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Influence of dual-task load on redundant signal processes

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Abstract ■ In high demand contexts, uni- or multi-modal signals are used to convey redundant information and improve performance. This is especially the case with improving the detection of discrete peripheral signals. However, how one processes peripheral signals may change depending on the greater environmental context. The underlying cognitive processing of signals is important to determine how they may influence the degree to which each signal enhances, as opposed to slows down, detection. Until now, it was unclear if i) the introduction of, or increased difficulty of, a second task changes how people combine peripheral signals (that is, in a parallel, serial, or coactive fashion) and ii) if processing efficiency depends on the salience of the peripheral signals or the presence/difficulty of a centrally located and continuous tracking task. This manuscript describes an application of Systems Factorial Technology to investigate the cognitive processing mechanisms of redundant signals in the context of a multiple object tracking (MOT) task. The MOT task load (track 0, 1, or 4 dots) and the salience of peripheral signals (bright, dim) were manipulated. The data indicate peoples' processing of peripheral signals changed depending on the MOT task load. Under a high MOT task load, most people processed redundant signals in a parallel fashion. Alternatively, nearly half of people processed the signals in a serial fashion when asked to simultaneously track 0 or 1 dot. Implications for the use and design of redundant signals in multi-task contexts that vary in task demands are discussed.

Keywords ■ Multi-tasking, cognitive workload, redundant signal processing.

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Introduction

Whether implicit or explicit, people constantly attempt to allocate resources to the demands of several tasks at the same time. This is a feat referred to as multitasking. An everyday example is driving: one must travel at the appropriate speed and stay within their lane but also detect, decipher, and respond to abrupt, and often peripheral, alerts. Despite the high prevalence of multitasking in the fast paced world, people have a finite amount of attentional resources and necessarily divide their attention between tasks (Norman & Bobrow, 1975). One particular view, resource theory (Norman & Bobrow, 1975; Kahneman, 1973; Wickens, 1984), posits multiple regions of workload: reserve capacity and cognitive overload. *Reserve capacity* is a state where one has an adequate amount of attentional resources in their reserve to maintain performance in two or more tasks. If demands of multiple tasks exceed the total supply of this reserve, performance decrements to one or both tasks will occur (e.g., Howard et al., 2021) – this is a state of *cognitive overload*.

The demands of one's primary task, for example, driving, may alter how, and how efficient, they process peripheral signals. For instance, when central task demands are high, people may take in more peripheral information simultaneously, known as parallel processing, but they may process each signal at a slower rate. Alternatively, when central task demands are low, people may process peripheral signals in sequential fashion, known as serial processing, but process each at the same rate as they would if the signal was presented in isolation.

System designers attempt to draw attention to critical peripheral signals by providing redundancy, referred to as redundant signals, or increasing the perceptual distinction, known as salience, from its environment. Often redundant peripheral signals are provided but only the detection of one is needed for a response, for example, lights and/or sirens of an ambulance. This is referred to as an "OR" decision rule. Redundant signals are often within a single modality (e.g., multiple flashing lights) or between two modalities (e.g., a light and sound). Peripheral signals can become more salient than its surroundings with adjustments to specific attributes such as the signal brightness or loudness. This empirical study investigates how signal salience, focused versus divided attention, and reserve capacity affect how, and how efficiently, people process peripheral signals.

The current work is motivated following a discussion of previous research involving redundant signals, signal salience, and context dependencies. Then, an overview of a cognitive-based mathematical framework is provided. This is paired with the argument for how and why it is necessarily applied in this empirical study. This factorial design and within-subjects experiment uncovers the underlying cognitive processes of redundant, peripheral signals under various multi-task demands. After a report of these data, the implications and future directions of this work are discussed.

Redundant Signal Processing

Redundant signals are two or more pieces of information that carry congruent meaning, each containing what is necessary to make a single decision. Redundant signals are presented in either a physically (Miller, 1982) or perceptually (for example, stimulus onset asynchony or SOA, Colonius & Diederich, 2004) simultaneous fashion and can enhance or harm performance depending on the stimuli and context. Readers can imagine an alerting ambulance with flashing lights and sirens that indicate an emergency. In this example, both the lights and sirens convey the need to bring the vehicle to a stop. How fast the car comes to a stop is expected to speed up with the combination of lights and sirens compared to either one alone, a mathematically defined prediction called *statistical facilitation* (Raab, 1962; Miller, 1982). However, performance with redundant signals can supersede the upper bound of what statistical facilitation can account for, meaning the pair of signals leads to faster detection times than what is *expected*, called *super capacity* processing (e.g., Townsend & Eidels, 2011; Yang et al., 2018; Goulet & Cousineau, 2020). If observed performance differs from what is expected, there is evidence that the underlying processing of each signal changed when the signals were paired together versus presented in isolation (more on this in a later section).

Alternatively, redundant signals may hinder performance through competition for limited attentional resources and reduced efficiency (Wickens, 2002). Interested readers can refer to Fox and Houpt (2016) for an example of limited capacity processing of complementary infrared and visible images. Estimating the efficiency and mechanism of redundant signals processing will inform future research and system design to effectively deploy multiple, congruent pieces of information. Systems factorial technology Townsend and Nozawa (SFT; 1995) and Houpt et al. (2014) is a mathematical framework that can be applied to pinpoint if, and how, people process signals differently when they are presented alone versus together. The SFT framework comprises multiple measures and a factorial experimental paradigm. These are described in a later section.

Salience

Several factors may influence the processing of redundant signals, especially when embedded alongside complex tasks that compete for common attentional resources. For instance, Otto et al. (2013) found that a pair of signals with low versus high salience yields quicker and more accurate detection than either signal alone, a phenomena called the principle of inverse effectiveness (Meredith & Stein, 1986). Here, improved performance and stronger neural responses (Senkowski et al., 2011) are attributed to the speed-up in the processing of each when presented together and/or the reduction of signal uncertainty. There is mixed evidence for the generalizability of this phenomenon to more complex contexts or different stimulus pairs (Leone & McCourt, 2013). Importantly, prior work has mainly focused on redundant signal processing in a single-task context. Until now, no research has examined how the salience of two task-*relevant* and *uni*-modal (i.e., two visual signals) signals influence their combined information processing efficiency.

Context dependence

Generalizing to a dual-task context, Thorpe et al. (2020) found a single highly salient peripheral signal typically leads to faster response times (RTs) and higher detection rates. Further, recent work set in a dual-task context demonstrates processing efficiency to a single peripherally-presented visual signal is reduced and cognitive processing strategies shift under high demands (Howard, Evans, et al., 2020; Garrett et al., 2019). They later found this may persist even with complementary redundant signals (Howard et al., 2022). The work described in this paper expands on Howard et al. (2022) to investigate the processing mechanisms of redundant signals while systematically manipulating the salience of the signals and the load of a centralized dual-task.

Specifically, the work described here investigates i) if the introduction of, or increased difficulty of, a central multiple object tracking (MOT) task changes how people combine two peripheral signals; both in processing capacity (i.e., limited or super capacity) and/or structure (e.g., in parallel or serial), and ii) if processing efficiency depends on the salience of the peripheral task signals or the presence/difficulty of a centralized and continuous task. An ancillary question that is assessed is whether these effects influence speed alone (using one measure of SFT) or jointly impacts speed and accuracy of responses (a second measure of SFT). The next section serves as a brief overview of SFT. Those interested in reading more about the development and use of SFT should refer to Houpt et al. (2014).

Systems Factorial Technology

The SFT framework includes multiple measures that identify the architecture, stopping rule, independence, and workload capacity of how a cognitive system processes two redundant signals. *Architecture* refers to the temporal structure of processing each signal, whether that be one-by-one (serial), simultaneously (parallel), or pooled into a single unit (coactive). *Stopping rule* is the number (one versus all) of signals that finish processing before one chooses to terminate a response (OR versus AND). *Workload capacity* is the the relative change in processing speed of each signal as the number of signals increases. Lastly, *independence* is whether the processing of each signal influences the other.

Numerous studies have applied SFT to investigate the processing mechanisms of redundant signals. For instance, SFT has been used in visual (Townsend & Eidels, 2011; Glavan et al., 2019), auditory (Lentz et al., 2014, 2017), audiovisual (Yang et al., 2018; Wang & Fox, 2021), memory (Howard, Belevski, et al., 2020; Shang et al., 2021), and automation (Yamani & McCarley, 2018; Kneeland et al., 2021) research. Many researchers have used SFT to show how context influences not only performance but also the mechanisms by which people process information (Donkin et al., 2014; Fific et al., 2008). Such work may be thought of as influencing the cognitive (i.e., attention) as opposed to perceptual (e.g., signal brightness) human limitations, coined "resource-limited" by Norman and Bobrow (1975). Only in recent years have researchers applied SFT to investigate how the larger task context, and hence the reserve resource supply, may influence the cognitive processing strategy in a peripheral task involving redundant signal detection (Howard et al., 2022; Morey et al., 2018). The research described in this paper extends previous work to investigate the cognitive mechanisms for how redundant signal are processed under various dual-task loads through the application of SFT.

Survivor and Mean Interaction Contrast

Processing architecture and stopping rule are examined using the Survivor Interaction Contrast (SIC) and Mean Interaction Contrast (MIC) (Townsend, 1974). The SIC value, $SIC(t)$, is estimated using the survivor function, $S(t)$, of RTs in conditions where the processing rate of each signal is manipulated. The interaction contrast is taken for $S(t)$ of four factorial combinations of fast (high, denoted by H) and slow (low, denoted by L) processing speeds of each signal, see Equation 1. The Houpt-Townsend statistic (Houpt & Townsend, 2012) is used to indicate whether positive (D+) and negative (D-) deviations in the SIC function are significantly different than zero. Serial-AND or coactive models have similar shaped SIC functions (an s-shape). The MIC is used to distinguish between these models, see Equation 2, such that a positive MIC corresponds to a coactive model and a zero MIC represents a serial-AND process.

$$SIC(t) = [S_{LL}(t) - S_{LH}(t)] - [S_{HL}(t) - S_{HH}(t)] \quad (1)$$

$$MIC = [M_{LL} - M_{LH}] - [M_{HL} - M_{HH}] \quad (2)$$

The Capacity Coefficient

Workload capacity is how efficiently one processes signal information as the amount of information available (that is, the number of signals) is manipulated (Houpt & Townsend, 2012; Townsend & Nozawa, 1995). The capacity coefficient quantifies workload capacity by comparing observed performance when all signals are presented to a UCIP model prediction of performance. The UCIP model assumes *U*nlimited *C*apacity, and *I*ndependent and *P*arallel processing of information; with these assumptions, the UCIP model is formed using the mathematical combination of performance with each source in isolation.

The current work focuses on the processing mechanisms involved in a peripheral *detection* task; therefore, only the Capacity-OR coefficient is introduced and applied. This work assumes efficiency is stable across time and ample data is collected across multiple sessions to apply the traditional, nonparametric measure of capacity (Houpt & Townsend, 2012) rather than a parametric model with Bayesian updating (Fox & Houpt, 2021). The formal comparison of performance to the UCIP model prediction for OR processing can be stated in terms of the ratio of integrated hazards functions, $H(t)$, which indicates the amount of processing completed up to a given time, t, see Equation 3. The capacity coefficient, $C(t)$, indicates the maintenance (unlimited capacity, $C(t) = 1$), decline (limited capacity, $C(t) < 1$), or improvement (super capacity, $C(t) > 1$) of processing efficiency as the number of signals increases above one.

$$C(t) = \frac{H_{1\ldots n}(t)}{\sum_{i=1}^{n} H_i(t)} \quad (3)$$

Another measure of SFT, the assessment function, $A(t)$ (Townsend & Altieri, 2012), reflects changes in workload capacity through a combination of accuracy and RT measures. Responses can be either "correct" or "incorrect" and "slow" or "fast." Responses are considered correct if the correct process ends before the incorrect process and vice versa for incorrect responses. Whether a response is slow or fast is dependent on if the response was made by time, *t*. The combined observation of response type and speed allows for a comparison with the UCIP model predictions (Townsend & Altieri, 2012; Donkin et al., 2014). Past work has found meaningful qualitative changes in $A(t)$ in addition to those exhibited in $C(t)$ across conditions (Donkin et al., 2014; Hsieh et al., 2020). An exploratory application of the assessment function to the data collected in this study is reported in the Results section, and reveals whether $A(t)$ can detect redundant signals changes across MOT load and signal salience.

Current Research

The goal of the current research is to identify how people process redundant signals in the periphery and assess if, and how, cognitive processes change in context of three centralized and continuous task difficulty levels. In a recent study, Howard et al. (2022) suggested workload capacity depends on centralized task difficulty and the stability of the task load over time. However, further research is needed to determine why this shift in capacity occurs. For instance, a parallel model with limited capacity processing may mimic performance of an unlimited and serial model (Townsend, 1971; Townsend, 1972). Therefore, the current study independently captures workload capacity and architecture through the application of the capacity coefficient and SIC/MIC, respectively.

Systematic changes to the salience of each signal is necessary in order to estimate the SIC/MIC. As such, this study uses the double factorial paradigm (DFP; detailed in Houpt et al., 2014) to present the appropriate balance of high/low salience and single/double signal combinations. The application of the DFP also allows for the investigation of a secondary research question: Does the degree of impact that peripheral redundant signals have on performance depend on the salience of the signals? Practically speaking, (how) does one's processing of ambulance lights and sirens change in adverse versus clear weather conditions? This work estimates the observed redundancy gain (or lack thereof) in a peripheral detection task and measures if, and how, it changes with signal strength (salience).

Lastly, this work extends previous research by including an additional measure of the SFT framework, the assessment function, that accounts for changes in both speed and accuracy. This is applied to characterize how the manipulation of centralized task difficulty and signal strength influences both the speed and accuracy of peripheral signal detection in fast and slow correct responses, respectively.

Methods

Participants

Participants included nine subject panel members and one ad hoc from the United States and ten National Cheng Kung University students from Taiwan, (N = 20). The US participants were either a part of a subject panel at Wright Patterson Air Force Base, who are long-term, part-time listeners compensated at an hourly rate or were recruited from the local area and received monetary compensation for their time. All US participants completed the experiment at home on a personal desktop computer. The participants from Taiwan were awarded class credit or NTD 160 per hour for their time. All Taiwan participants completed the task in a controlled laboratory.

Tasks

Multiple Object Tracking (MOT)

After every 15-second MOT trial, accuracy was measured as the number of correctly labeled dots (10 total). To-be-tracked dots appeared blue for 3 seconds before turning red to match the non-target dots. The dots moved randomly across the screen for the duration of the trial. Each dot was $\approx .286^\circ$ of visual angle at 60 cm viewing distance. Dots moved randomly in a box (width: $\approx 6.2^\circ$, height: $\approx 2.19^\circ$) at a rate of 16.66 frames/second for the duration of the trial. Dots could overlap briefly if their paths crossed and they bounced randomly away if they reached the edge of the display area.

The number of dots to-be-tracked (0, 1, or 4 dots) was manipulated in each block in a randomized fashion. Each block consisted of 30 MOT trials and two blocks of each load type (0, 1, or 4 dots) occurred per session (180 trials/session).

Detection Reaction Task (DRT)

Performance in a detection reaction task (DRT) was measured as participants' RT to accurately detect one or two red squares that occasionally appeared in the periphery. Identical to previous work (Howard et al., 2022), a red square ($\approx 1.05°$ of visual angle) could appear slightly to the left and/or right of center directly above the MOT task. Left and right signal locations were $\approx 3.15°$ apart. The color of the square varied for High (RGB[130, 0, 0]) and Low (RGB[55, 0, 0]) signals. Example signals are illustrated in Figure 1. Signal onset times were sampled from a uniform distribution (3-5 seconds) (International Organization for Standardization, 2016). Dynamic visual Gaussian noise was applied to the entire location of the DRT for the duration of the block regardless of signal presence. The noise was a rectangle with approximately $6.39°$ width and $2.19°$ height, as shown in Figure 1. High/Low salience signals and the noise distribution were fixed across participants and blocks. The DRT occurred during all MOT trials and no signals were administered between MOT trials.

The DFP informed the design of the DRT in this study (Houpt et al., 2014). Specifically, two squares occurred on 60% of trials and High or Low (or one of each) salience squares were equally probable. On the remaining trials, a single High/Low salience square was presented in the left-/right DRT location with equal probability.

Procedure

Data were collected during the COVID-19 global health crisis. The US participants completed the experiment from their home. The Taiwan participants completed the study at the National Cheng Kung University and adhered to local health requirements. After agreeing to participant in the study, each participant completed three identical sessions (2-hours/session).

Taiwan participants used a chin-rest (60 cm from monitor) to prevent head movements. Following one practice block (15 trials with 2 dots-to-track), participants completed 2 blocks (30 trials/block) of each MOT load (0, 1, or 4 dots). Participants took a mandatory break after every 15 trials. Participants sent their data to the experimenter (US) or were thanked and credited for their time (Taiwan) after each session.

Equipment

Taiwan participants used a desktop computer equipped with a 2.40 GHz Intel Pentium IV processor and 27-inch, 1920 × 1080 pixel resolution, LCD monitor (ACER XB273). Each US participant used a standard desktop computer and monitor. The US participants all self-reported that they used the same computer and work station setup to complete all sessions of the experiment.

Results

A Bayesian analysis of variance (ANOVA; Rouder et al., 2012) was used for group-level analyses. A noninformative Jeffreys prior ($\frac{\sqrt{2}}{2}$: "medium" amount of dispersion around the mean) was used to scale expected effect size (Rouder et al., 2012). In brief, Bayesian analyses examine the credibility and probability of a factor despite the shifts in probability going from a priori to posterior parameters (Kruschke & Liddell, 2018). The *Bayes Factor* (BF) appraises the likelihood of the null and the alternative hypotheses by determining the probability of obtaining the observed data under the null versus the alternative hypothesis. The BF demonstrates evidence in favor of one hypothesis versus the other. The Bayesian ANOVA compares multiple competing models and returns a BF for each main effect model and their interaction(s). Thus, this approach compares models and adequately penalizes each regarding its complexity. Model comparisons are reported using BF_{ratio}. The *Highest Density Interval* (HDI) is the interval that has the most credible parameter values. Where appropriate, the 95% HDI is provided in brackets in the results reported below.

Following a report of how the data were cleaned and a check of experimental manipulations, the results of the capacity coefficient and SIC/MIC are illustrated and summarized. The results section closes with a report of the findings from the exploratory reanalysis of the data using the assessment function, specifically for correct and fast or slow responses.

Data Cleaning

For the DRT task, RTs were constrained to be within a 100 to 1000 ms interval in order to eliminate false alarms (FAs) and anticipatory responding. In what follows, all RTs will be reported in ms. One participant was removed due to a high FA (15.1%) and miss rate (22.0%). In what follows, all accuracy, FA, and miss rates will be reported in percentages (0-100). The remaining participants achieved a 1.57 FA and a 3.73 miss rate. Session 1 was treated as practice; all results reported here only include the data from Session 2 and 3. Similarly, practice trials at the beginning of each Session (tracking load of 2 dots) were excluded.

Manipulation Checks

Controlling for within-participant variability and condition type, there was strong evidence for no difference in RTs between the US (Participant 1-10, 7 was excluded), $M = 475.7$ $[429.3,\ 522.8]$, and Taiwan (Participant 11-20), $M = 487.3$ $[441.4,\ 534.9]$ participants, $BF = 0.22$. Therefore, participants were combined for all further analyses. Controlling for within-participant variability, MOT performance varied across conditions as expected. Specifically,

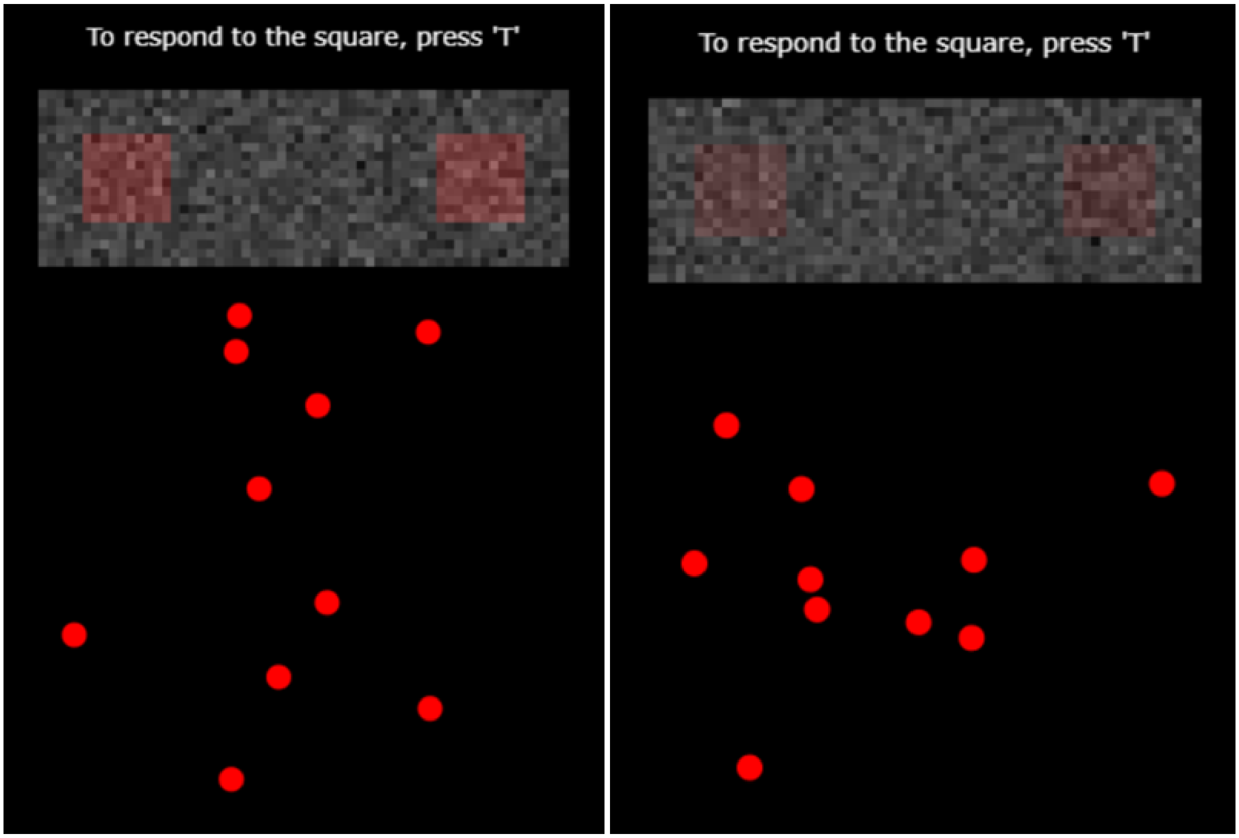

Figure 1 ■ Example DRT and MOT task signals. Left: dual-target HH DRT signal. Right: dual-target LL DRT signal.

accuracy in the MOT task was lower when tracking 4 dots $M = 76.6, [72.5, 80.7]$ compared to the 1 dot condition $M = 98.7, [94.7, 100.0], BF > 1000$.

DRT

Similarly, accuracy (Acc) and speed (RT) in the DRT task varied as a function of tracking load and salience, as shown in Figure 2 (left: RT, right: accuracy). Further, the results of a Bayesian ANOVA with a noninformative Jeffrey prior ($\frac{\sqrt{2}}{2}$) revealed support for a model that included both main effects (salience, dots to track) and their interaction to predict DRT accuracy (ACC) and RT, $BF > 1000$, compared to the next most likely model with both main effects, $ACC : BF_{ratio} > 1000$, $RT : BF_{ratio} = 7.7$. More specifically, participants achieved very high accuracy to detect DRT signals in the 0 dot, $M = 98.6\ [95.9, 100]$, and 1 dot conditions, $M = 97.8\ [95.0, 100]$, with slightly lower accuracy in the 4 dot condition, $M = 90.5\ [87.8, 93.1]$. Generally this did not vary depending on whether the signals were of HH, $M = 96.8\ [93.8, 99.6]$, or LL, $M = 95.2\ [92.3, 98.0]$, salience levels. Participants RTs to DRT signals varied across conditions. Participant RTs were fastest in the 0 dot condition, $M = 415.0\ [389.7, 442.6]$, followed by the 1 dot condition, $M = 492.2\ [466.9, 520.0]$, and slowest in the 4 dot condition $M = 556.2\ [530.7, 584.1]$. Responses to redundant HH stimuli, $M = 461.2\ [434.6, 490.1]$, were faster than LL signals, $M = 499.9\ [473.2, 528.8]$.

To interpret SIC/MIC results, individuals' RT distributions per condition must be ordered such that the HH condition was fastest and the LL was the slowest, or $S(t)_{HH} \geq S(t)_{HL}$, $S(t)_{LH} \leq S(t)_{LL}$. The Kolmogorov–Smirnov (K–S) test was applied to indicate which participants exhibit an incorrect pattern of results such that at least one of HL, LH > HH or HL, LH < LL is found. No participants were excluded from the 0 dot condition, 2 participants (Participant 4 & 16) were excluded from the 1 dot condition, and 1 participant (Participant 6) was excluded from the 4 dot condition.

Survivor Interaction Contrast (SIC) and Mean Interaction Contrast (MIC)

The SIC results in a function where D+/D- values indicate the positive/negative deviation from zero and the Houpt-Townsend statistic tests whether that difference was significant. A *p* = .33 significance criteria was used to ensure an unbiased result (Houpt & Burns, 2017)

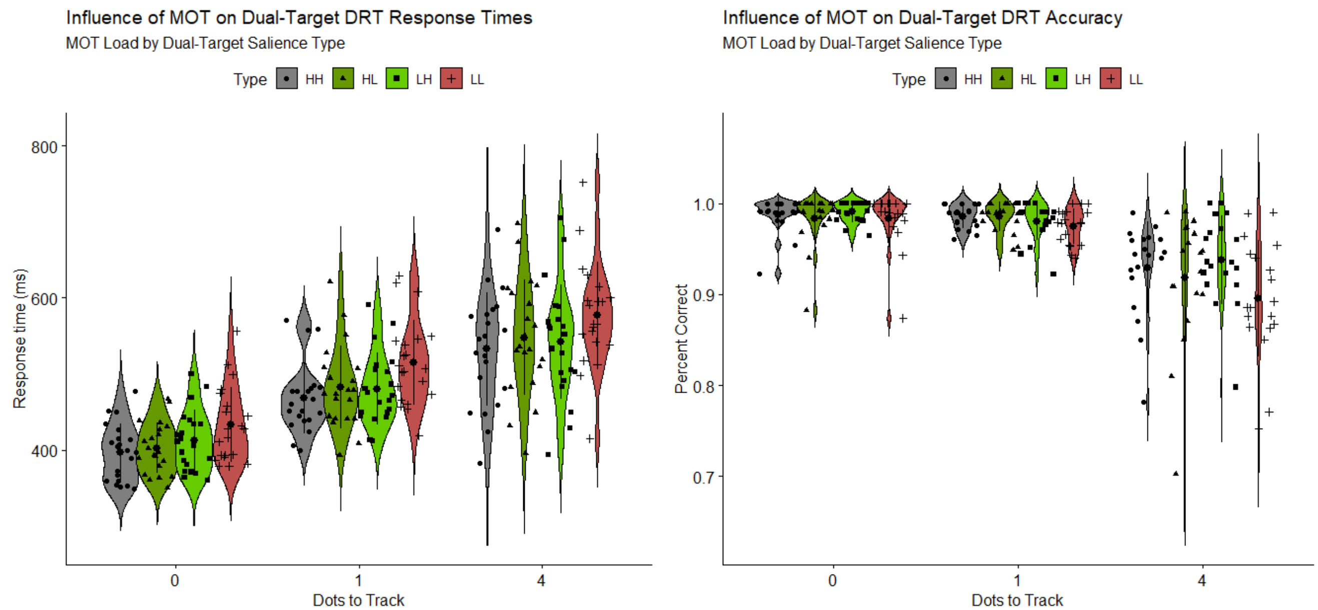

Figure 2 ■ Influence of MOT task load on dual-target DRT RTs (left) and accuracy (right).

Overall, a parallel-OR processing architecture was found across tracking loads. Further, 6 participants (Participant 1, 3, 10, 15, 17, 18) processed redundant signals in a parallel-OR fashion in all tracking load conditions. For the remaining participants, processing architecture (and sometimes stopping rule) changed depending on the number of dots to track in the MOT task. The most notable finding here is that more parallel processing of redundant visual signals was found as the task demands increased. Specifically:

- 0 dots (10 parallel, 9 serial): 10 participants processed redundant signals in a parallel fashion when presented in the periphery, all of which used an OR stopping rule; 9 participants processed redundant signals in a serial fashion when presented in the periphery, 3 of which used an AND stopping rule.
- 1 dot (12 parallel, 5 serial): 12 participants processed redundant signals in a parallel fashion, 1 of which used an AND stopping rule; 5 participants processed redundant signals in a serial fashion when paired with a 1 dot tracking task, all of which used an OR stopping rule.
- 4 dots (16 parallel, 2 serial): 16 participants processed redundant signals in a parallel fashion when paired with a 4 dot tracking task, 3 of which used an AND stopping rule; 2 participants processed redundant signals in a serial fashion when paired with a 4 dot tracking task and both used an OR stopping rule.

Interested readers can refer to the Appendix for further statistical reporting of these SIC/MIC findings.

Capacity Coefficient

Next, individuals' capacity to process DRT signals is reported. To recapitulate, the capacity coefficient is used to measure workload capacity. It is defined as the ratio of observed hazard function of RTs when both squares are presented to the UCIP model, which is formed using the combination of one's hazard function of RTs with each square when presented alone (left and right). A separate UCIP baseline was derived per individual and salience combination. Generally, the individualized model results indicate most participants maintained the same capacity (i.e., limited) across all MOT and salience conditions, see Figure 3.

A Bayesian ANOVA on MOT load and salience indicated evidence against any main effect or interaction, maximum $BF = 0.43$. Individuals' $C(t)$ z-score, Cz, was no different across conditions: 0 dot, $M = -3.7\,[-4.2,\ -3.2]$, 1 dot, $M = -3.8\,[-4.3,\ -3.4]$, and 4 dot, $M = -3.6\,[-4.1,\ -3.1]$. Similarly, there was evidence against an effect between HH, $M = -3.8\,[-4.2,\ -3.4]$ and LL, $M = -3.6\,[-4.0,\ -3.2]$, Cz estimates.

Assessment Functions

Assessment function results, $A(t)$, are interpreted in a way similar to $C(t)$ except in the case of slow RTs where $A(t) > 1$ indicates limited and $A(t) < 1$ indicates super capacity.

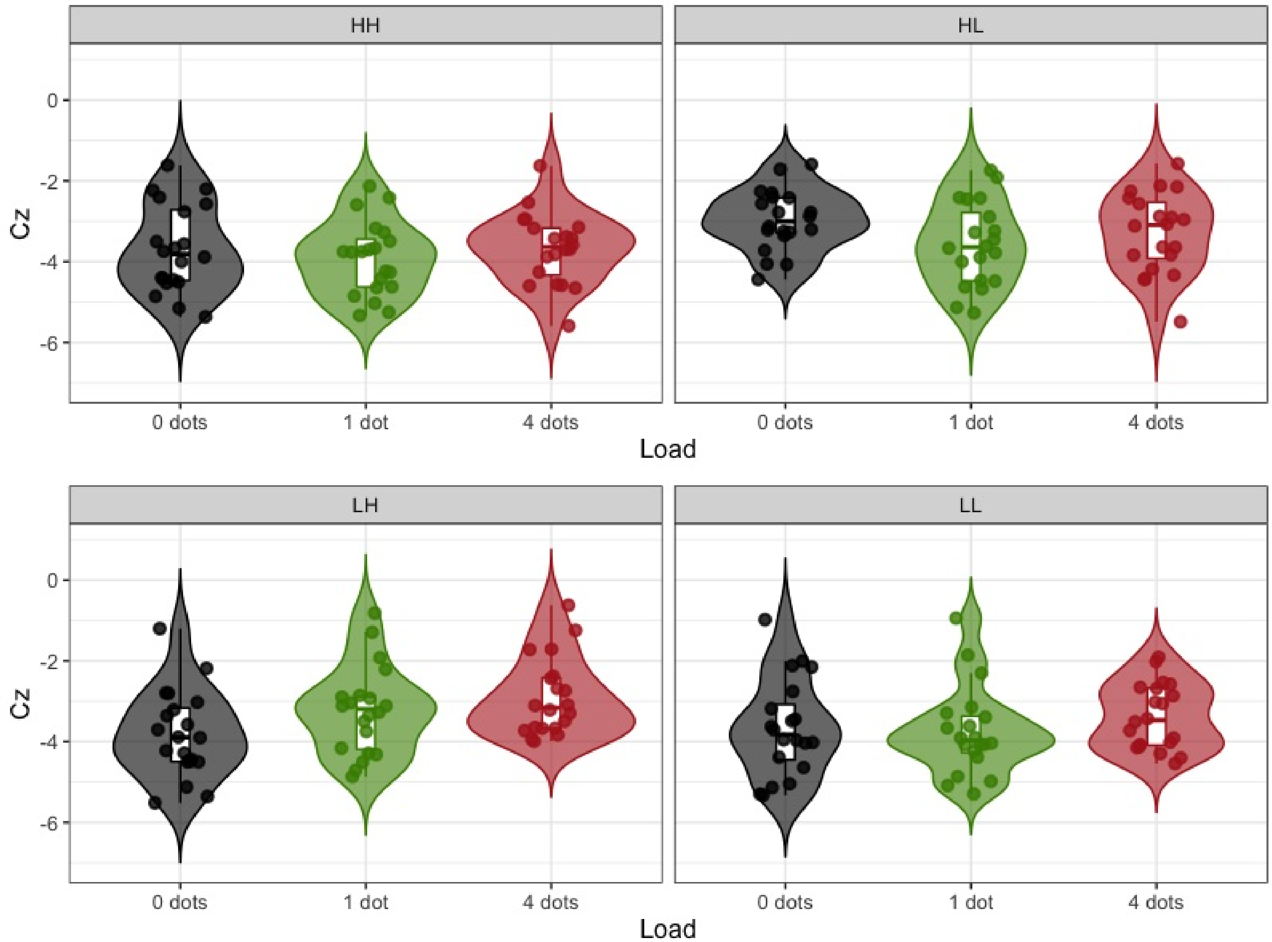

Figure 3 ■ Group-level capacity z-scores, Cz, by MOT load (0, 1, 4) and redundant signal salience combination (HH, HL, LH, LL).

In sum, $A(t)$ for correct and fast RTs was limited capacity across all conditions - a result found with $C(t)$.

However, $A(t)$ becomes less limited as MOT task difficulty increased: $A(t)_{4dots} > A(t)_{1dot} > A(t)_{0dots}$. In contrast, $A(t)$ for correct and slow RTs consistently indicated unlimited to limited capacity performance across all conditions. These findings are considered alongside the SIC and $C(t)$ results in the Discussion below.

Discussion

This application of the DFP and measures of SFT allowed for the investigation of the underlying cognitive mechanisms of redundant signals in single- and multi-task contexts. Specifically, the conditions collected from a controlled and counterbalanced paradigm served as the basis to develop individualized and cognitive-based mathematical models of UCIP performance. This allowed for the investigation of how peripheral and redundant signal processing change depending on centralized task load and signal salience. Before this study, researchers found peoples' capacity to process peripheral redundant signals changed depending on the presence and difficulty of a dual-task (Howard et al., 2022). The findings of Howard et al. (2022) suggested context influences redundant signal processing in the periphery. However, the current work was necessary to determine how and why the changes in cognitive processing occurred. Specifically, this work necessarily separated workload capacity from architecture and stopping rule.

In sum, the majority of both US and Taiwan participants processed redundant visual signals in a parallel-OR fashion; a finding in line with existing literature. Moreover, Fox and Houpt (2016) found redundant visual information presented side-by-side (in an isolated task context) was processed in a parallel and self-terminating fashion, categorized as Parallel-OR processing. In the current study, six participants consistently processed redundant signals in a parallel-OR fashion regardless of MOT task load. The remaining participants' mechanism for processing the DRT signals changed as MOT load increased. Specifically, more participants processed redundant visual signals in a parallel fashion as demands increased.

Delving into this finding a bit more may offer some useful insights regarding the cognitive processing and design of peripheral signals in multi-task contexts. Further, these data suggest the design of the 0 dot condition provided the opportunity for participants to effectively ignore the central task and fixate on where DRT signals were presented. In this condition, about half (n = 9 of 19 total) of the participants processed redundant signals in a sequential fashion, and most of those (n = 6) effectively ignored one signal (i.e., serial-OR: n = 6; serial-AND: n = 3), and used that (those) to make a decision. Serial processing violates the parallel assumption of the UCIP model prediction, thereby demonstrating that the limited capacity findings for these participants is attributed, at least in part, to their less efficient architecture to process the redundant signals. Further, a serial-AND mechanism implies that people waited until the processing of both signals was finished to make a response. An AND process paired with sequential processing is highly inefficient. Indeed, the participants with Serial-AND processing exhibited slower performance than expected by the individualized UCIP model prediction. However, the extent of peoples' limited capacity Cz was consistent across all MOT load and salience conditions.

An important distinction among the MOT load conditions was the degree to which one could divide their visual resources among the two tasks (MOT and DRT) while maintaining high accuracy in the centralized MOT task. In the 0 dot condition, the MOT task did not demand any attentional resources - all dots were red (to-be-ignored) at the start of each trial. Participants were not instructed where to fixate, nonetheless, motivated participants would maximize performance by fixating directly where the DRT signals may appear.

For the 1 dot condition, participants necessarily attended to the central MOT task. Indeed, participants achieved high MOT task accuracy, demonstrating adequate attention was allocated to track the target dot as instructed. While participants tracked the single dot, they peripherally monitored for DRT signals which may appear directly above the location of the MOT dots. In this condition, more participants utilized a parallel (n = 12 of N = 17), specifically Parallel-OR (1 Parallel-AND), mechanism to process the redundant DRT signals. Most notably, fewer participants utilized a serial process in the dual-task condition (n = 5) compared to the single-task condition (0 dots).

Lastly, for the 4 dot condition, nearly all (16 of 18 total) participants processed the DRT signals in a parallel fashion (13 parallel-OR; 3 parallel-AND). Only two participants processed the stimuli in a serial-OR fashion. Similar to the 0 and 1 dot conditions, all participants exhibited a limited capacity and the extent of their limited capacity performance did not depend on the tracking load of the MOT task.

In this work, two conditions required participants to continuously track 1 or 4 dots to accurately respond in the MOT task. Therefore, the participants had to use peripheral vision to simultaneously monitor and respond to signals in the DRT. Although eye-tracking measurements were not used in this study, it is reasonable to suspect participants fixated on the target dots in the MOT task. The MOT dots moved in such a way that depending on their location at a given time the DRT signals could be simultaneously detected using (para)foveal vision (within 6 degrees of visual angle). Thus, DRT signals presented while target dots were closer to the top of the MOT task area were more likely to be processed with central vision, and with higher acuity than the periphery. Furthermore, in the 4 dot condition participants were more likely to have fixate in the middle of the MOT task area in order to effectively track all of the target dots, leaving less opportunity to move central attention closer to the location of where DRT signals may appear.

In future work, researchers may consider the usefulness of physiological monitoring of attentional focus. These measures may more specifically assess if, and how, one's dual-tasking strategy predicts how peripheral redundant signals are processed. For example, attention tracking can be achieved in real-time through the use of eye-tracking (Durant et al., 2021) or neural activity (Fox et al., 2022). Based on the findings presented here, one may hypothesize that people process two side-by-side visual signals in a more parallel fashion as eccentricity from central vision increases. Further, the number of eye movements between the DRT and MOT task may decrease as a function of the MOT task load. Alternatively, participants may indeed fixate on the MOT task but a higher load decreases their functional field of view (Crundall et al., 2002; Williams, 1982, 1985; Wittmann et al., 2006). If such a case occurs, no relationship between eye fixations, load, and processing mechanisms would be found. Rather, the size of the functional field of view would drive the mechanism by which people process the DRT signals from serial to parallel processing.

People exhibited no benefit from two redundant versus one visual DRT signal(s). In fact, participants processed each less efficiently than predicted by an unlimited capacity, independent, and parallel model. This result is not new; for instance, Morey et al. (2018) conducted a series of experiments examining the question of how peripheral, redundant signal processing is influenced by its dual-task context. Similar to Howard et al. (2022) and the work reported here, Morey et al. (2018) manipulated the load of a centralized and continuous moving object tracking task. However, their participants used a joystick to maneuver a cursor to follow a dynamic signal for the duration of the trial under various task loads. This differs from the current and recent work which required participants to hold their focus on the location of to-be-tracked dots and report their location only after a 15 second tracking period – hence, no required manual tracking of a dynamic signal(s). The signals and decision rule used in the peripheral task of Morey et al. (2018) also differed from the current study. Their participants simultaneously monitored two peripheral visual signals, presented in the top left and/or right corners of the screen, and pressed a button when signals (but not distractors) appeared. Here, mean RTs to the peripheral task increased with changes to the central task. They found that redundant signal processing was limited capacity – slower than one would predict with UCIP processing of both signals. Importantly, this limited processing capacity of redundant left and right signals did not significantly change depending on the difficulty of task, or even when the participants were instructed to ignore the central tracking altogether.

More recently, Howard et al. (2022) investigated whether peoples' limited capacity performance, as shown in Morey et al. (2018), to process peripheral redundant signals may change when the presence, difficulty, and *stability* of the centralized and continuous task was manipulated. Howard et al. (2022) manipulated how long participants completed the centralized task at a level of difficulty before switching to a higher or lower load; shifts occurred from 0 or 1 (low) to 3 or 4 (high) dots to track after 15 (short) or 30 (long) trials, respectively. They found that contrary to Morey et al. (2018), capacity decreased with higher demands in a centralized and continuous task, and this decrease depended on the type of demand manipulation. Surprisingly, they found that less stable conditions (frequent shifts in centralized task difficulty) led to greater capacity compared to less frequent changes. Their work not only suggests redundant signal processing is influenced by the degree to which tasks compete for common attentional resources (Kahneman, 1973; Wickens, 2002) but also that the environmental stability impacts the overall level and fluctuation of integration efficiency across time. While this is beyond the scope of the current manuscript, future work could investigate if, and how, processing architecture may change depending on the stability of cognitive demands across time.

In the current study, fewer participants exhibited patterns of performance that indicate a serial processing strategy to process redundant signals as the difficulty of the context increased. Violations of independence in a serial process could affect detection rates; for instance, a serial system may work harder to process the source of information and increase the rate that each source finishes processing (Townsend & Wenger, 2004) resulting in limited capacity performance. Such processing strategy may contribute, in part, to participants' limited capacity performance under no and low dual-task demands (0 and 1 dot conditions, respectively); which is a violation of the parallel and independence assumptions of the UCIP model prediction.

On the other hand, participants more often, and almost entirely, processed redundant signals in parallel when simultaneously performing a 4 dot tracking task. Interestingly, participants still exhibited limited capacity performance, a finding similar to Townsend and Nozawa (1995) and Morey et al. (2018). Townsend and Nozawa (1995) found parallel and self-terminating (OR) processing to detect two visual, centrally-located dots with a limited capacity. The current findings suggest that a cognitive system with high overall demands will process redundant signals in parallel when presented in the periphery, but each source may be processed at a slower rate; which is a violation of the unlimited capacity assumption of the UCIP model prediction.

Principles of attentional resource theory can further explain these data. Resource theory suggests that humans have a finite amount of attentional resources (Kahneman, 1973). Specific to the work presented here, multiple visual tasks tax the same pool of resources more so than those with noncompeting modalities (Wickens, 1984). Hence, visual resources are highly taxed when attempting to track 4 moving dots, leaving fewer residual resources to detect peripheral signals than the 0 or 1 dot conditions. When fewer resources are available to recruit to a peripheral task, peoples' cognitive system will utilize an efficient processing strategy (parallel) to accommodate the increase in overall task demands. The findings reported here support this theory.

The data collected in the current work were reexamined using the assessment function to model joint efficiency using speed and accuracy to redundant signal detection. This additional exploratory analysis indicated that i) the extent of limited capacity for correct and fast RTs depended on the MOT task load, and ii) unlimited to limited capacity performance was exhibited in correct and slow RTs. These findings did not depend on whether the squares were of a High or Low salience. Specifically for correct and fast RTs, $A(t)_{4dots} > A(t)_{1dot} > A(t)_{0dots}$. This result, in combination with the SIC, suggests the presence and load of a central and continuous task influences not only how peripheral redundant signals are processed structurally (i.e., parallel vs. serial) but also the degree to which redundant signals provide a joint benefit to speed and accuracy. Specifically, people more often processed redundant signals in parallel and, in the case of fast responses, with less limited capacity than when competing attentional demands are lower (1 dot) or absent (0 dots).

Readers should take note that the experiment was designed to enable participants to achieve high accuracy. As such, accuracy was near ceiling-level for single and dual DRT signals in the 0 and 1 dot condition, and slightly lower accuracy was found in the 4 dot condition. A very small decrease in accuracy was found between a single High versus Low salience DRT signal. Therefore, there was no room for improved accuracy in the 0 dot condition, very little in the 1 dot condition, and the most potential for redundancy gain in the 4 dot condition. Further investigation is warranted to examine contexts where demands are higher than the conditions reported here, and there is a larger potential benefit from redundant visual signals.

Limitations and Future Research

It is important to consider limitations and directions for future research. One consideration is that this study required high performance in the MOT task but performance decreased as the MOT difficulty level increased. The DRT was present in all conditions, therefore, baseline MOT task performance was not collected nor compared across conditions; hence, the degree of change in dual-task trade-off was not measured between the MOT task and DRT in this study. Further mathematical modeling development that involves the combination of the capacity coefficient (and/or assessment function) and a recently derived measure of Multitasking Throughput (MT; Fox et al., 2021) could offer a tool to investigate workload capacity in a peripheral task and account for dual-task trade-offs. In short, the MT coefficient provides an estimate of efficiency and includes the trade-off in performance when completing multiple tasks simultaneously. Further expansion of MT could account for one's redundancy gains (or lack thereof) and multi-task efficiency within and between several competing tasks demands.

Note that potential shifts in capacity and multi-task strategy may have occurred over time. The performance reported in this study was collected over multiple days in order to achieve adequate statistical power. Future research may leverage recent advances in mathematical psychology to characterize cognitive processes with fewer observations of performance in each condition type. For instance, Fox and Houpt (2021) use the Weibull distribution and its conjugate prior to develop a Bayesian model of the capacity coefficient that allows for the real-time estimation of capacity across trials. This Bayesian modeling approach easily extends to other measures of efficiency, such as Multi-tasking Throughput, and may serve as a way to investigate when and how shifts in strategy to process redundant signals occur as the broader multi-task context change over time.

Conclusions

The questions addressed in this study were i) does the introduction of, or increased difficulty of, a second task change how people combine multiple peripheral signals and ii) does processing efficiency depend on the salience of peripheral signals and/or the presence/difficulty of a second task. Findings suggest that the introduction of, and difficulty of, another task does influence how people process side-by-side redundant signals in a peripheral detection task. Specifically, more people utilize efficient parallel processing strategies when competing task demands are high versus low or absent. Nonetheless, peoples' workload capacity to process the signals remains severely limited across these contexts. In this study, peoples' workload capacity changed across conditions when accounting for both speed and accuracy, an effect that should be explored in future work. This novel work builds on previous findings by applying a framework which allowed for the investigation of the underlying processing mechanisms of redundant signals in multi-task contexts. This work provides insights for what may drive more or less efficient processes. Next steps are provided to further investigate how multitask context influences one's trade-off between tasks and the joint efficiency to complete multiple tasks simultaneously.

Authors' note

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Appendix A

The following sections provide the statistical details that complement the high-level description of the SIC/MIC findings reported in the Results section.

0 dots

For the 0 dot condition (Table 1), positive, $M_{D+} = 0.185,\ [0.059,\ 0.332]$, negative, $M_{D-} = 0.083,\ [0.008,\ 0.180]$, and overall, $M_{MIC} = 11.097,\ [-20.733,\ 69.434]$, deviations from zero for each participant were examined. Ten participants had significant positive SIC deviations from zero, (D^+ [0.146, 0.332], *p* [.002, .300]), and non-significant negative SIC deviation from zero, (D^- [0.008, .116], *p* [.477, .996]). Of those 10, seven had significant MIC deviations, (MIC [-5.480, 69.434], *p* [.000, .279]), while two had non-significant MIC deviations from zero, (MIC [3.574, 22.122], *p* [.506, .674]). The significant positive SIC deviations and non-significant negative SIC deviations from zero demonstrate a parallel-OR architecture in these participants. Six participants had non-significant positive SIC deviations from zero, (D^+ [0.059, 0.121], *p* [.447, .834]), non-significant negative SIC deviations from zero, (D^- [0.067, 0.129], *p* [.404, .768]), and non-significant MIC deviations from zero, (MIC [-13.381, 9.023], *p* [.498, .976]). The non-significant positive and negative deviations from zero identify the processing architecture as serial-OR. Lastly, three participants had significant positive SIC deviations, (D^+ [0.167, 0.221], *p* [0.091, 0.235]), significant negative SIC deviations, (D^- [0.143, 0.180], *p* [.206, .322]), and non-significant MIC deviations from zero, (MIC [-20.733, -0.664], *p* [.435, .715]). Both significant positive and negative SIC deviations from zero could be either coactive processing or serial-AND processing, however, the MIC values were not significantly different than zero, so the processing architecture was identified as serial-AND.

1 dot

In the 1 dot condition (Table 2), the positive, $M_{D+} = 0.181,\ [0.059,\ 0.367]$, negative, $M_{D-} = 0.083,\ [0.003,\ 0.195]$, and overall, $M_{MIC} = 19.756,\ [-21.887,\ 82.510]$, deviations from zero of the 17 participants were examined. Eleven participants had significant positive SIC deviations from zero, (D^+ [0.153, 0.367], *p* [.001, .316]), and non-significant SIC deviations from zero, (D^- [0.003, 0.116], *p* [.526, 1.00]). Nine of those 11 had significant MIC deviations, (MIC [-3.462, 82.510], *p* [.000, .257]), while two had non-significant MIC deviations from zero, (MIC [5.983, 33.994], *p* [.612, .826]). All 11 participants had parallel-OR processing due to the significant positive SIC deviations and non-significant negative SIC deviations. Five of the participants had non-significant positive SIC deviations, (D^+ [0.059, 0.130], *p* [.406, .835]), non-significant negative SIC deviations, (D^- [0.103, 0.143], *p* [.347, .566]), and non-significant MIC deviations, (MIC [-16.728, 16.454], *p* [.612, .965]). The lack of significant positive or negative SIC deviations indicates serial-OR processing for the five participants. One participant had non-significant positive SIC deviations, (D^+ [0.101], *p* [.589]), and significant negative SIC deviations, (D^- [0.195], *p* [.0137]). This participant did not have significant MIC deviation from zero, (MIC = -21.887, *p* = .643), a pattern of results that indicates a parallel-AND processing architecture and stopping-rule.

4 dots

In the 4 dot condition (Table 3), the positive, $M_{D+} = 0.194\ [0.010,\ 0.368]$, negative, $M_{D-} = 0.097\ [0.010,\ 0.225]$, and overall, $M_{MIC} = 14.962\ [-60.274,\ 60.493]$, deviation from zero for 18 participants were examined. Thirteen participants had significant positive SIC deviations, (D^+ [0.154, 0.368], *p* [.001, .326]), and non-significant negative SIC deviations, (D^- [0.010, 0.111], *p* [.531, .995]). Of these 13 participants, 10 had significant MIC deviations from zero, (MIC [8.763, 60.493], *p* [.000, .260]), while three had non-significant MIC deviations from zero, (MIC [3.582, 25.951], *p* [.342, .527]). Despite the differences in the MIC deviations, all 13 of these participants have parallel-OR processing. Two participants had non-significant positive SIC deviations, (D^+ [0.093, 0.128], *p* [.478, .691]), non-significant negative SIC deviations, (D^- [0.096, .147], *p* [.394, .659]), and non-significant MIC deviations, (MIC [-14.010, 1.655], *p* [.663, .816]). These two participants' interaction contrast indicated serial-OR processing of redundant DRT signals. Three participants had non-significant positive SIC deviations from zero, (D^+ [0.010, 0.119], *p* [.536, .996]), and significant negative deviation from zero, (D^- [0.160, 0.225], *p* [.145, .304]). One of the three participants had a significant MIC deviation, (MIC = -60.274, *p*

= .092), while two did not have significant MIC deviations from zero, (MIC [-2.669, -0.876], p [.756, .855]). These three participants interaction contrast indicated parallel-AND processing due to the lack of significant positive SIC deviations and the presence of significant negative SIC deviations.

Table 1 ■ The SIC and MIC results for architecture in 0 dot tracking load.

Subject	D+	D-	MIC	Predicted model	Cz HH	Cz LL
1	0.332*	0.008	35.7*	Parallel-OR	-4.53*	-5.13*
2	0.077	0.067	4.63	Serial-OR	-1.61	-0.98
3	0.295*	0.017	69.4*	Parallel-OR	-4.45*	-5.33*
4	0.167*	0.148*	-8.017	Serial-AND	-2.77*	-2.76*
5	0.116	0.077	-2.284	Serial-OR	-3.89*	-3.49*
6	0.221*	0.180*	-0.664	Serial-AND	-2.57*	-5.30*
8	0.176*	0.089	22.122	Parallel-OR	-3.51*	-3.95*
9	0.173*	0.143*	-20.733	Serial-AND	-2.24*	-2.15*
10	0.285*	0.050	10.501*	Parallel-OR	-5.15*	-2.00*
11	0.061	0.104	-5.445	Serial-OR	-3.66*	-2.11*
12	0.068	0.120	-13.381	Serial-OR	-4.40*	-4.02*
13	0.121	0.129	9.023	Serial-OR	-4.00*	-4.64*
14	0.258*	0.019	21.479*	Parallel-OR	-4.41*	-3.62*
15	0.146*	0.088	3.574	Parallel-OR	-2.41*	-3.70*
16	0.201*	0.056	16.483*	Parallel-OR	-3.56*	-4.04*
17	0.240*	0.058	42.449*	Parallel-OR	-4.86*	-4.38*
18	0.302*	0.021	28.593*	Parallel-OR	-5.37*	-3.96*
19	0.217*	0.116	-5.480*	Parallel-OR	-3.74*	-3.44*
20	0.059	0.093	2.887	Serial-OR	-4.50*	-3.18*

Note. *: p < criterion, where the D+/D- criterion is $p < 0.33$ and the Cz (HH/LL) criterion is $p < .05$. Participant 7 was excluded.

Open practices

The *Open Data* badge was earned because the data of the experiment(s) are available on osf.io/vntwu/
The *Open Material* badge was earned because supplementary material(s) are available on osf.io/vntwu/

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Tables 2 and 3 follow.

Table 2 ■ The SIC and MIC results for architecture in 1 dot tracking load.

Subject	D+	D-	MIC	Predicted model	Cz HH	Cz LL
1	0.331*	0.019	38.844*	Parallel-OR	-4.85*	-4.04*
2	0.080	0.117	-3.309	Serial-OR	-3.77*	-3.66*
3	0.333*	0.008	76.666*	Parallel-OR	-4.62*	-4.23*
5	0.059	0.143	-7.481	Serial-OR	-2.59*	-3.90*
6	0.068	0.143	-16.728	Serial-OR	-3.17*	-4.86*
8	0.274*	0.003	82.510*	Parallel-OR	-3.66*	-4.98*
9	0.179*	0.011	36.276*	Parallel-OR	-4.24*	-3.15*
10	0.367*	0.020	54.263*	Parallel-OR	-3.75*	4.38*
11	0.235*	0.085	29.651*	Parallel-OR	-5.33*	-5.29*
12	0.130	0.103	16.454	Serial-OR	-2.13*	-5.09*
13	0.184*	0.053	19.676*	Parallel-OR	-4.64*	-4.07*
14	0.101	0.195*	-21.887	Parallel-AND	-4.26*	-1.86
15	0.159*	0.079	-3.462*	Parallel-OR	-5.03*	-2.30*
17	0.177*	0.103	3.656*	Parallel-OR	-3.28*	-3.91*
18	0.187*	0.116	33.994	Parallel-OR	-3.75*	-3.39*
19	0.067	0.132	-9.262	Serial-OR	-4.42*	-0.94
20	0.153*	0.078	5.983	Parallel-OR	-3.49*	-4.08*

Note. *: p < criterion, where the D+/D- criterion is $p < 0.33$ and the Cz (HH/LL) criterion is $p < .05$. Three participants (4, 7, 16) were excluded.

Table 3 ■ The SIC and MIC results for architecture in 4 dot tracking load.

Subject	D+	D-	MIC	Predicted model	Cz HH	Cz LL
1	0.349*	0.010	60.493*	Parallel-OR	-3.43*	-3.91*
2	0.194*	0.081	3.582	Parallel-OR	-3.88*	-1.91
3	0.214*	0.041	44.582*	Parallel-OR	-3.17*	-4.54*
4	0.172*	0.110	8.763*	Parallel-OR	-3.43*	-2.02*
5	0.277*	0.045	21.636*	Parallel-OR	-3.70*	-4.07*
8	0.128	0.096	1.655	Serial-OR	-2.95*	-3.02*
9	0.179*	0.111	6.542	Parallel-OR	-4.65*	-3.72*
10	0.207*	0.095	25.951	Parallel-OR	-3.82*	-2.86*
11	0.116	0.160*	-2.669	Parallel-AND	-3.69*	-4.12*
12	0.192*	0.050	39.025*	Parallel-OR	-4.58*	-4.29*
13	0.119	0.217*	-0.876	Parallel-AND	-4.26*	-4.02*
14	0.262*	0.092	35.699*	Parallel-OR	-3.15*	-3.51*
15	0.250*	0.062	39.782*	Parallel-OR	-2.53*	-4.40*
16	0.010	0.225*	-60.274*	Parallel-AND	-1.63	-3.43*
17	0.368*	0.087	14.842*	Parallel-OR	-4.60*	-2.65*
18	0.154*	0.068	10.667	Parallel-OR	-4.56*	-2.58*
19	0.208*	0.040	33.924*	Parallel-OR	-3.59*	-4.15*
20	0.093	0.147	-14.010	Serial-OR	-3.38*	-2.53*

Note. *: p < criterion, where the D+/D- criterion is $p < 0.33$ and the Cz (HH/LL) criterion is $p < .05$. Two participants (6, 7) were excluded.