate attempted to maintain while operating the vehicle in the supervisory control condition.

After familiarising themselves with the vehicle controls, participants completed a brief practice task comprised of two phases. In the first phase, the vehicle operated in the supervisory control mode, autonomously driving from one town to a second, nearby town. Thus, for the first part, participants were only required to perform the detection task. After a short break to complete the SSQ, participants completed the second phase of the practice task during which the vehicle was switched to the teleoperation mode. The second practice phase required the participant to manually control the vehicle using the steering wheel and foot pedals, while still performing the monitoring task. Participants received verbal feedback throughout the practice.

Once comfortable with performing both the vehicle control and target-detection task, participants began the experimental session. Half the participants began in supervisory control; the other half began in teleoperation. To ensure participants completed the teleoperation task in approximately the same amount of time as the supervisory control task, we emphasised the importance of completing the task as quickly as possible without exceeding speed limits. We emphasised that the target detection and the vehicle control tasks should be given equally priority. Half way though the scenario, the vehicle reached a stop sign indicating that is was time to switch control modes. Participants stopped the scenario and completed the SSQ and the NASA-TLX for the control mode they had just performed. After a short break, they began the second block, using the alternate control mode. At the end of the second block, participants once again completed the SSQ and the NASA-TLX.

The total time in the experimental task was approximately 35 minutes, though this varied depending on performance. The full testing session lasted approximately 70 minutes.

Statistical Analyses

We analysed the workload, detection, and vehicle control data using Bayesian parameter estimation through Markov chain Monte Carlo (MCMC) sampling (Kruschke, 2013, 2015; Lee & Wagenmakers, 2013). This procedure begins with a prior distribution on a parameter of interest, then uses probabilistic sampling to update parameter estimates based on the observed data, resulting in estimates of the posterior distribution of parameter values (Kruschke, 2015). For each analysis, we calculated 95% Bayesian Credible Intervals (BCI; Kruschke, 2013, 2015) around the parameters of interest. Parameter estimation was carried out using the R package, 'JAGS' (Plummer, 2015). Estimates were based on four chains of length 62,500 iterations each; visual inspection of these chains indicated chains were mixing. Iterations were thinned to every fifth step ($N_{\text{eff}} > 29000$). Each chain began with a burn-in sequence of 10,000 iterations.

We analysed workload data using a model based on Kruschke (2013, 2015) that modelled a one-sample, within-subjects design. The model fitted a likelihood distribution with broad priors on the mean and standard deviation. Because NASA-TLX workload scores must lie between 0 and 100, we set a uniform prior (0, 100) on the group-level mean of the workload scores, and a uniform prior (0, 100) on the group-level standard deviation. We used the one-sample model to estimate parameter values separately for the supervisory control and teleoperation conditions, and to estimate the difference score between conditions. To estimate parameter values for the speed and critical incident data, we used a similar model to the above, but we changed the prior to fit a normal likelihood distribution.

To assess performance on the detection task between teleoperation and supervisory control, we first broke detection responses into separate 500 ms bins from target onset to response timeout, then analysed cumulative *d*' and *c* as a function of time bin. Analyses thus show both the asymptotic level of performance within each condition, and the time course with which target detectability and response bias changed as the participant approached a target. We used a model from Rouder and Lu (2005) to estimate *d*' and *c*, based on the cumulative hit and false alarm rates for each time bin.

Results

Workload

We compared workload across driving conditions to ensure that participants found the teleoperation task more demanding than the supervisory control task. As expected, total NASA-TLX workload scores were higher for the teleoperation block (M = 61.61, 95% BCI = [56.35, 66.92]) than for the supervisory control block (M = 53.06, 95% BCI = [45.45, 60.65]), (supervisory control minus teleoperation difference: M_{Diff} = 8.56, 95% BCI = [3.10, 14.01], d = 0.70), suggesting that the teleoperation was more cognitively demanding than supervisory control. As overall workload scores on the NASA-TLX are out of 100, these scores suggest both conditions produced moderate levels of workload.

Detection Performance

Because participants produced no false alarms within the first two time bins in the supervisory control condition, estimated values of *d*' and *c* within those bins were greatly inflated. Thus, here, we only report estimated parameters from the 5th time bin onwards, by which point both conditions had accumulated a modest number of false alarms. Parameter estimates for the first four time bins are included in Appendix E.

Figure 6-1a presents the mean and 95% BCI of *d*' as a function of time bin, and Figure 6-1b presents the mean and 95% BCI of the difference score between *d*' values for the supervisory control and teleoperation conditions. Data trended towards greater *d*' the longer a target remained on screen, though the change in *d'* from the 5th to the 10th time bins indicated that this pattern was not credible for either condition (supervisory control: M_{Diff} = 0.31, 95% BCI = [-0.26, 0.86]; teleoperation: M_{Diff} = 0.32, 95% BCI = [-0.22, 0.86]). In contrast to expectations, values of *d*' in teleoperation and supervisory control did not differ credibly from one another within any time interval.

Figure 6-2a presents the mean and 95% BCI of *c* as a function of time bin, and Figure 6-2b presents the mean and 95% BCI of the difference score between values of *c* for the supervisory control and teleoperation conditions. Data indicate that participants adopted a very conservative response bias in the detection task but tended to become less conservative as target screen time increased. Notably, this effect was only credible (between the 5th and 10th time bins) for the supervisory control condition (M_{Diff} = -0.52, 95% BCI = [-0.96, -0.11]). Teleoperation did not show a credible change in response bias over time (M_{Diff} = -0.37, 95% BCI = [-0.77, 0.03]). Additionally, at no time interval did *c* differ credibly between teleoperation and supervisory control.

Inspection of raw hit and false alarm rates provides a perhaps more intuitive view of the data. Figure 6-3 below presents the estimated mean value and 95% BCI for hit rate, along with the mean and 95% BCI for the difference score between conditions. As shown, hit rates steadily increased over time within both conditions, but reached a maximum of just under 0.50. Thus, detection rates were low regardless of condition. Though hit rates did not differ credibly between conditions during the first 4000 ms after appearing on screen, mean difference scores indicate hit rates were credibly greater in supervisory control than teleoperation in the 4500 ms and 5000 ms time bins. Given that neither *d*' nor *c* differed between conditions, however, this difference in hit rates seems likely to be spurious effect, reflecting a happenstance combination of sensitivity and bias values in those particular time bins rather than a true difference in ability between conditions.

Analysis of false alarm rates over time indicated that participants were generally successful at withholding responses to non-targets, with false alarm rates below 0.05 for most time intervals (see Figure 6-4a). The difference in false alarm rates between conditions was not credibly different from zero within any time bin (Figure 6-4b).

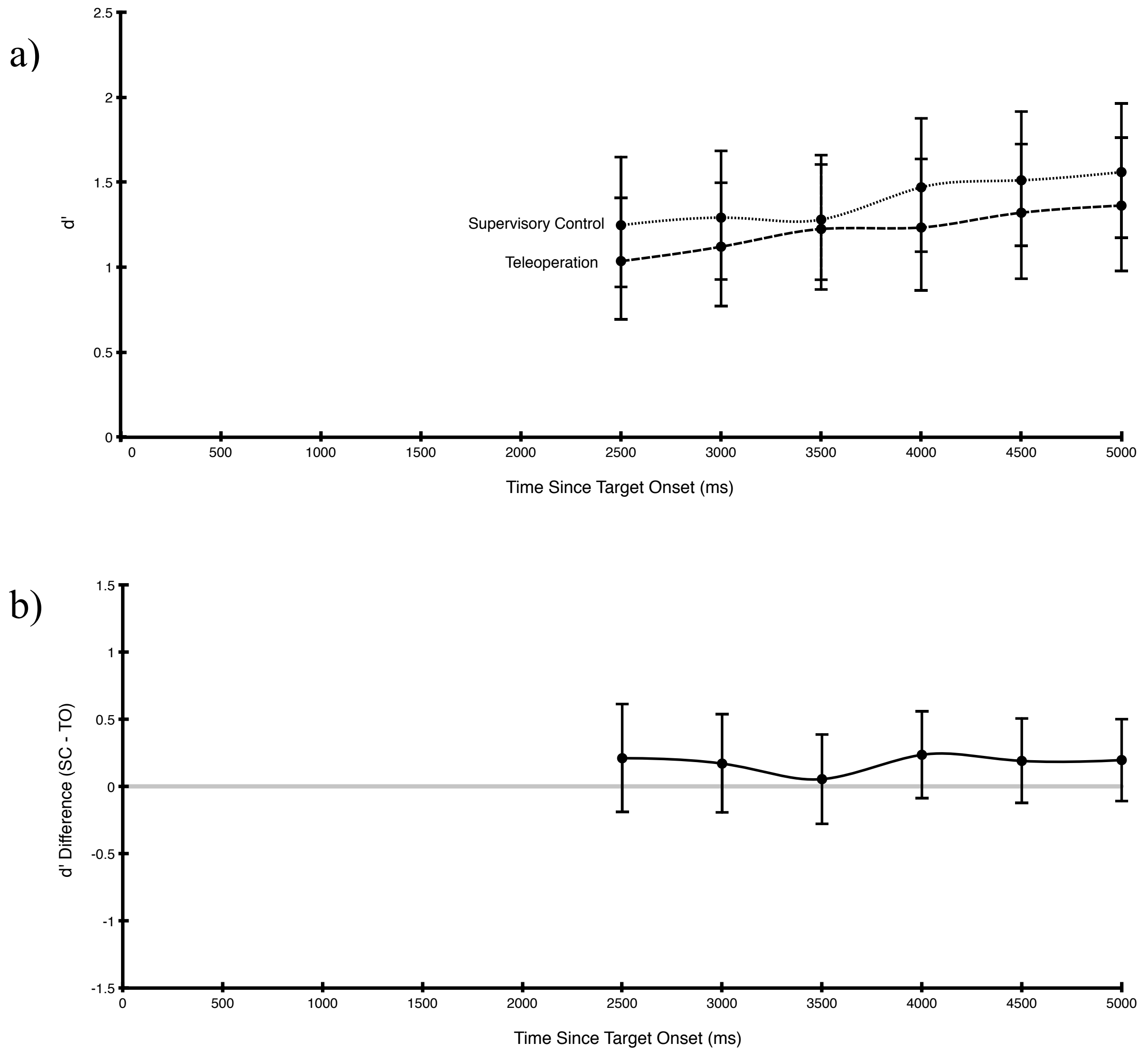
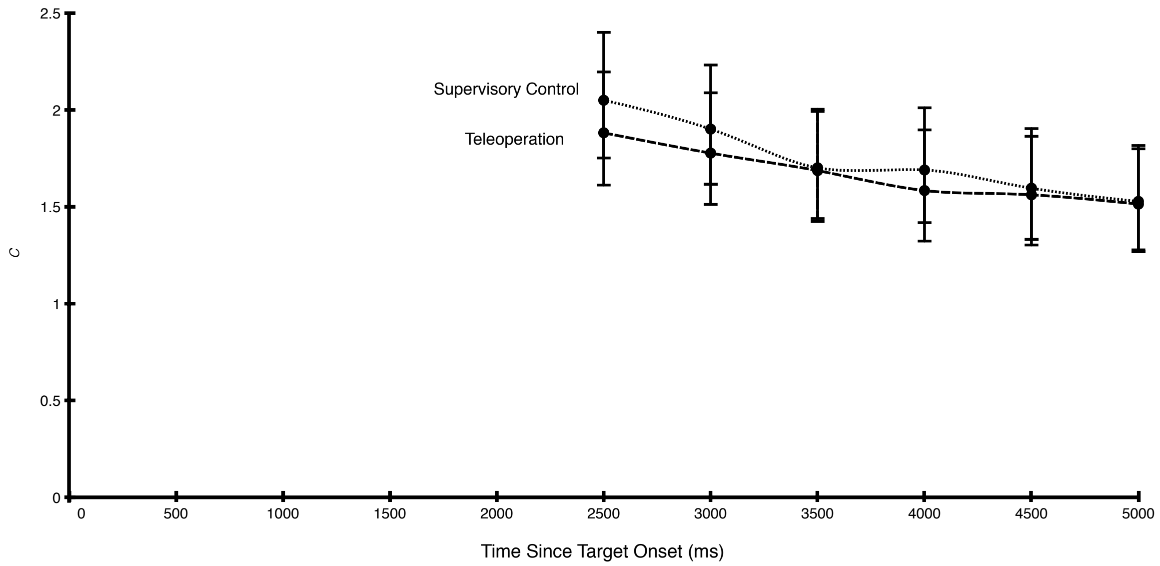


Figure 6-1. a. Mean cumulative sensitivity, *d*', across time within each condition. Error bars represent 95% BCIs. *b.* Mean *d*' difference score (supervisory control – teleoperation) and 95% BCIs for each time bin. Error bars overlapping the grey zero line represent non-credible differences between conditions.

a)



b)

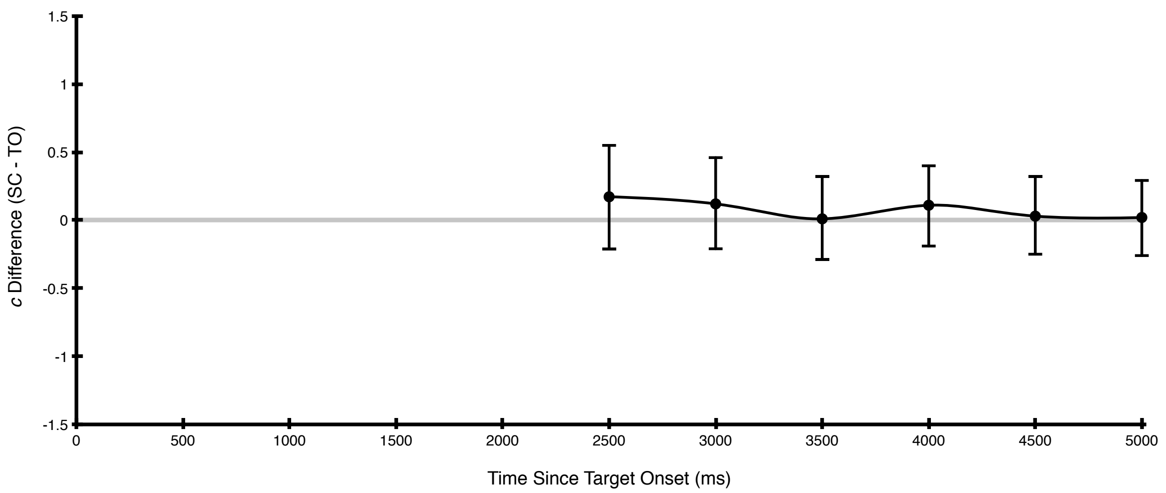


Figure 6-2. a. Mean cumulative decision criterion, *c*, across time for supervisory control and teleoperation. Error bars represent 95% BCIs. *b.* Mean *c* difference score (supervisory control – teleoperation) and 95% BCIs for each time bin. Error bars overlapping the grey zero line represent non-credible differences between conditions.

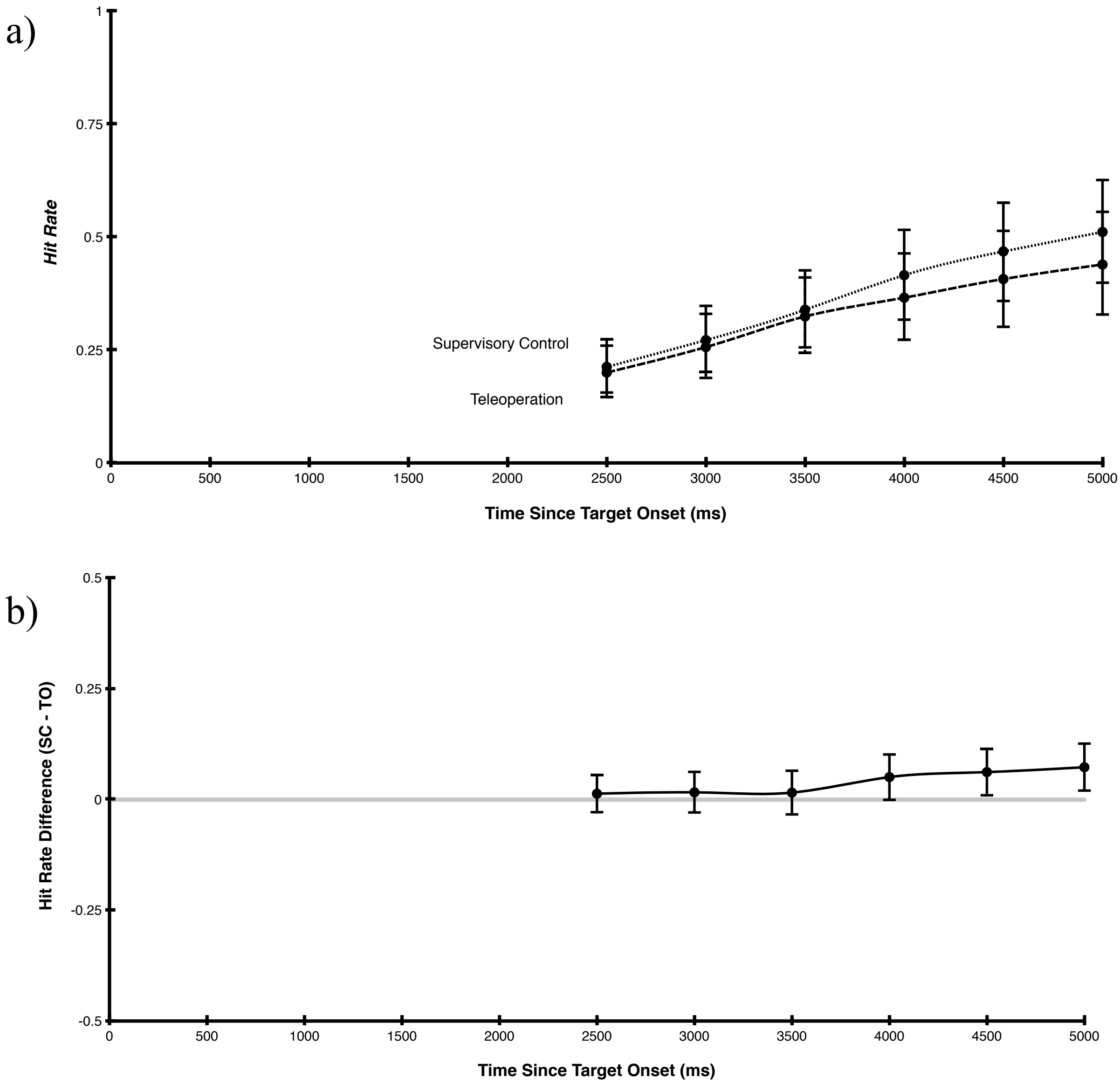


Figure 6-3. a. Mean cumulative hit rates across time for supervisory control and teleoperation. Error bars represent 95% BCIs. *b.* Mean hit rate difference (supervisory control – teleoperation) and 95% BCIs for each time bin. Error bars overlapping the grey zero line indicate non-credible differences between conditions.

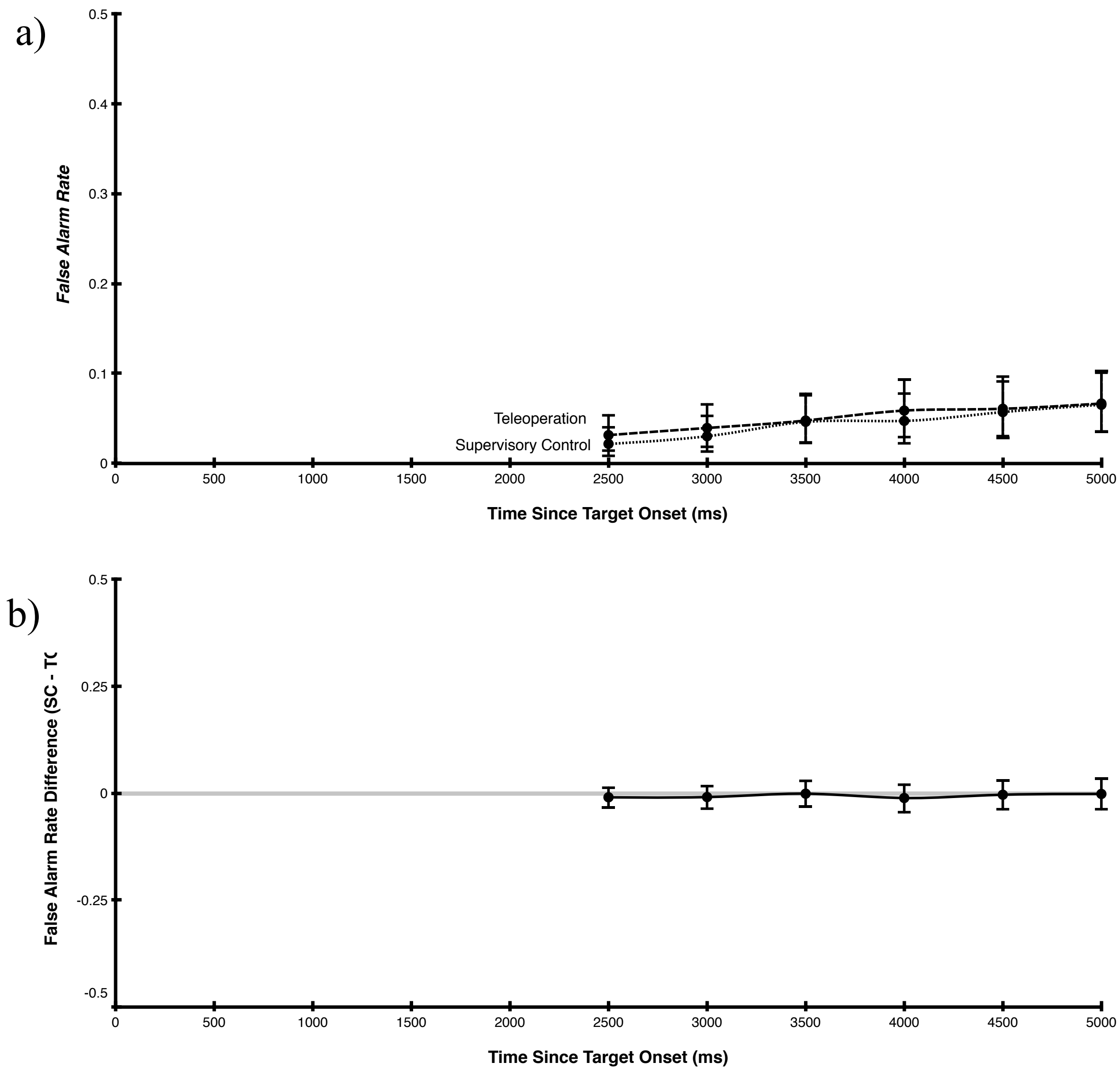


Figure 6-4. a. Mean cumulative false alarm rates (and 95% BCIs) across time for supervisory control and teleoperation. *b.* Mean false alarm rate difference (supervisory control – teleoperation) and 95% BCIs for each time bin. Error bars overlapping the grey zero line indicate non-credible differences between conditions.

Vehicle Control Performance

Speed control. In the current study, the vehicle control task acted as a loading on top of the target detection task. We were still interested in vehicle control performance, however, to ensure participants had followed instructions and had made a valid attempt to traverse from the starting point to the destination as quickly and safely as possible. Because of difficulties measuring lane deviation in the simulation, our main measure of driving performance was speed. This measure also allowed us to compare performance of the vehicle under supervisory (autonomous) conditions with performance when teleoperated by participants.

Comparing vehicle speeds between the two conditions found mean speeds were lower for teleoperation (M = 52.78 kph, 95% BCI = [49.55, 56.09]) than supervisory control (M = 62.54 kph, 95% BCI = [59.26, 65.77]), (M_{Diff} = 9.75 kph, 95% BCI = [5.31, 14.10], d = 0.97). This indicates that participants operated the vehicle cautiously, driving slower than instructed, resulting in lower speeds than the vehicle operating in supervisory control (i.e., when the confederate was driving).

Number of critical incidents. In addition to the speed measures of vehicle performance, we recorded the number of critical incidents participants experienced throughout the scenario. So that we had a baseline to compare against participants' teleoperation performance, we also recorded all critical incidents that occurred during the supervisory control block. Because our confederate received extensive training on the task, we expected fewer critical incidents in the supervisory control condition than in the teleoperation condition. As expected, a greater number of critical incidents occurred, per session, during the teleoperation block (M = 2.62, 95% BCI = [1.96, 3.27]) than the supervisory control block (M = 0.69, 95% BCI = [0.04, 1.35]), (M_{Diff} = 1.93, 95% BCI = [1.03, 2.80], d = 0.95). However, as the number of critical incidents in the teleoperation condition was reasonably low, we have some evidence that participants followed instructions to navigate the vehicle as safely as possible. The most common critical incident in both the supervisory control condition (M = 0.5 incidents per session, SD = 0.69) and the teleoperation condition (M = 1.90 incidents per session, SD = 1.21) was a collision with a stationary object, such as a building or street sign.

Discussion

Increasing automation reduces the number of tasks an operator must perform at any one time, helping to reduce cognitive workload and also potentially increase performance on other tasks. The current study examined whether automating a vehicle control task could improve performance on a primary visual monitoring task. By manipulating whether participants supervised or remotely operated a vehicle, we manipulated whether participants were performing only a single- or dual-task, respectively. Our general premise was that the increased cognitive load associated with performing both the teleoperation and monitoring tasks simultaneously would reduce monitoring performance for visual targets when compared with performing the monitoring task alone. These analyses uncovered two main findings about monitoring performance in the detection task. Firstly, as predicted, the supervisory control condition resulted in lower workload than the teleoperation condition. Secondly, neither sensitivity nor response bias differed credibly between the supervisory control and teleoperation conditions. Participants tended to use a highly conservative response bias, regardless of condition. This style of responding meant participants produced low hit rates (reaching a maximum of 50%) and extremely low false alarm rates (around 5%). Moreover, discrimination between targets and non-targets did not vary at any stage between the two conditions. Thus, contrary to expectations, the reduced workload in the supervisory control condition did not result in better target discrimination, nor did it change response bias, compared with teleoperation.

We measured cognitive workload in the current study to ensure participants found the teleoperation condition more demanding than supervisory control. In line with expectations, workload scores were higher in the condition where participants had to teleoperate the vehicle while monitoring for visual targets. Thus, performing the teleoperation task did increase cognitive demand beyond the monitoring task alone. Existing literature shows that increasing cognitive demand may reduce the size of a person's visual field (Ikeda & Takeuchi, 1975; Rantanen & Goldberg, 1999), causing a 'tunnel vision' effect (Williams, 1985), and can reduce how quickly people respond to critical events (Strayer & Johnston, 2001). What is interesting, then, is why the added cognitive load of the teleoperation condition did not also reduce visual monitoring performance. One explanation may be that the cognitive workload was not high enough to influence visual information processing. Recall that teleoperation and supervisory control both produced only moderate levels of workload. Thus, though teleoperating the vehicle was more cognitively-demanding than simply supervising it, this extra cognitive demand still may have not been enough to influence detection.

A more likely explanation for finding no difference in target detection between the two task-load conditions is that participants compensated for the added load of the teleoperation condition by reducing their vehicle speed. Though we instructed them to follow strict speed limits throughout the task (i.e., 50-kph in urban areas and 80-kph in rural areas), participants tended to err on the side of caution by maintaining a lower than recommended speed. Consequently, speeds during teleoperation were lower than those in supervisory control when the confederate was regulating the vehicle's speed. This implies that participants may have strategically traded-off performance on the vehicle control task to minimise the risk of missed targets in the monitoring task. Thus, though we instructed participants to prioritise both tasks equally during the dual-task block, our findings hint toward participants prioritising the monitoring task at the expense of the teleoperation. This difference in task prioritisation, and the resulting difference in speed, may have masked a difference in sensitivity between the teleoperation and supervisory control conditions.

Conversely, though, faster speeds in the supervisory control condition may have encouraged a spurious performance advantage. If the vehicle was moving at faster speeds during supervisory control than during teleoperation, then at any moment following the onset of a possible target, the vehicle would have been closer to the target during supervisory control than teleoperation. This would suggest the supervisory control condition was easier purely on the basis of the distance between the vehicle and possible targets, and thus, could explain any detection benefits within supervisory control.

Another point to mention here is that, on the whole, detection rates were very low in the current task. We designed the task to simulate a realistic scenario, and hence, incorporated targets that ranged from extremely easy (e.g., standing next to the road) to extremely difficult (e.g., standing behind trees in the periphery) to detect. However, given the high frequency of target events (targets/non-targets appeared every 15 seconds or so) and the high target-to-distractor ratio, it is particularly surprising that response bias was conservative across conditions. It is possible that the conservative responding reflected how we framed the detection task and by the limited time frame for responding to a potential target. Although we did not punish incorrect responses (i.e., false alarms or misses), participants may have responded more conservatively based on the hypothetical risk of making a false alarm in the real world. As military environments often entail high-risk consequences for judgements (e.g., risk of civilian death if personnel incorrectly fire at an unknown identity), in this study, participants may have simply been over-cautious in making judgements about possible targets. Such an effect may have been further enhanced by the limited time window for making a response. Because participants only had a total of 5000 ms to make a response after a potential target became visible in the scenario, overly-cautious responders may have responded too late to record a response, leading to very low hit and false alarm rates. Had we presented targets for a longer duration, for instance, up to 10 000 ms, we may have found higher response rates overall. Considering hit rates, in general, were low, extending the response period may have captured additional detections that were missed in the current study due to the limited time window for responding.

Finally, it is important to recognise that the monitoring-only condition provided an extremely non-demanding supervisory control task. During supervisory control, participants only had to monitor for visual targets and did not need to attend to the performance of the vehicle as they were never required to step-in and regain vehicle control in the case of errors. Thus, some may argue that the current study's supervisory control mode is less of an example of a semi-autonomous supervisory control mode than used in previous studies (e.g., Kessel & Wickens, 1982; Wickens & Kessel, 1979; Young & Stanton, 2004) and is more of a full task offloading. Though this is true, it makes the fact we found no effect of task load on target detection measures more surprising. If participants were equally poor at detecting targets across conditions even when the baseline condition involved near-perfect automation requiring no operator input, it gives little hope that a supervisory monitoring task that demands careful attention will improve concurrent visual target detection. Considering participants were predominantly comprised of untrained civilians, future research may benefit from including trained military personnel who are experienced in target detection tasks. Such research would help identify whether the reduced load from an automated system can assist visual processing among experienced personnel.

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CHAPTER 7: GENERAL DISCUSSION

Over the years, a variety of different measures have been used to assess *processing capacity* or *processing efficiency* for visual information. In many studies, the interest has focused on processing capacity while under single-task load; in other words, how efficiently we can process multiple sources of information when we are wholly focused on those different pieces of information. In the current set of studies, I used a handful of converging measures—workload capacity (Houpt & Townsend, 2012; Townsend & Nozawa, 1995), workload resilience (Houpt et al., 2013; Houpt & Little, 2017), and detection measures of SDT (Green & Swets, 1966; Stanislaw & Todorov, 1999)—to assess visual processing efficiency under concurrent task load. These studies of capacity had two main aims. Firstly, they sought to determine whether processing efficiency decreases with increases in concurrent task load. Secondly, they aimed to identify potential factors that influence processing capacity when a person is under increased levels of task load.

Cognitive Capacity Under Dual-Task Load

One aim for this set of studies was to examine whether visual processing capacity is reduced when an observer divides attention between a target detection or recognition task and a concurrent visuo-manual task. Before I go on, however, I should first reiterate what processing efficiency tells us. In all these studies except Study 5, I measured processing efficiency using either the resilience or capacity coefficient measures. Both of these measures gauge the efficiency of multiple-item processing—such as when two targets appear concurrently or when a target appears alongside a distractor—relative to single-item processing. Thus, these measures provide ratios of processing efficiency that we can compare between different experimental conditions. *Processing efficiency* is therefore different from *processing quality*, which focuses on how quickly or how accurately single targets are processed. Critically, equivalent processing efficiencies do not necessarily imply that the underlying processing rates, and hence, processing qualities, are also equivalent. Thus, in the following sections, when I state that processing efficiency does not vary across conditions, I refer to the ratios of multiple-item to single-item processing, rather than the rates of the underlying channels.

Across all these studies except one, I found processing capacity to be limited. More importantly, I found no evidence that target processing efficiency is further limited by concurrent visuo-manual task load. Thus, dividing attention between tasks did not further reduce the efficiency of an already limited-capacity system. Experiments 1 and 2 of Study 1 examined processing efficiency for widely-separated visual targets in uncluttered displays, while the participant performed the detection task alone or with a concurrent visuo-manual tracking task. Both experiments found resilience to be limited capacity, producing less efficient performance than predicted by the standard parallel model, or the unlimited capacity independent processing model (UCIP; Houpt & Townsend, 2012; Townsend & Nozawa, 1995). However, neither experiment found a difference in workload resilience across levels of task load. Study 2 replicated the null effect of task load using workload capacity for distractor-absent displays. Thus, both workload resilience for distractor-present displays and workload capacity for distractor-absent displays appear resistant to changes in concurrent task load. The same pattern was found in Study 1, Experiment 3, in which displays were designed to demand serial processing of targets and distractors. As expected, resilience reached super-capacity levels when stimuli required serial processing (Houpt & Little, 2017; Little et al., 2015). Nevertheless, resilience level was unaffected by a concurrent tracking task.

The findings for these experiments may be best explained by an attention-switching model (e.g., Wickens & Gopher, 1977) in which the target detection/discrimination and manual tracking tasks are interleaved. In such a model, performance on the continuous tracking task in the dual-task condition is interrupted by the onset of targets and distractors in the periphery. These onsets capture attention away from the tracking task, drawing attention to the peripheral stimuli (Yantis & Jonides, 1990). Because of the time needed to shift attention from the tracking task to the peripheral stimuli, RTs to targets in the dual-task condition are longer than those in the single-task condition. However, once attention switches to the detection task, stimuli are processed similarly to those in the single-task condition. Thus, in both conditions, information is processed with similar efficiency; the only difference in target detection/discrimination between conditions is a base-time cost resulting from task-switching. This model would allow processing of targets to occur in parallel, even though attention is switching between tasks in serial.

The lack of a task load effect also appeared in Study 5. Rather than directly measuring processing using the capacity coefficient or resilience measures, Study 5 inferred capacity from signal detection performance in a conventional analysis of dual-task costs. Results generalised the findings of the previous studies, replicating the lack of any task load effect. Thus, despite increasing operator mental workload relative to supervisory control (single-task), teleoperation (dual-task) showed no evidence of compromising visual processing. Thus, using a higher-fidelity realistic task produced very similar results to the controlled laboratory studies: increasing task demand did not reduce visual processing efficiency.

The Roles of Eccentricity, Visual Field, and Salience in Driving Processing Efficiency

The second aim of the current set of studies was to identify task characteristics that might moderate processing capacity while under task load. These factors included a target's location in the visual field, whether that be the eccentricity of the target from centre or the location of the target within the upper or lower visual field, as well as target salience.

In Study 3, Experiment 1, I explored whether increasing target eccentricity could decrease processing capacity for redundant peripheral targets. In line with theories that presume attention is biased toward the central visual field (e.g., Carrasco, Evert, Chang, & Katz, 1995; Carrasco, McLean, Katz, & Frieder, 1998; Crundall, Underwood, & Chapman, 1999; Williams, 1985), I predicted low eccentricity targets would be processed more efficiently than high eccentricity targets. In Experiment 2, I predicted processing efficiency to be greater in the LVF than the UVF. But, despite shorter RTs for targets appearing at low eccentricities or in the LVF, I found no evidence that target location affected processing resilience. The visual search literature demonstrates that the quality of processing varies across the visual field, with clear RT benefits for targets appearing closer to, rather than further from, fixation (e.g., Carrasco & Yeshurun, 1998; Carrasco et al., 1995, 1998; Wolfe, O'Neill, & Bennett, 1998). Similarly, target RT benefits are greater in the LVF rather than UVF (e.g., Intriligator & Cavanagh, 2001; Rezec & Dobkins, 2004). These differences in processing quality, though, do not change the efficiency with which attention is divided over multiple channels.

Information salience was the final factor I explored in relation to information processing under load. Generally, information that is higher in salience, meaning that it stands out more against its background or against other information (Itti & Koch, 2000; Wolfe, 1998), is detected faster and more accurately than information that is lower in salience (e.g., Duncan & Humphreys, 1989; Steelman, McCarley, & Wickens, 2013; Ververs & Wickens, 1998; Wickens, Sebok, McCormick, & Walters, 2016). In Study 4, I examined whether increasing salience can bolster capacity even under distraction by a concurrent visuo-manual task. As predicted, salient targets were not only processed faster, but they were also processed more efficiently, than low salience targets. This effect was consistent across both the single- and dual-task conditions, suggesting that, in contrast to task load, target salience is critical in driving processing efficiency.

This salience effect is consistent with research that shows enhanced detection when targets are higher contrast levels from their backgrounds (e.g., Duncan & Humphreys, 1989; Lamy, Leber, & Egeth, 2004; Theeuwes, 1994; Wickens et al., 2016). More critically, these findings support current guidelines for designing systems or displays that encourage efficient performance (e.g., Federal Aviation Administration, 2011; General Aviation Manufacturers Association, 2000; Wickens et al., 2016). Given salience was effective for increasing processing capacity both when participants only detected the targets and when distracted by the concurrent task, I have evidence supporting salience as a valuable factor for enhancing multiple-item processing in more complex environments. As workload capacity scores under high salience were very close to UCIP performance, these findings also point towards salience driving processing that is almost equivalent to unlimited capacity parallel models. These findings directly contrast the limited capacity values of my earlier studies. Thus, of the different factors I explored in the current studies, target salience appears to have the greatest potential for enhancing processing under dual-task load. Further research exploring salience benefits to capacity when loaded by multiple concurrent tasks may assist display design within complex workspaces.

The Role of Cognitive Architecture in Explaining Capacity

Though not directly relevant to my research question, one final important concept that relates to workload capacity and that is relevant to the current set of studies is cognitive architecture. As mentioned earlier on, architecture refers to the structure of the system processing, such as whether information is processed in parallel, serially, or coactively (Townsend & Ashby, 1983). Although I did not directly test architecture using Systems Factorial Technology (SFT) in the current set of studies, I did indirectly infer architecture from measures of workload capacity and resilience. Across all of these experiments (except Study 1, Experiment 3, in which participants were forced to process targets in serial) I found consistent evidence of capacity limitations. The notion of a limited capacity parallel model was supported by almost equivalent levels of processing efficiency in distractor-absent displays (Study 2) and distractor-present displays (Study 1, Experiments 1 and 2). In contrast, when we forced participants to adopt a serial processing strategy (Study 1, Experiment 3), processing increased to super-capacity levels, as predicted by Little et al. (2015).

As noted earlier, it is important to remember that architecture is a separate and independent concept from capacity. The findings from the current set of studies do, however, demonstrate how capacity and architecture interact, and they also show how different contexts or stimuli may engender different processing structures, as well as different levels of efficiency.

Summarising Cognitive Capacity Under Task Load

The current studies examined a range of factors that may explain visual information processing while dividing attention between tasks. Overall, I found that, regardless of a target's location within the display or the presence or absence of distractors, visual processing efficiency is consistently limited capacity, performing poorer than predicted by the UCIP model. More importantly, I found increasing resource demand by performing a concurrent task made no difference to processing efficiency. The only factors that demonstrated clear evidence for changing capacity were target salience and processing architecture. The current studies identified few instances of variations to capacity, and they suggest that processing, by and large, is capacity-limited. Thus, these findings support recent arguments that limited capacity and super-capacity are more common phenomena than unlimited capacity (Blaha, 2017a).

The current studies employed two different ways to conceptualise, and hence, measure, capacity: the first involved a normalised score, whereas the second measured a change in detection performance over time. Despite clear differences in the methods for assessing capacity across these studies, overall, I discovered evidence for two similar findings. Firstly, I found that visual processing is not affected by dual-task load, and secondly, I discovered that visual processing is, overarchingly, inefficient.

Notably, these studies only considered capacity when performing either a single task alone or two tasks concurrently. As many real-world contexts, such as operating a vehicle or flying an aeroplane, involve performing multiple concurrent tasks, it would be valuable to assess whether performing additional tasks may eventually deplete cognitive resources, and consequently, limit processing capacity (see Fox & Houpt, 2018). Thus, future research may hint at whether increasing the number of concurrent tasks reduces capacity further, or whether capacity is stable in response to any and all variations in task load. In addition, the current findings identified clear capacity benefits for high rather than low salience targets, both under single- and dual-task load. Because of the potential benefit of increasing multiple-item processing in high-stress, operational environments, exploring whether salience can also increase processing efficiency in real-world contexts may be a valuable avenue for future research.

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APPENDIX A

Additional Experiments Excluded from Study 1 (Chapter 2)

The following two experiments were follow-ups to Study 1, Experiment 1 that were cut from the article 'Redundant Target Processing is Robust Against Changes to Task Load' by Morey, Thomas & McCarley (2018) prior to publishing. This section also contains a within-study meta-analysis to examine the overall effects of task load on processing capacity using the data pooled from some of the original published experiments and the additional experiments below. This appendix also contains extra material focusing on the role of leftward attentional biases in target processing. Following reviewer suggestions, and to increase the coherence of the manuscript, this section was cut from the published version.

Note that these experiments contain the original analyses, and thus do not contain difference means and BCIs for each comparison (differences are inferred by overlapping BCIs between conditions).

A Leftward Bias in Target Processing?

By default, attention tends to rest unevenly and asymmetrically across the visual field. An inherent bias toward the central visual field prioritises stimuli near the fixation over those that are more eccentric (Carrasco & Yeshurun, 1998; Carrasco, Evert, Chang, & Katz, 1995; Wolfe, O'Neill, & Bennett, 1998). Similarly, a modest attentional bias towards the left side of space produces a corresponding neglect of the right (Mattingley et al., 2004; Nicholls, Loftus, Orr, & Barre, 2008). This asymmetry, known as *pseudoneglect*, manifests in simple perceptual and cognitive tasks (e.g., Fecteau, Enns, & Kingstone, 2000; Śmigasiewicz et al., 2010; Thomas, Castine, Loetscher, & Nicholls, 2015; Thomas, Loetscher, & Nicholls, 2014; Thomas & Elias, 2011), and in visuomotor tasks ranging from sports performance (Nicholls, Loetscher, & Rademacher, 2010), through to locomotor (Nicholls et al., 2008; Nicholls, Loftus, Mayer, & Mattingley, 2007) and vehicular navigation (Nicholls, Hadgraft, et al., 2010; Nicholls, Jones, & Robertson, 2016).

Some evidence suggests that pseudoneglect also affects drivers' ability to notice objects or events in traffic scenes (Benedetto, Pedrotti, Bremond, & Baccino, 2013). Benedetto et al. (2013) tested for leftward attentional biases within a simulated driving task. Participants controlled a vehicle within a desktop simulator, responding to road signs that occasionally instructed them to change lanes. Signs appeared in pairs, one each on the left and right roadside, and the two signs within a pair always provided the same instruction. Despite this symmetry of the stimulus information, participants' eye movements showed a strong leftward bias, with approximately 90% of fixations directed to the road sign on the left. Benedetto et al. concluded that a leftward attentional bias affects performance even in complex, naturalistic tasks such as driving. However, by only presenting the targets redundantly within each trial, Benedetto et al. were unable to determine whether the leftward bias was the result of an inherent processing constraint that favours the left field, or was rather a strategic bias adopted by the participants. That is, their data did not reveal whether a left-field advantage might have been present when targets were presented singly, on only one side of visual space.

Experiment 1c

Peripheral target processing efficiency was limited in both the single and dual-task conditions of Experiment 1 (See Chapter 2). However, targets were randomly rotated letters T and L, characters distinguished only by the spatial arrangement of common features. Theories of visual attention often hold that the ability to recognise or detect conjunctions or configurations of features demands focused attention, but that elementary visual properties are processed in parallel across the visual field by high-capacity feature detectors (Treisman & Gelade, 1980; Wolfe & Bennett, 1997). This implies that, although target processing efficiency was limited in the first experiment, it may be closer to unlimited when targets and distractors are distinguished by basic, highly-discriminable features. Therefore, Experiment 1c replicated Experiment 1b using target and distractor characters (X and O for target and distractor, respectively) that were distinguishable by elementary visual properties.

Method

Participants. Twenty-two Flinders University students (14 female) were recruited for AU$10 or for course credit. The mean age of participants was 22.55 years (*SD* = 9.57, *Range* = 18 to 63). None of the participants had taken part in Experiments 1a or 1b. All participants were fluent in English, had normal colour vision, and had normal, or corrected-to-normal, visual acuity. The minimum FLANDERS score required for inclusion was +5 (*M* = +9.31, SD = 1.36). Eleven participants had current driver's licences with between 0.5 and 30 years of driving experience (*M* = 5.59, SD = 8.33).

Apparatus and stimuli. Experiment 1c employed the same materials, computer program, and apparatus as Experiment 1b. The stimuli in this experiment differed in that the target was now an X and the distractor an O.

Procedure. Participants were instructed to make a joystick button press response if an X appeared in either of the peripheral stimulus locations and to refrain from making a response when only Os appeared. All other aspects of the experiment remained the same.

Analysis. Analysis was the same as for the experiments above.

Results

Error rates. In Experiment 1c, two participants with excessive false alarm rates (>.30) were removed from analysis. Mean false alarm rate for the remaining 20 participants was lower than 10 percent (*M* = 0.06, *SE* = 0.01). Participants were generally very good at responding to targets, with extremely low miss rates for all target conditions (left single: *M* = 0.01, *SE* < 0.01; right single: *M* = 0.01, *SE* < 0.01; redundant: *M* < 0.01, *SE* < 0.01).

Throughout the testing session, participants made approximately the same number of correct responses to targets on the left (*M* = 71.9, *SE* = 0.28), targets on the right (*M* = 71.55, *SE* = 0.29), and to redundant targets (*M* = 71.65, *SE* = 0.24).

RTs. A comparison of mean RTs for left single targets (*M* = 537 ms, 95% BCI = [489, 583]) against right single targets (*M* = 529 ms, 95% BCI = [482, 576]) produced no credible difference, *d* = 0.19. Furthermore, evidence found the more discriminable stimuli, X and O, produced a faster mean single-target RT (*M* = 534 ms, 95% BCI = [485, 583]), than did the T and L stimuli from Experiment 1b, *d* = 0.95.

As in Experiment 1, data gave strong evidence for a redundancy gain when comparing the fastest single-target RTs (*M* = 518 ms, 95% BCI = [471, 565]) and the redundant-target RTs (*M* = 493 ms, 95% BCI = [447, 540]), *d* = 0.75. Comparing the size of the redundancy gain for the current experiment (M_{RSE} = 25 ms, 95% BCI = [10, 39]) to that of Experiment 1a, *d* = 0.51, and to that of Experiment 1b, *d* = 0.17, found no credible evidence of a difference for either comparisons.

Resilience. As mentioned above, employing stimuli distinguished by basic features was expected to increase parallel processing efficiency for redundant targets, resulting in higher resilience values. Surprisingly, *Rz* remained extremely limited in Experiment 2 (M_{Rz} = -3.06, 95% BCI [-3.59, -2.53]), *d* = 2.78, showing no evidence of a difference when compared with Experiment 1b, *d* = 0.51. Thus, despite producing faster RTs, increasing target-distractor discriminability failed to boost resilience scores. The similarity in processing efficiency across experiments is consistent with a parallel process model (Little et al., 2015).

Tracking performance. Relative to the single-task condition in Experiment 1a, mean RMSE was smaller, (M_{RMSE} = 15.09°, 95% BCI = [12.80, 17.34]), suggesting that participants performed the tracking task as instructed. Data gave no credible evidence for a relationship between RMSE and *Rz* scores, *r*(18) = .22, 95% BCI = [-0.27, 0.72].

Experiment 1d

Experiments 1 and 2 compared redundant-target RTs to trials in which a single target is accompanied by distractor occupying the alternative location. Under these conditions, either a serial or parallel processing architecture can produce a redundancy gain (Houpt & Little, 2016; Townsend, 1990) and low resilience values (Little et al., 2015). For example, a parallel process with a modest or no redundancy gain will produce limited resilience values. When items are processed in parallel, distractors produce little competition for processing resources, and hence, the presence of distractors does not impair target discrimination. Thus, RTs for redundant-target trials will be equal or similar to RTs for single-target trials, resulting in little no redundancy gain, and consequently, limited resilience values.

It is also possible, however, that limited resilience values result from a serial model in which targets are prioritised over distractors (Wolfe, 1994). Wolfe's (1994) revised model of guided search suggests that visual search involves an initial parallel processing of information across the visual field to generate independent maps, or *feature maps*, of basic visual features, such as shape or colour. These feature maps thus lead the observer to pre-attentively identify locations within the visual field with higher featural activation, which then lead to the serial processing of the items based on activation level. Based on this model, if, on single-target trials, feature maps for targets have higher levels of activation than those of distractors, on average, targets will be detected and fixated faster than distractors. Thus, even though all items are processed in serial, detection RTs on single-target trials will be faster than those within a standard serial model in which targets and distractors are processed equally likely. Notably, however, although detections on redundant-target trials will likely be faster than on single-target trials, the smaller redundancy gain will result in lower resilience scores, overall.

Hence, the data for the first two experiments are consistent with both a parallel model and a serial model where targets were prioritised over distractors. To clarify the processing architecture for peripheral redundant targets, Experiment 1d, therefore, replicated the general procedure of Experiment 1b, but removed all distractors from the single-target trials, thus making it a pure target detection task. As noted above, redundant-target processing efficiency measured relative to a single-target condition without distractors is termed capacity (Little et al., 2015). Capacity, unlike resilience, is unaffected by potential costs of distractor processing. A redundancy gain as compared to a single-target condition with no distractors implies a parallel processing model (Townsend, 1990), and in conjunction with a redundancy gain, normalised capacity scores less than zero imply processing less efficient than predicted by the UCIP model. Converging evidence for or against a parallel model is possible from a comparison of capacity and resilience scores. Holding stimulus characteristics and task demands otherwise equal, a parallel processing model suggests that capacity and resilience scores should be similar, and thus comparable (Little et al., 2015). Conversely, a serial model suggests that capacity should be more limited than resilience, as target detection will produce a smaller (or no) redundancy gain in the absence, rather than presence, of distractors. As such, Experiment 1d tested this notion by assessing capacity within a distractor-absent display.

Method

Participants. Twenty-one Flinders University students (16 female) completed the experiment for AU$10 payment. The mean age was 22.57 years (*SD* = 6.67, *Range* = 18 to 48). No participants had taken part in any of the previous experiments. The eligibility requirements were English fluency, normal colour vision, and normal or corrected-to-normal visual acuity. All participants had a minimum FLANDERS score of +5 (*M* = +9.52, *SD* = 0.93). Fourteen participants held current driver’s licences, with a mean of 4.45 years of driving experience (*SD* = 6.62, *Range* = 0.5 to 30 years).

Apparatus and stimuli. Experiment 1d employed the same materials as Experiment 1b; however, all distractors were replaced with a blank space. As such, only targets (Ts) were presented. All other aspects of the task remained the same.

Procedure. The procedure for the joystick task was identical to that of Experiments 1b and 2. For the target-detection task, participants were instructed to initiate a button press if a target (T) appeared, but to refrain from making a response when no targets were presented. All other aspects of the task remained the same.

Analysis. Analysis was the same as for the experiments above.

Results

Error rates. In Experiment 1d, no distractors were presented, and consequently, a false alarm meant the participant responded when no stimuli were present. Unsurprisingly, this was an uncommon occurrence, and false alarm rates were lower than in the first three experiments (M = 0.02, SE < 0.01). One participant was removed from analyses for having an excessive miss rate (> 0.60). For the remaining 20 participants, miss rates for single targets on the left (M = 0.03, SE = 0.01), single targets on the right (M = 0.02, SE = 0.01), and redundant targets (M = 0.02, SE = 0.01) were very low. The mean number of targets correctly detected was approximately equal across trial types (left targets: M = 71.25, SD = 0.36; right targets: M = 71.05, SD = 0.37; redundant targets: M = 71.05, SD = 0.41).

RTs. Similar to previous findings, data gave substantial evidence in favour of the null when comparing RTs for single targets presented on the left (M = 511 ms, 95% BCI = [466, 556]) with those on the right (M = 515 ms, 95% BCI = [471, 560]), d = 0.10. Thus, once again, RTs showed no evidence of a leftward attentional bias.

The mean single-target RT (M = 513 ms, 95% BCI [469, 557]) was considerably faster than that of Experiment 1b, d = 1.19. However, there was no credible difference in the mean single-target RT when compared with that of Experiment 1c, d = 0.20. Responses to redundant targets were only slightly faster (*M* = 471 ms, 95% BCI = [426, 515]) than those to the fastest single targets (*M* = 499 ms, 95% BCI = [454, 542]), *d* = 1.00, producing a mean raw redundancy gain of 28 ms, 95% BCI = [15, 40]. Comparisons of the redundancy gain with those of Experiments 1b and c found no credible differences in both cases, *d* = 0.10, vs. Experiment 1b, and *d* = 0.08, vs. Experiment 1c.

Capacity. Analogous to the resilience scores, for statistical analysis, raw capacity scores were converted to the standardised capacity score, *Cz*. As with *Rz, Cz* values of zero indicate unlimited capacity, values greater than zero indicate super-capacity, and values less than zero indicate limited capacity. Consistent with the previous experiments, capacity scores were still highly limited (M_{Rz} = -2.44, 95% BCI = [-3.15, -1.73]), *d* = 1.65. Thus, even when distractors were removed capacity remained well below that of a UCIP model. Furthermore, there was substantial evidence suggesting against any difference in the normalised capacity scores between the distractor-free condition in the current experiment and the normalised resilience scores of the distractor-present condition of the earlier experiment using similar stimuli (Experiment 1b), *d* = 0.01. The similarity of resilience and capacity again provides additional evidence consistent with a parallel processing architecture.

Tracking performance. Mean RMSE on the tracking task was 17.29˚, 95% BCI = [13.53, 21.04], (as compared with 29.84˚, 95% BCI = [25.28, 34.43] in Experiment 1a), suggesting participants were engaged in the task. Data failed to reveal any correlation between tracking error and standardied capacity scores, *r*(18) = -.07, 95% BCI = [-0.58, 0.44].

Cross-Experiment Meta-Analyses (MA). Data from all previous experiments were used to calculate meta-analyses for the attentional bias RTs (see Figure A-1) and capacity/resilience scores (see Figure A-2). Analyses were calculated using a Bayesian hierarchical model (Kruschke, 2015), implemented in JAGS 4.1.0 statistical software

(Plummer, 2015). All three meta-analyses assumed normal priors on the grand mean, with a gamma prior and uniform distributions on the priors of the grand mean and SD, respectively. Analyses were carried out using four chains of 50,000 samples. In Figure A-1, MA is very close to the centre line (M = -6, 95% BCI = [-17, 5]), and its credible interval overlaps zero, thus showing no evidence of a spatial bias effect for single-target RTs. Figure A-2 shows MA for processing efficiency was limited capacity (M = -2.65, 95% BCI = [-2.99, -2.31]), and the narrow credible intervals around MA illustrates that this was a consistent effect throughout Experiments 1b-d.

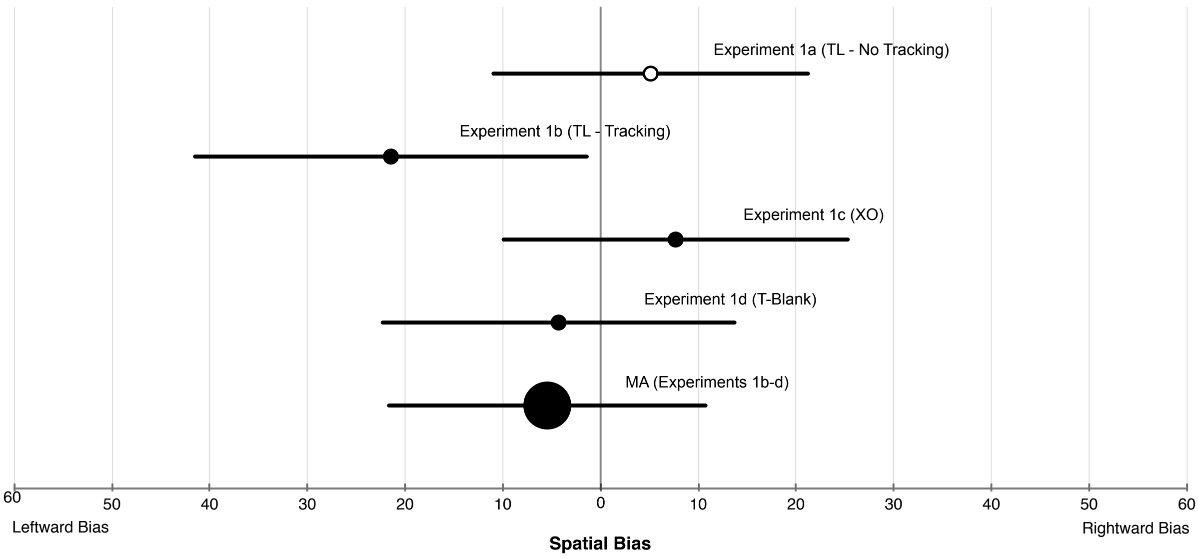

Figure A-1. 95% BCIs for lateral bias scores for each experiment. The single-task experiment (Experiment 1a) is represented by a hollow circle whereas the three dual-task experiments (Experiments 1b-d) are represented by full circles. The symbol labeled MA represents the mean value estimated from a Bayesian hierarchical meta-analysis of the three dual-task experiments. The radius of each symbol is proportional to N for the corresponding analysis. Bias scores were calculated by subtracting left single-target RTs from right single-target RTs. Consequently, negative values represent a leftward bias and positive values represent a rightward bias.

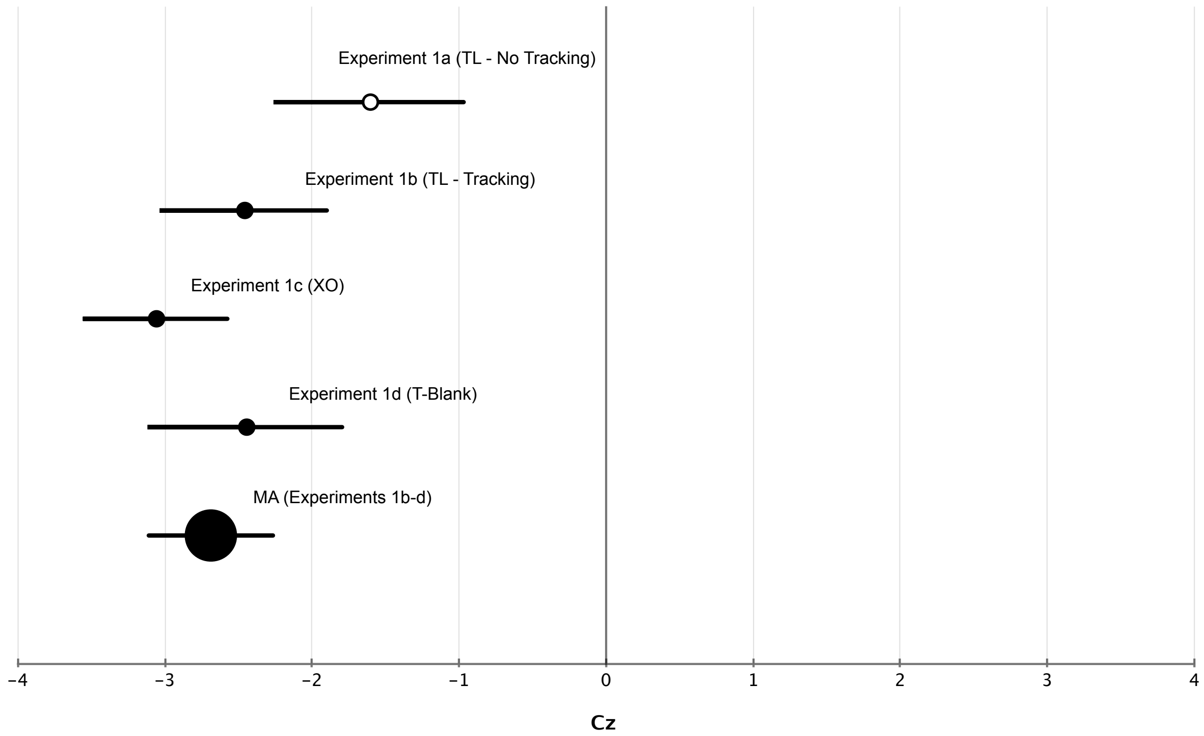

Figure A-2. 95% BCIs for standardised capacity/resilience scores for each experiment. The single-task experiment (Experiment 1a) is represented by a hollow circle whereas the three dual-task experiments (Experiments 1b-d) are represented by full circles. The symbol labeled MA represents the mean value estimated from a Bayesian hierarchical meta-analysis of the three dual-task experiments. The radius of each symbol is proportional to *N* for the corresponding analysis. Positive scores represent super-capacity, whereas negative scores represent limited capacity. Where $Cz = 0/Rz = 0$, processing is equivalent to that of a UCIP model.

Discussion

Experiment 1d examined processing efficiency within a distractor-absent dual-task condition. When compared with distractor-present displays (Experiment 1b), Experiment 1d produced faster single-target RTs. However, redundancy gains between the two experiments were not credibly different. Thus, consistent with a parallel process model (Little et al., 2015) processing efficiency did not vary as a function of distractor presence. In fact, target processing efficiency was equally limited capacity in both experiments, providing evidence for a limited-capacity parallel model of target processing.

General Discussion

Across all experiments, there was no leftward bias for target detection, with the 95% credible intervals for all experiments overlapping zero. These findings contrast with those of Benedetto et al. (2013), who found a strong attentional bias toward targets presented on the left. The procedure and stimuli of the current experiments differed from Benedetto et al.'s in multiple ways, making it difficult to attribute the differences in outcomes to any specific factor. Benedetto et al. employed a more high-fidelity driving simulator, and gauged attentional bias from oculomotor behavior rather than RTs. One particularly interesting explanation for the difference between Benedetto's findings and the current results relates to the spatial distribution of target information. In Benedetto et al.'s (2013) experiment, target symbols, when they appeared, were always presented bilaterally. Consequently, participants could consistently look at either the left or right road sign to determine when to change lanes. Under this circumstance, a strategy of focusing attention on a single information channel may ease information access or reduce an operator's workload. In the present study, however, participants needed to attend to both sides of the display or risk missing a target. As such, participants were required to distribute their attention more evenly across the visual field. This suggests that operators may be more prone to displaying a leftward bias when information is presented bilaterally. Thus, when an operator is aware that the same information will be presented bilaterally, they may have a tendency to focus on only the left side of a display. When the placement of the information is less predictable, they may distribute their attention bilaterally to increase their chances of accurately detecting targets. Thus, a leftward attentional bias may drive target detection, but only when other factors, such as target redundancy or operator expectancy, are favorable.

Although pseudoneglect has been observed in a range of tasks (e.g., Mattingley et al., 2004; McCourt, 1999; Nicholls et al., 2007; Nicholls & Roberts, 2002; Thomas & Elias, 2011; Thomas, Stuckel, Gutwin, & Elias, 2009), the null evidence of lateral bias across the present experiments raise the question of how broadly the phenomenon generalises. These results echo other recent findings showing that lateralised attentional biases are not present for detection of target stimuli (Learmonth, Gallagher, Gibson, Thut, & Harvey, 2015). Furthermore, they are consistent with evidence of low correlations between the various tasks used to examine spatial biases (e.g., line bisection, greyscales, lateralised visual detection tasks), suggesting that pseudoneglect may be a multi-component phenomenon that manifests differently across different tasks (Learmonth et al., 2015). The implications for display design are that, controlling all other factors (i.e., target expectancies and eccentricities), targets are likely to be detected equally well when presented on the left and right sides of the display.

APPENDIX B

Error Rates for Study 3, Experiment 1 (Eccentricity Experiment – Chapter 4)

Table B-1.

Miss Rates and the Number of Correct Target-Present Trials from Study 3, Expt 1

	Low Eccentricity		High Eccentricity	
	Miss Rate (*M*, [*Range*])	No. Correct Responses (*M*, [*Range*])	Miss Rate (*M*, [*Range*])	No. Correct Responses (*M*, [*Range*])
Left Single	0.02 [0.00 – 0.26]	74,70 [37 – 85]	0.02 [0 – 0.28]	74.07 [41 – 83]
Right Single	0.03 [0 – 0.18]	70.90 [20 – 84]	0.02 [0 – 0.23]	71.33 [34 – 83]
Redundant	0.02 [0 – 0.20]	78 [43 – 84]	0.02 [0 – 0.22]	71.60 [21 – 84]

APPENDIX C

Error Rates for Study 3, Experiment 2 (Visual Field Experiment – Chapter 4)

Table C-1.

Miss Rates and the Number of Correct Target-Present Trials from Study 3, Expt 2

	Upper Visual Field		Lower Visual Field	
	Miss Rate (*M*, [*Range*])	No. Correct Responses (*M*, [*Range*])	Miss Rate (*M*, [*Range*])	No. Correct Responses (*M*, [*Range*])
Left Single	0.03 [0.00 – 0.20]	72.03 [20 – 83]	0.03 [0.00 – 0.12]	70.07 [38 – 83]
Right Single	0.03 [0.00 – 0.19]	65.62 [17 – 84]	0.04 [0.00 – 0.17]	69.60 [20 – 84]
Redundant	0.03 [0.00 – 0.28]	70.72 [39 – 85]	0.02 [0.00 – 0.12]	73.41 [38 – 83]

APPENDIX D

Error Rates for Study 4 (Salience Experiment – Chapter 5)

Table D-1.

Miss Rates and Number of Correct Target-Present Trials from Study 4

	Single-Task		Dual-Task	
	Miss Rate (*M*, [*Range*])	No. of correct responses (*M*, [*Range*])	Miss Rate (*M*, [*Range*])	No. of correct responses (*M*, [*Range*])
Low S; Distractor-absent	0.01 [0 – 0.07]	54.53 [42 – 58]	0.02 [0 – 0.17]	54.63 [44 – 58]
Low S; Distractor-present	0.01 [0 – 0.06]	54.97 [41 – 58]	0.02 [0 – 0.10]	54.83 [43 – 58
High S; Distractor-absent	0.01 [0 – 0.05]	54.73 [42 – 59]	0.02 [0 – 0.13]	54.73 [45 – 58]
High S; Distractor-present	<0.01 [0 – 0.07	54.97 [41 – 58]	0.02 [0 – 0.16]	54.83 [43 – 58]

APPENDIX E

Detection Data Excluded from Study 4 (Simulation Detection Study – Chapter 6)

Table E-1.

Detection Means [95% BCIs] for Excluded Time Bins (Bins 1-4) from Study 4

		Time Bin			
		1	2	3	4
		500 ms	1000 ms	1500 ms	2000 ms
	SC	25.74 [2.22, 70.24]	25.43 [2.39, 69.69]	1.69 [0.99, 2.65]	1.26 [0.83, 1.80]
d'	TO	1.65 [0.21, 7.92]	0.77 [0.25, 1.78]	0.85 [0.44, 1.37]	0.98 [0.60, 1.46]
	Diff	24.10 [1.12, 68.64]	24.66 [1.65, 68.91]	0.84 [0.12, 1.77]	0.28 [-0.20, 0.78]
	SC	27.93 [4.42, 72.42]	27.13 [4.09, 71.41]	3.03 [2.37, 3.98]	2.34 [1.96, 2.86]
c	TO	3.66 [2.27, 9.94]	2.39 [1.92, 3.38]	2.20 [1.84, 2.69]	2.09 [1.76, 2.53]
	Diff	24.27 [1.29, 68.84]	24.74 [1.74, 68.99]	0.84 [0.13, 1.75]	0.26 [-0.20, 0.72]
	SC	<.01 [<.01, < .01]	<.01 [<.01, <.01]	<.01 [<.01, .01]	.01 [<.01, .03]
FAR	TO	<.01 [<.01, .01]	.01 [<.01, .03]	.02 [<.01, .03]	.02 [.01, .04]
	Diff	-0.01 [-0.01, -0.01]	-0.01 [-0.03, -0.01]	-0.01 [-0.03, -0.01]	-0.01 [-0.03, 0.01]
	SC	0.01 [0.01, 0.03]	0.05 [0.01, 0.03]	0.09 [0.06, 0.12]	0.14 [0.10, 0.19]
HR	TO	0.02 [0.01, 0.04]	0.05 [0.03, 0.08]	0.09 [0.06, 0.12]	0.14 [0.10, 0.18]
	Diff	-0.01 [-0.02, 0.01]	-0.01 [-0.03, 0.01]	< 0.01 [-0.03, 0.03]	0.01 [-0.03, 0.04]

Note. *Diff* = difference scores (supervisory control – teleoperation)