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**Absence of Motor Coactivation in Bimodal Divided Attention:
Two Case Studies**

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Abstract

When attention is divided across vision and hearing, participants typically respond faster when a visual and an auditory target are presented together as compared to when only one of the visual or auditory targets is presented alone. Coactive models of divided attention account for this so-called bimodal advantage by positing a brain architecture whereby the neural activity inspired independently by concurrently presented auditory and visual targets is first processed in parallel and then pooled into a common resource. However, it remains unclear whether such pooling of activation occurs in the perceptual/cognitive processing of targets or later in the physical (motor) execution of the response. Here, two empirical case studies are reported examining the locus of coactivation in bimodal divided attention by way of planned theoretically driven analysis of each individual's response times (RTs) and peak response forces (pRFs) to weak and energetic pulses of sound and light. Individually for both participants, RT was found to decrease with increased stimulus intensity and to be faster when both auditory and visual targets were presented together than the fastest RTs obtained when either target was presented alone. In contrast, pRF remained unaffected by either experimental manipulation. The results support current theoretical accounts of the bimodal advantage which posit an early or central locus of coactivation, with a subsequent motor component that ensues in a relatively invariant manner.

Keywords: Bimodal Attention, Response Force, Systems Factorial Technology

Introduction

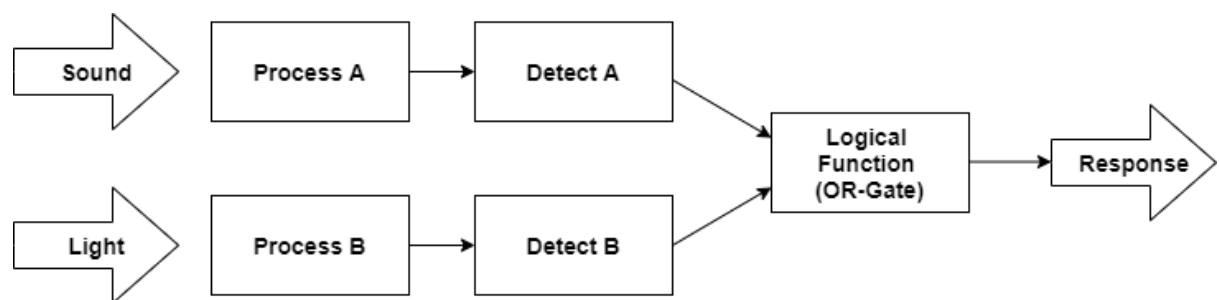
The mechanisms of human attention allow us to focus on certain sensory events and objects for processing, while ignoring other events, essentially underpinning our ability to operate in a necessarily noisy and cluttered world. However, despite widespread agreement that attention operates as a selective filter (Driver, 2001; Desimone & Duncan, 1995; Treisman, 2009) there are nonetheless times when it appears possible for people to operate more effectively given two sources of information as compared to presentation of either source of information alone. This capability is operationalized in the classic redundant-target experiments, typically comprising an auditory target and a visual target presented either alone or together. The participant's task is simply to make a single button press, as fast as possible, whenever a target stimulus is presented in either modality. In this regard, the bimodal combination of both auditory and visual stimuli is redundant, because the same simple reaction is required for either target irrespective of modality. Most usually, reaction times (RTs) to combined targets (henceforth *bimodal* or *multimodal* targets) are faster than to either (*unimodal*) target presented alone; an observation regularly termed the redundant signals effect (RSE) or intersensory facilitation (Hershenson, 1962). Although early investigations (Todd, 1912) provided at best ambiguous support for the RSE, a number of subsequent replication endeavours (Blurton, Greenlee & Gondan, 2014; Diedrich & Colonius, 1987, 2004; Harrar, Harris & Spence, 2016; Hecht, Reiner & Karni, 2008; Patching & Quinlan, 2004; Plat, Praamstra & Horstink, 2000) have garnered indisputable empirical support of the RSE.

Independent Race Models. One of the most parsimonious explanations of the RSE now forms the basis of a class of cognitive models known as *independent race models* (Mordkoff & Yantis, 1991; Raab, 1962; Townsend & Nozawa, 1997). In race models of attention, the two perceptual codes generated by redundant signals compete on parallel channels in a horse

race-like manner, and by analogy the first signal to be processed ‘wins’ the race and independently activates the observer’s physical response. As first demonstrated by Raab (1962), a simple horse race model can produce faster mean RT on bimodal as compared to unimodal trials without necessitating any interaction between streams of neural activation inspired independently by simultaneously presented auditory and visual signals. This effect, termed *statistical facilitation*, is purely stochastic in nature, and may effectively arise merely by sampling from multiple independent RT distributions on bimodal trials (Figure 1).

Figure 1

Independent Race Model Processing of Redundant Signals.



Note. Provided the distribution of processing times for the visual signals overlaps with the distribution of processing times to auditory signals, the mean RT produced by the independent race model will be faster on bimodal trials as compared to unimodal trials simply as a result of statistical facilitation.

Subsequently, Miller (1982) formulated a highly influential mathematical inequality that provides for a procedure to test for an implicit prediction made by independent race models, namely that no response on bimodal trials can be faster than the fastest response on unimodal trials. In particular, Miller (1982) detailed a so-called *race model inequality* (RMI): a mathematical relationship which constitutes a theoretical upper bound to the RT facilitation that can be produced by independent race models. This inequality takes the form:

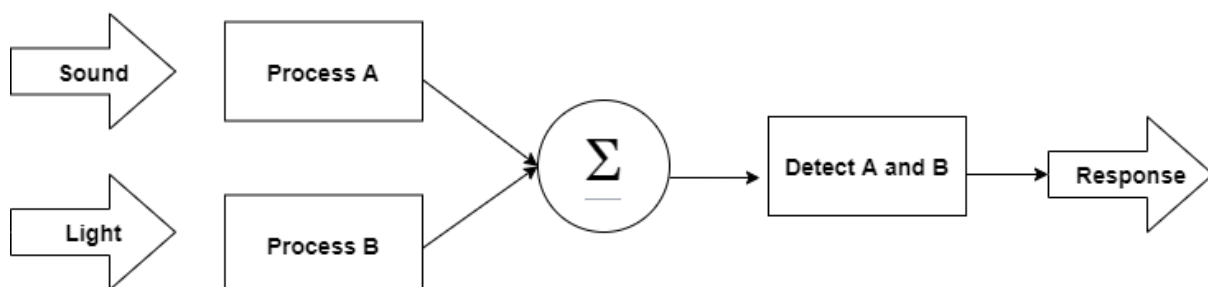
$$P(\text{RT} < t | C_1 \text{ and } C_2) \leq P(\text{RT} < t | C_1) + P(\text{RT} < t | C_2) \quad (1)$$

The left-hand term of Equation 1 refers to the cumulative probability of making a response before time t given that signals are concurrently processed on channel 1 *and* channel 2. The sum of the two right-hand terms refer to the sum of the cumulative probabilities that a response was made before time t given that a unimodal signal was present on either channel 1 *or* channel 2.

Coactive Models of Attention. A violation of the constraints imposed by the RMI implies that the observed RT distribution on bimodal as compared to unimodal trials could not have been produced by statistical facilitation alone. Classically, violation of the RMI is taken to indicate that integration of the two redundant perceptual codes has occurred via some form of neural mechanism which Miller (1982) generically termed *coactivation*. According to coactive models of attention, the initial separate channel processing outputs are fed to a single channel which in turn feeds its output to a decisional operator that gates the response initiation mechanism (Figure 2).

Figure 2

Coactive Processing of Redundant Signals.



Note. In coactive models of attention, the processing outputs of channel A and B are typically assumed to be pooled prior to detection and subsequent response initiation. The resulting RT distributions produced by coactive models of attention cannot be accounted for by statistical facilitation alone.

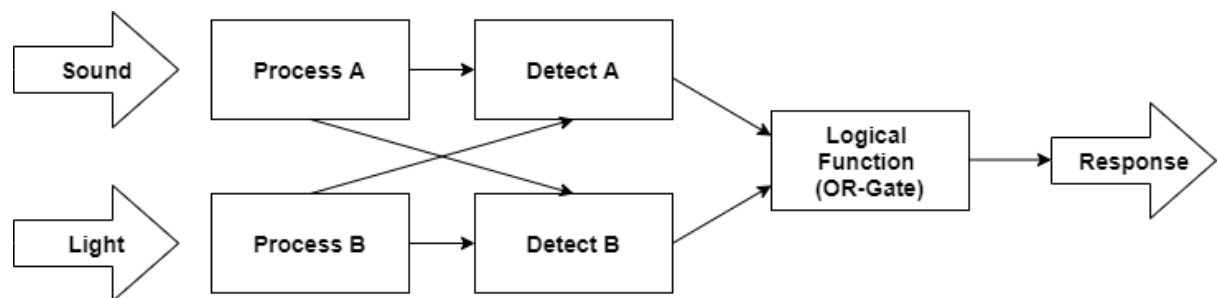
Following Schwarz's (1989) neural superposition model of coactivation, activity summation from multiple channels is conceptualized by assuming that an attended sensory event induces a neural counting process which has to pass some pre-set criterion for the stimuli to be detected, and that coactive detection of redundant targets simply involves a superposition of individual counting events. In support of this view, neurophysiological studies suggest that a class of multimodally receptive neurons exist in the mammalian cerebral cortex (Beauchamp, Lee, Argall & Martin, 2004; Molholm et al., 2006), as well as subcortically in the superior colliculus (Bell et al., 2006, Meredith & Stein, 1986), which potentially operate in manner akin to the integrative action postulated by Schwarz (1989).

Violations of the RMI have consistently been observed in investigations of bimodal divided attention (Diedrich & Colonius, 1987, 2004; Miller, 1982, 1986, 1991; Patching & Quinlan, 2004) as well as in divided visual attention (Miller, Beutinger & Ulrich, 2008; Mordkoff, Miller & Roch, 1996; Mordkoff & Danek, 2010; Mordkoff & Yantis, 1993).

Interactive Race Models. A violation of the constraints imposed by the RMI is not a safe guarantee for a latent coactive mechanism, because other models can mimic the performance of coactive models (Miller, 2015). In particular, Mordkoff and Yantis (1991) proposed an *interactive race model* of attention that allows for crosstalk between parallel streams of neural activation (hence violating the commonly made assumption of context independence of processing pathways) as an alternative to models positing independent parallel processing coupled to a simple mechanisms of neural summation (cf., Miller, 1982; Schwarz, 1989). According to Mordkoff and Yantis, interactive crosstalk is possible on the basis that stochastic interstimulus contingencies exist, whereby the detection of a target on channel A informs the observer something about the prospect of a target on channel B (and vice versa, see Figure 3).

Figure 3

Interactive Race Model Processing of Redundant Signals.

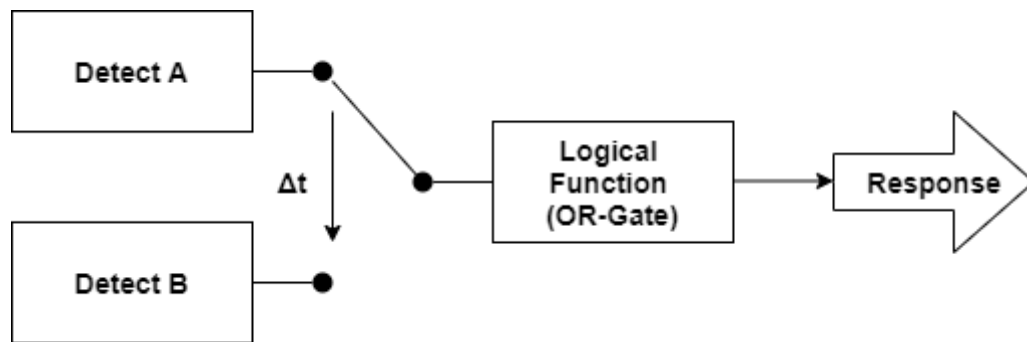


Note. In interactive models of attention, crosstalk between parallel channels can produce RT distributions which mimic those of coactive models due to inter-channel crosstalk.

Modality Switching Effects. A further possibility is that switching attention from modality A to B on unimodal trials incurs a temporal processing cost in comparison to bimodal trials (Patching & Quinlan, 2004; Townsend & Nozawa, 1997). Such a modality switching cost could possibly ‘hurt’ performance on unimodal trials in tasks that require the observer to divide their attention across multiple sensory streams but leave bimodal RTs unaffected - giving rise to what appears to be a bimodal RT advantage but which is actually a unimodal RT cost (Figure 3). However, as argued by Gondan, Lange, Rösler and Röder (2004), modality switching effects (MSEs) ought only to be present when stimulus sequences are random, so that presentation of a target in modality B can follow a target in modality A. Gondan and colleagues (2004) found the RSE to persist even when sequences of target signals were non-random and predictable, and therefore reasoned that MSEs cannot fully account for the RSE.

Figure 4

Switch Mechanism in Parallel Cognitive Architecture.



Note. If switching attention from channel A to channel B comes at a temporal expense, this mechanism may potentially slow RTs to unimodal auditory or visual signals as compared to bimodal auditory and visual signals.

Systems Factorial Technology. A grave problem highlighted by Townsend & Nozawa (1995, 1997) is that very many different model architectures can give rise to seemingly indistinguishable patterns of RT performance in standard divided attention tasks. Due to problems associated with so called model mimicry, Townsend and Nozawa (1995) developed and devised the methodological approach of Systems Factorial Technology (SFT) in an effort to distinguish between theoretical accounts of multichannel processing systems with roughly overlapping distributional properties. After Townsend and colleagues (Townsend, 1971 1990; Townsend & Nozawa, 1995, 1997; Wenger & Townsend, 2000), SFT aims to extend the prospects for drawing inference about latent mental architectures and processing styles based purely on knowledge of the links between sensory input and behavioral output. On the basis of SFT, the double factorial design is a class of experimental procedures that allows for the twofold factorial analysis of RT distributions, typically by employing a redundant targets task and conjoint stimulus intensity manipulation of some sort. Most often manipulations of target

numerosity (e.g. unimodal or bimodal) compose Factor 1, and manipulations of stimulus saliency (e.g. stimulus strength, duration) compose Factor 2.

Factor 1 is a manipulation of attentional workload that evaluates the systems information processing workload capacity. This rather abstract notion of processing capacity has been likened by Wenger and Townsend (2000) to the capacity of a mechanical system to do a certain amount of physical work within a given amount of time. By presenting the observer with either unimodal or bimodal trial types, and consequently manipulating their perceptual workload, the capacity of the sensory processing system under consideration can be formally assessed by computing the *capacity coefficient*. Capacity analysis assumes that a system exists which incorporates the assumptions of *unlimited capacity independent parallel* (UCIP) processing with a self-terminating (OR) stopping rule. It then uses the performance of such a UCIP-OR system as a baseline for comparison. Algebraically, capacity is defined as the ratio of the integrated hazard function of the bimodal RT distribution relative to the sum of the integrated hazard functions for the unimodal trials across all values of $t > 0$ according to the formula,

$$C_{OR}(t) = H_{12}(t) / H_1(t) + H_2(t) \quad (2)$$

In this case, a capacity coefficient of unity [$C_{OR}(t) \sim 1$] is said to be indicative of *unlimited capacity* (as in the case of a UCIP-OR-system), a coefficient of > 1 is indicative of *super capacity* and some sort of underlying intersensory facilitation of performance. Correspondingly, a coefficient of < 1 is indicative of *limited capacity* and of performance decrements on bimodal trials (cf., Hugenschmidt, Hayasaka, Peiffer & Laurienti, 2010).

Factor 2 is in turn a manipulation of detectability which allows for additional evaluation of information processing architecture and stopping rule. After Altieri, Fifić, Little, and Yang (2017) identification of processing architectures and stopping rules can be achieved by subjecting the RT distributions from bimodal trials to a *survivor interaction contrast* (SIC).

The SIC is computed by contrasting the survivor functions $S(t)$ of four bimodal RT distributions according to the following equation,

$$\text{SIC}(t) = [S_{LL}(t) > S_{LH}(t)] - [S_{HL}(t) - S_{HH}(t)] \quad (3)$$

The subscripts LL, LH, HL and HH in Equation 3 denote the saliency levels of the two stimulus components (Low-Low, Low-High, High-Low and High-High) belonging to that trial type and its associated survivor distribution function. Just like the mean interaction contrast of Sternberg (1969) the SIC is essentially a test of selective vs. interactive influence of processing stages. After Altieri and colleagues (2017), four distinct models (other than coactive models) can be distinguished based on the characteristics of their survivor functions, termed serial independent and parallel independent models with either exhaustive or self-terminating stopping rules.

The distinction between serial and parallel processing concerns the possibilities of temporal (and perhaps also physical) overlap between the stages of information processing at which auditory and visual perceptual codes are attended to and processed in the human brain. The characteristic of a serial processing systems is that the time taken to process subtask A and B together is equivalent to the total sum of the time taken to process A and B independently. However, for parallel architectures the time taken to process subtask A and B will depend on the workload capacity of the system under consideration (Townsend, 1990). As for stopping rules, exhaustive processing posits a process in which the participant always checks both modalities exhaustively for the presence or absence of signals before making a response (i.e. all the sensory information is processed prior to the response). Alternatively, a self-terminating stopping rule implies that the participant is ready to make a response on bimodal trials as soon as a signal is detected on either of the two information streams.

Motor Coactivation. Yet, SFT does not inform about the precise loci of attentional mechanisms underlying the RSE in the sensory-motor chain of processing target events (cf.,

Minakata & Gondan, 2018). The experimental work presented in the present paper was inspired by the main findings of Giray and Ulrich (1993) who recorded more forceful responses on redundant trials as compared to unimodal trials. Giray and Ulrich termed this effect *motor coactivation* and suggested that it supports the notion of a late-stage loci of the RSE. Remarkably, motor coactivation as proposed by Giray and Ulrich is at odds with the commonly held view that the motor component of the response proceeds in a relatively invariant manner in most RT paradigms (cf., Luce 1986).

Variable Output Models and Intensity Effects. Evidence against the principle of motor invariance in a RT task was first brought to light by Angel (1973), who recorded increased electromyographic signal amplitudes in the thenar muscles of participants responding to pulses of light, sound, and electric current, with increasing stimulus intensity. Systematically increasing stimulus intensity (i.e., brightness, loudness, etc) in an experimental setting is well known to systematically decrease RT according to a modality specific inverse parabolic function which saturates at very high stimulus intensities - a relationship known as Piéron's law (Piéron, 1914). Piéron's law is assumed to reflect neurophysiological accrual processes located at the early sensory stages of stimulus reception (Bonnet, Gurlekian & Harris, 1992; Baumgardt, 1959; Pins & Bonnet, 1996, 1997, 2000) and consequently thought to be relatively independent of late (motor) stage processing.

In contrast to the notion of motion invariance, Ulrich, Rinckenhauer and Miller (1998) outlined a class of variant motor component models which incorporate a *continuous transmission* mechanism from perceptual to motor systems upon detection of a valid target, termed 'variable output models'. By incorporating continuous transmission, variable output models, as opposed to motor invariance models, predict that additional measurement of response force should scale as a function of stimulus intensity. In this manner, notions of motor invariance fit with Angel's (1973) original finding of increased thenar activity with

increasing stimulus intensity, and with other studies which have shown a decrease in RT together with an increase in response force with increased stimulus intensity. For instance, studies examining response force in the context of auditory detection generally conform with notions of an invariant auditory-motor coupling (Jaśkowski, & Włodarczyk, 2005; Miller, Franz & Ulrich, 1999). However, there is far less evidence to suggest that analogous intensity-force relations hold for the visual modality. Multiple experimental attempts have failed to demonstrate convincing force-brightness correspondences in visual detection tasks (Jaśkowski, & Włodarczyk, 2006; Jaśkowski, et al., 1995, Patching & Bååth, 2013).

Moreover, Ulrich and Mattes (1996) have expressed doubts about the precise extent to which loudness effects on force output ought to be considered sensory-motor invariance proper, or rather a mere artefact of auditory induced physiological arousal. Indeed, the notion that an alerting-arousing property can be ascribed to the auditory modality, but not to the visual modality, has been proposed by various researchers (e.g., Nissen, 1977; Posner, 1978, Sanders, 1983). Nonetheless, Jaśkowski, and Włodarczyk (2006) have argued that relations between visual stimulus intensity and response force do exist, given that changes in the intensity of visual targets are comparable to changes in the intensity of auditory targets.

Aims of Thesis. The present research seeks to apply existing theoretical benchmarks of the RSE, as well as to provide new metrics by which to assess potential cognitive architectures, and mechanisms of attention, underlying dual task performance. More specifically, the aims were (a) to replicate the RSE, i.e. the classic finding that responses are faster to bimodal (auditory and visual) targets than to unimodal (auditory or visual) targets; (b) to test the CDFs of the RT distributions against the RMI; and (c) to apply the full mathematical toolbox of SFT to the RT data.

A further purpose of the study was to provide new clues about human perception-action links underlying the RSE, by supplementing traditional measurement of RT with novel

measurement of the peak pressure applied to the response button (here termed peak response force [pRF]) on unimodal as compared to bimodal trials. The purpose of this was to test Giray and Ulrich's (1993) motor coactivation account of the RSE, which predicts that responses ought to be more forceful on bimodal trials as compared to unimodal ones. The design of the experiment further also provides for a critical assessment of all variable output models, which predict that pRF ought to increase as a function of stimulus intensity. Finally, the research seeks to develop a new metric of performance in the processing of simple sensory signals, by subjecting the RT and pRF data to a joint analysis to assess for possible shifts in the amount of force transferred to the response button per unit time ('power') as a function of both stimulus intensity and redundancy.

A limitation of the present work was the availability of participants to take part in the study¹. However, this limitation was turned to an advantage by making two detailed case studies of the data obtained. A critical issue approached by the present research concerns the possibility of fundamental differences between participants in the perceptual / cognitive processing of auditory and visual signals. This issue has been recently highlighted by Thiele, Haaf and Rouder (2017), but has yet to be investigated in the context of bimodal divided attention. In the present study comprehensive theoretically driven analyses of both RT and pRF distributions are presented separately for two individual participants, by which to shed new light on individual differences in the processing of auditory and visual signals presented alone and together.

¹ The experimental study was set-up and scheduled to be conducted just before all universities in Sweden were closed due the SARS-CoV-2 pandemic, 2020.

Methods

Simple RT and pRF was measured by way of participants' making a single button press whenever a pulse of sound or light was presented, following the redundant-targets paradigm. Auditory targets comprised a soft or a loud tone. Visual targets comprised a dim or a bright square patch of light. Targets were presented either alone or in one of 2×2 factorial combinations yielding 8 unique trial types, pseudo-randomly intermixed throughout the experiment. The participants, PF and GP, were instructed to respond as fast as possible by making a simple button press whenever a visual *or* auditory signal was presented. The timing between trials was random to avoid rhythmic responses, circumventing the inclusion of 'catch trials' in the present experimental design.

Participants

Two participants, PF (woman) and GP (man), were recruited through personal contact. Participant PF was 21 years of age, and participant GP was 54 years old. PF was naive to the purpose of the experiment and was not informed that the forcefulness of her responses would be measured throughout. GP was apprised of the experimental task. Both participants reported normal or corrected-to-normal vision and hearing.

Apparatus

A microcomputer (Dell Precision PWS380, Dell Inc., Round Rock, Texas) running a 32-bit Windows operating system (Windows 7 Enterprise, Microsoft Corporation, 2009) and MATLAB (The MathWorks, Inc., 2015b) controlled the experiment. Stimulus presentation and timing were controlled using the Psychophysics Toolbox extensions (Brainard, 1997; Pelli, 1997). RTs were collected by way of a response key connected to the microcomputer via a U3-LV Labjack USB DAQ device (LabJack Corporation, Colorado). The pressure applied to the response button was recorded using the equipment described in detail by Englund and Patching (2009). Timing tests of the experimental setup, including measurement

of RTs, were conducted using the Black Box Toolkit (Version 1; Plant & Hammond, 2002).

Extensive testing of the experimental set-up using the Black Box Toolkit verified the consistency of the timings requested and recorded by the experiment script.

Visual stimuli were presented on a 21-inch (40.5 cm × 30.5 cm viewable area) ViewSonic G220f video monitor (ViewSonic Corporation, Walnut, California), using a Cambridge Research Systems Bits++ digital video processor (Cambridge Research Systems Ltd., Rochester, Kent, United Kingdom). Luminance was measured using a ColorCal optical photometer (Cambridge Research Systems Ltd.). The auditory stimuli were presented via two Dell speakers (Model A215) placed either side of the video monitor, 30 cm from the centre of the screen. The pixel resolution of the video monitor was 1024 × 768, with a refresh rate of 100 Hz. Background illumination of the monitor was held constant at 0.1 cd/m². A chinrest was fixed at a distance of 57 cm from the screen of the video monitor to ensure a constant viewing distance. All equipment was concealed behind black poster board, whereby only the screen of the monitor was visible to participants.

Stimuli

The visual target was a luminant square presented centrally on the video monitor. The intensities of the bright and the dim squares were 27 and 0.2 cd/m², respectively. Viewed from 57 cm, the target square subtended 3° × 3° of visual angle and measured 3 cm × 3 cm in extent. Auditory targets were either a soft or a loud 440 cycle sine waves synthesized digitally with a sampling rate of 44.1 kHz and presented binaurally through the stereo speakers. All visual and auditory targets were presented for 200 milliseconds.

Design

Participants, PF and GP, were tested individually in a quiet darkened room in a single session comprising 416 trials. The loud and the soft tones and the bright and the dim visual square were presented alone on unimodal trials and together in factorial combination on

bimodal trials, yielding 8 different stimulus conditions; 1) unimodal loud tone, 2) unimodal soft tone, 3) unimodal bright visual square, 4) unimodal dim visual square, 5) bimodal loud tone – bright square, 6) bimodal soft tone – bright square, 7) bimodal loud tone – dim square, 8) bimodal soft tone – dim square. The stimuli were shown in pseudo-randomly constructed cycles of 16 trials, containing two instances of each different stimulus condition. New pseudorandom orders were used for each participant. The first 16 trials were deemed as practice trials and removed from all analysis. There was no obvious transition between the practice and experimental sections. The remaining 400 trials were divided into 2 blocks of 200 trials, each block comprising 25 instances of each different stimulus condition. So, in total each unimodal and bimodal stimulus condition was presented 50 times over the course of all the experiment trials. To avoid rhythmic responses, the inter-trial interval was randomly drawn from an exponential distribution with a mean of 1 sec.

Procedure

At the start of the session, PF and GP were presented with the written instructions on the monitor to respond as quickly as possible whenever a visual or auditory stimulus was presented, using the index finger of their right hand. At the end of the first block of 200 trials the experimental procedure was paused, and the task instructions were re-presented. A button press was required to initiate the next block of 200 trials. This provided the opportunity for PF and GP to take a short break if required, but in no case did either participant leave the darkened testing room during the experimental procedure. For both participants, the entire experimental session took about 45 min to complete. RT was measured from stimulus onset to the closure of a microswitch, via the Labjack USB DAQ device; the pressure applied to the response button was sampled for 1,500 milliseconds from stimulus onset at a sampling rate of 1000 Hz. In all respect, the experiment was conducted in accordance with the rules and

regulations laid down by the Swedish Research Council's ethics committee and the European Research Council's ethics committees for research with human participants.

Data Analysis

The data were first inspected for anomalies: all responses less than 100 milliseconds were considered anticipations, and all responses greater than 1,000 milliseconds considered misses. 0.25 % of responses were classified as misses (0.5% PF, 0% GP) and removed from all further analysis. No responses were classified as anticipations.

Then, to examine relations between pRF and RT, the remaining pRFs and RTs were standardized [here denoted $Z(\text{pRF})$ and $Z(\text{RT})$] and, separately for PF and GP, submitted to a Bayesian linear model with reasonably weak priors,

$$\begin{aligned} Z(\text{pRF}_i) &\sim \text{Normal}(\mu_i, \sigma) && \text{[likelihood]} \\ \mu_i &= b_0 + b_1 Z(\text{RT}_i) && \text{[linear model]} \\ (b_0, b_1) &\sim \text{Normal}(0, 1) && \text{[Intercept and slope priors]} \\ \sigma &\sim \text{HalfCauchy}(0, 1) && \text{[Sigma (residual) prior].} \end{aligned}$$

This analysis showed hardly any relation between $Z(\text{pRF})$ and $Z(\text{RT})$.

For clarity, all further theoretically driven data analyses were conducted in 4 parts, separately for PF and GP.

Reaction Time (RT) Analysis. First, the unimodal and bimodal RT data was entered into a joint linear model for each participant separately to assess for faster RT on bimodal trial type, essentially serving as a test of the classic RSE finding. This model was specified as follows with very weakly informed priors,

$RT \sim \text{Normal}(\mu, \sigma)$	[likelihood]
$\mu = b_0 + b_1 \text{redundancy}_j$	[linear model]
$(b_0, b_1) \sim \text{Normal}(0, 1e4)$	$[b_0, b_1 \text{priors}]$
$\sigma \sim \text{HalfCauchy}(0, 1e4)$	$[\sigma \text{ prior}]$.

Redundancy was dummy coded as 0 for unimodal targets and 1 for bimodal targets. Bayes Factors (*BFs*) were then computed for the RSE models as compared to a model incorporating an intercept (M_0) as the only predictor. This analysis revealed support for the RSE model in the case of both participants.

Secondly, a Bayesian linear model was fit to the unimodal RT data, independently for PF and GP, to predict RT based on possible main and interaction effects of intensity (weak or strong) and modality (visual or auditory). Stimulus intensity and modality were dummy coded as 0 = low or visual and 1 = high or auditory, respectively. Accordingly, a linear model with very weak priors was formulated as follows,

$RT \sim \text{Normal}(\mu, \sigma)$	[likelihood]
$\mu = b_0 + b_1 \text{intensity}_j + b_2 \text{modality}_j + b_3 \text{intensity}_j \times \text{modality}_j$	[linear model]
$(b_0, b_1, b_2, b_3) \sim \text{Normal}(0, 1e4)$	$[b_0, b_1, b_2, b_3, \text{priors}]$
$\sigma \sim \text{HalfCauchy}(0, 1e4)$	$[\sigma \text{ prior}]$

The fit of the redundancy models incorporating modality and intensity effects was then compared to that of an intercept-only model by means of BF analysis as described above for the RSE analysis. Overall, this analysis showed evidence of a main effect of intensity on unimodal RT for both PF and GP, and a main effect of modality on unimodal RT for GP.

Finally, the bimodal RT data were similarly submitted to a Bayesian linear model to predict RT based on possible main and interaction effects of stimulus intensity in the auditory (soft or loud) and visual (dim or bright) modality. Stimulus intensities were here coded as 0 = soft or dim and 1 = loud or bright, respectively. This linear model was formulated as follows, using the same weak priors as used in analysis of the unimodal data,

$$\begin{aligned} \text{RT} &\sim \text{Normal}(\mu, \sigma) && \text{[likelihood]} \\ \mu &= b_0 + b_1\text{brightness}_j + b_2\text{loudness}_j + b_3\text{brightness}_j \times \text{loudness} && \text{[linear model]} \end{aligned}$$

BFs were then computed for models incorporating brightness and loudness effects as compared to a model incorporating an intercept (M_0) as the only predictor. Overall, these analyses show that loudness as well as brightness predicted GPs RT performance on bimodal trials, but not that of PF.

Systems Factorial Analysis. First, the RT data of both participants was tested against the RMI following the procedures advocated by Ulrich, Miller and Schröter (2007). Visual inspection of the CDFs revealed that PF's RT performance on weak signal component trials violated the RMI in the 5th to 45th quantile range, whereas the inequality was not violated for strong signal component trials. GP's RT data did on the other hand violate the RMI across every quantile for weak and strong signal component trials alike.

Next, the bimodal RT distributions or from each participant separately were subject to a SIC analysis after Altieri and colleagues (2017) to characterize latent cognitive architecture and stopping rule. This analysis showed that the SIC-curves of both participants were approximately S-shaped, covering some initial negative area before resurging into the positive domain.

Finally, capacity analysis was conducted following the procedures described by Houpt, Blaha, McIntire, Having, and Townsend (2013). This was done twice for each participant, once for the RT distributions from weak signal component intensity trials and once for strong signal intensity trials. This analysis revealed that capacity was consistently enhanced on bimodal trials, although this effect was perhaps somewhat attenuated on loud-bright trials as compared to soft-dim trials.

Peak Response Force (pRF) Analysis. First, the unimodal and bimodal pRF data was entered into a joint linear model for each participant to assess for enhanced pRF on bimodal trial types as predicted by motor coactivation. This model was specified exactly as the RSE model for the RT data described above, using the same weakly informed priors. Contrary to the motor coactivation prediction, this analysis revealed support for the intercept model in the case of both participants.

To further assess for possible motor variance effects due to increased stimulus intensity, the pRF data obtained on the unimodal and bimodal trials were also separately analysed according to the same procedures as that used for analysis of the unimodal and bimodal RT data. This analysis revealed that neither intensity nor modality predicted pRF to a noteworthy extent, in line with models incorporating a punctuated motor transmission mechanism. No further analysis of these pRF data was conducted to examine survivor interaction contrasts, RMI, or the capacity coefficient $C(t)$, which are all restricted to analysis of the RT data.

Processing Power Analysis. RT and pRF measures were further combined in a joint analysis, to assess possible effects of experimental factors on the peak energy transferred to the response button per unit time ('power'). First, the data was transformed by taking the product of the speed and the peak forcefulness of responses ($1/RT \times pRF$). The transformed data was then entered into two separate analyses of peak processing power for the unimodal and bimodal trials following the same procedures as that commonly used for analysis of the

RT and pRF data. This analysis revealed an intensity effect on output power for both PF and GP on unimodal trials, as well as a modality effect for GP on bimodal trials.

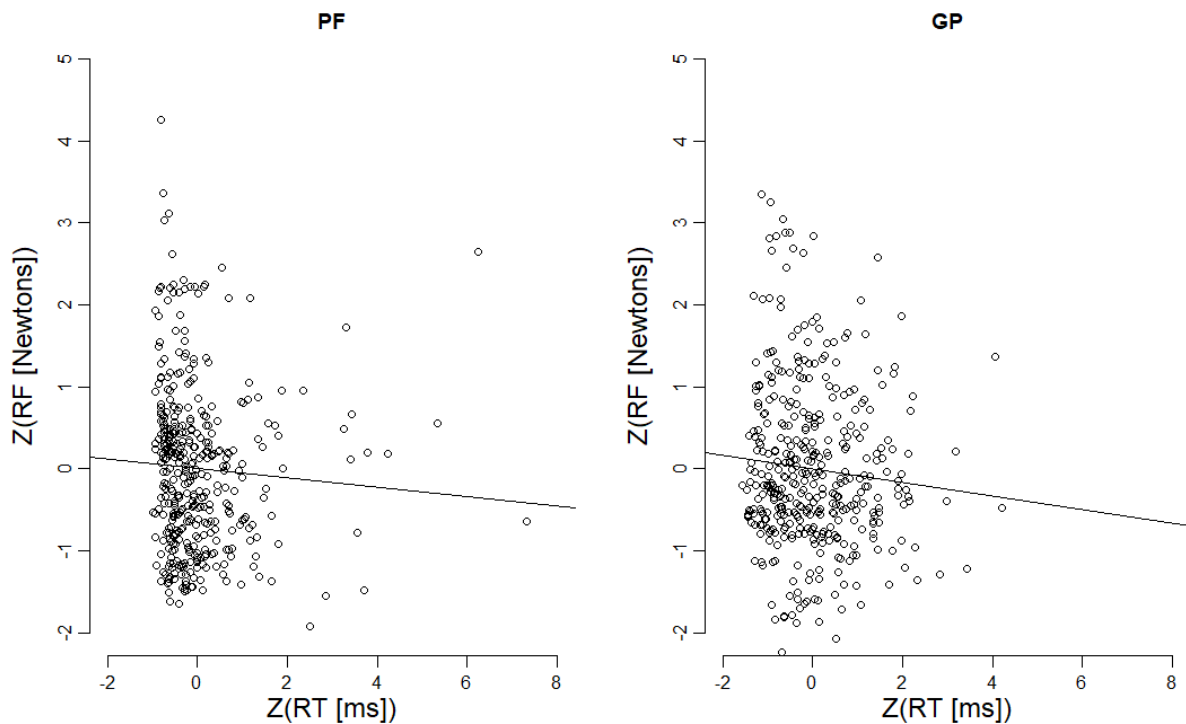
Computational Methods. All data analyses were conducted using R (R Core Team, 2020) and Stan (Stan Development Team, 2018), along with the BayesFactor package (Morey & Rouder, 2018), the sft package (Houpt et al., 2013) and the Rethinking package (McElreath, 2020). All Bayesian analyses computed using Hamiltonian Monte Carlo (HMC) methods are based on 2,000 warmup steps, and 3,000 sampled steps, for each of 3 independent chains, which showed little autocorrelation. Good convergence was obtained between the multiple chains as tested with the \hat{R} statistic (Gelman & Rubin, 1992), which was found to be less than 1.01 in every case. The resulting HMC samples are therefore highly representative of the underlying posterior distributions. Because the models are fully Bayesian, estimates for all of the parameters are readily available after the models have been fitted, including reliability measures in the form of credible intervals, here presented in terms of the 95% highest density interval (HDI) as advocated by Kruschke (2015; also McElreath, 2020). The experimental data and R-scripts used for data analyses are freely available from a [GitHub](#) repository.

Results

Figure 5 shows linear relations between standardized RT ($Z[RT]$) and standardized pRF ($Z[RF]$), as fit by Bayesian regression, for PF and GP separately. For participant PF, $b_0 = 0.00$, $b_1 = -0.06$, $\sigma = 1.00$, 95% HDIs $[-0.10, 0.10]$, $[-0.16, 0.04]$, and $[0.93, 1.07]$, respectively. For participant GP, $b_0 = 0.00$, $b_1 = -0.08$, $\sigma = 1.00$, 95% HDIs $[-0.10, 0.10]$, $[-0.18, 0.02]$, and $[0.93, 1.07]$.

Figure 5

Relations Between Reaction Time (RT) and Peak Response Force (pRF)



Note. Relations between standardized (Z-scores) RT in milliseconds and pRF performance in Newtons for PF (*left panel*) and GP (*right panel*).

Reaction Time. In milliseconds, the parameter estimates for the linear model predicting RT based on redundancy for PF were $b_0 = 319.29$, $b_1 = -52.56$, $\sigma = 83.35$, 95% HDIs [307.80, 331.09], [-69.12, -36.11] and [77.67, 89.48], respectively. For GP, the same parameters were estimated to $b_0 = 349.52$, $b_1 = -65.48$, $\sigma = 51.24$, 95% HDIs [342.48, 356.57], [-75.39, -55.64], and [47.81, 55.04]. The RSE model outperformed the intercept model in predicting RT with a good margin ($BFs > 100$) in the case of both participants.

Unimodal RT predictions in milliseconds for PF were $b_0 = 346$, $b_1 = 0$, $b_2 = -40$, $b_3 = -25$, $\sigma = 100$, 95% HDIs [317, 374], [-40, 39], [-80, 0], [-83, 30] and [90, 111], respectively. For GP, $b_0 = 395$, $b_1 = -25$, $b_2 = -51$, $b_3 = -30$, $\sigma = 49$, 95% HDIs [381, 409], [-83, 30], [-72, -32],

[-58, -3], and [45, 55]. A model M_1 incorporating a main effect of intensity gave best fit for PFs performance ($BF_{10} > 100$), whereas a model M_2 incorporating main effects of both modality and intensity, and a modality-intensity interaction effect, gave best fit for GP ($BF_{20} > 100$).

Bimodal RT predictions in milliseconds for PF were $b_0 = 286$, $b_1 = -22$, $b_2 = -19$, $b_3 = 5$, $\sigma = 56$, 95% HDIs [270, 301], [-44, 0], [-41, 2], [-25, 37] and [51, 62], respectively. For GP $b_0 = 312$, $b_1 = -42$, $b_2 = -17$, $b_3 = 6$, $\sigma = 27$, 95% HDIs [304, 320], [-53, -32], [-28, -6], [-8, 21], and [24, 30]. Whereas no model provided adequate fit to PF's bimodal RT data ($0.3 < BF_s < 3$), a model M_4 incorporating main effects of auditory and visual intensity provided good fit to GP's bimodal RT data ($BF_{40} > 100$). Figure 6 shows the results of analysing the unimodal and bimodal RT and pRF data.

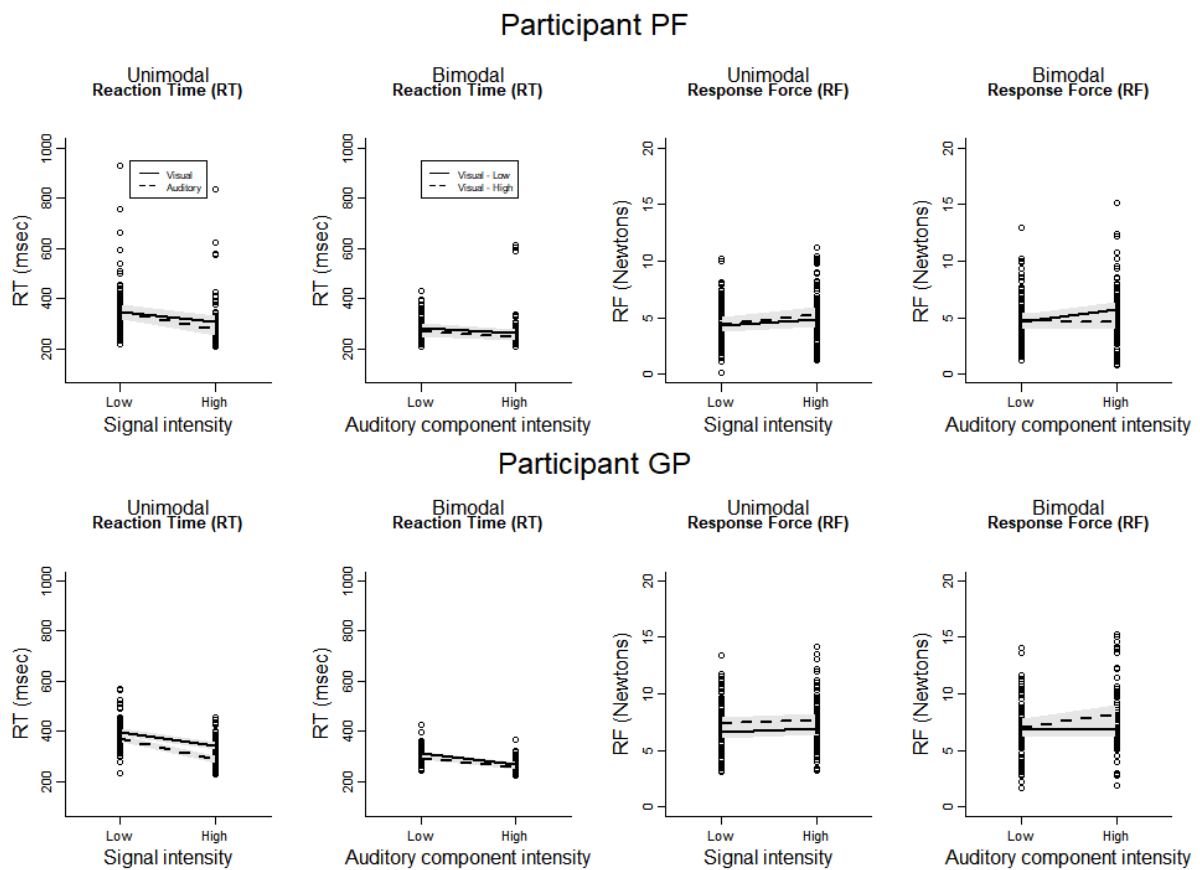
Peak Response Force. The parameters of the motor coactivation model predicting pRF based on redundancy for PF were $b_0 = 4.72$, $b_1 = 0.21$, $\sigma = 2.43$, 95% HDIs [6.12, 7.55], [-0.91, 1.13], and [-0.74, 1.28], respectively. For GP, the same predictions were $b_0 = 7.17$, $b_1 = 0.13$, $\sigma = 2.41$, 95% HDIs [6.84, 7.49], [-0.34, 0.60], and [2.25, 2.58]. The motor coactivation models were outperformed by intercept models in the case of both participants ($BF_s < 0.3$).

Unimodal pRF predictions in Newtons for PF were $b_0 = 4.35$, $b_1 = 0.06$, $b_2 = 0.50$, $b_3 = 0.33$, $\sigma = 2.34$, 95% HDIs [3.71, 5.00], [-0.85, 0.98], [-0.41, 1.41], [-0.97, 1.61], and [2.12, 2.58], respectively. For GP, $b_0 = 6.65$, $b_1 = 0.70$, $b_2 = 0.34$, $b_3 = 0.00$, $\sigma = 2.19$, 95% HDIs [6.06, 7.24], [-0.53, 1.19], [-0.53, 1.19], [-1.21, 1.18], and [1.99, 2.34]. For participant PF, an intercept model M_0 predicted unimodal pRF better than all other models ($BF_s < 0.3$) except for an intensity model M_3 where performance was equivocal with the intercept model ($BF_{30} \sim 1$). For participant GP the intercept model M_0 predicted unimodal pRF better than all other models ($BF_s < 0.3$) except for a modality model M_4 which performed equivalent to the intercept model ($BF_{40} \sim 1$).

Bimodal peak response force (pRF) predictions in Newtons for PF were $b_0 = 4.63$, $b_1 = 1.04$, $b_2 = 0.13$, $b_3 = -1.14$, $\sigma = 2.51$, 95% HDIs [3.94, 5.32], [0.05, 2.02], [-0.86, 1.12], [-2.52, 0.25], and [2.27, 2.78], respectively. For GP $b_0 = 6.84$, $b_1 = 0.09$, $b_2 = 0.25$, $b_3 = 1.11$, $\sigma = 2.56$, 95% HDIs [6.12, 7.55], [-0.91, 1.13], [-0.74, 1.28], [-0.31, 2.52], and [2.32, 2.83], respectively. No model provided adequate fit to the bimodal pRF data for either participant ($0.3 < BF_s < 3$).

Figure 6

Reaction Time (RT) and Peak Response Force (pRF) Data

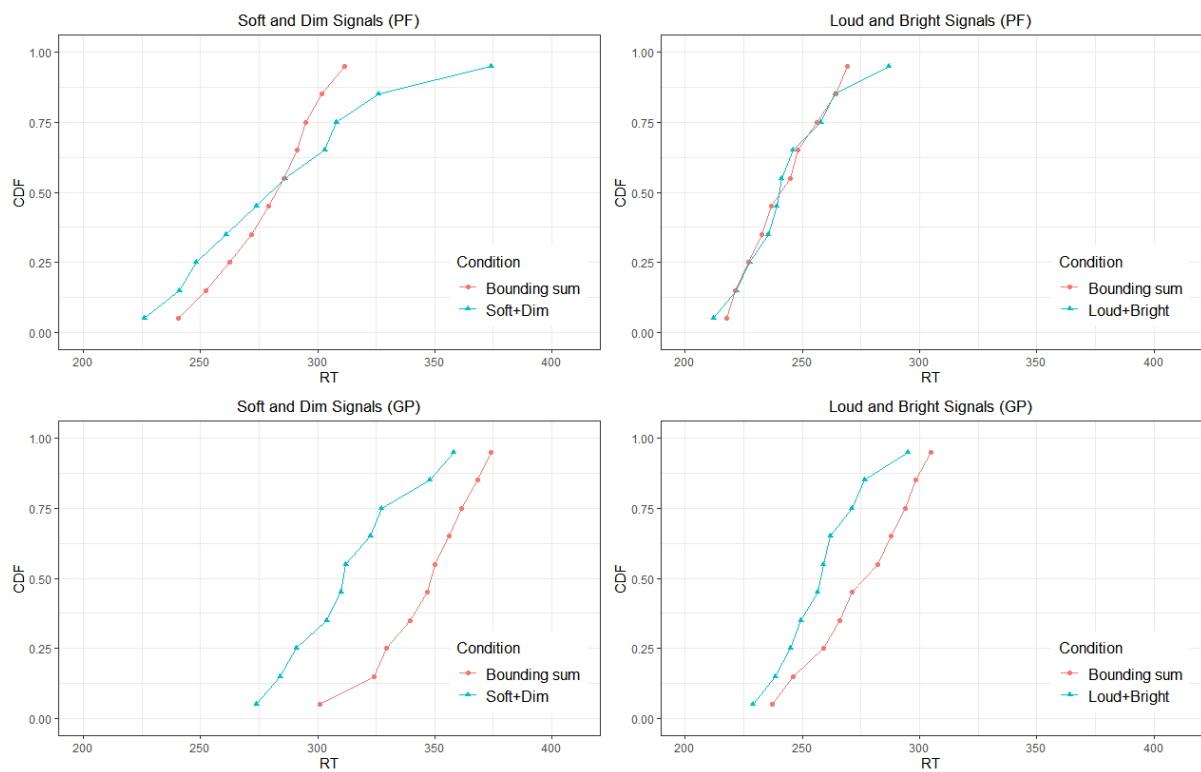


Note. Line plots of mean RT in milliseconds and pRF in Newtons performance for participant PF (*top row*) and participant GP (*bottom row*).

Cognitive Architecture. After Miller (1982), the four panels in Figure 7 show the sum of the cumulative distribution functions (CDFs) obtained for the unimodal trials compared to the CDF obtained for the bimodal trials for both participants and signal intensities. Visual inspection of these plots revealed that Miller's inequality for race models was violated in all instances except for in the case of PF on strong signal intensity (loud and bright) trials.

Figure 7

The Race Model Inequality

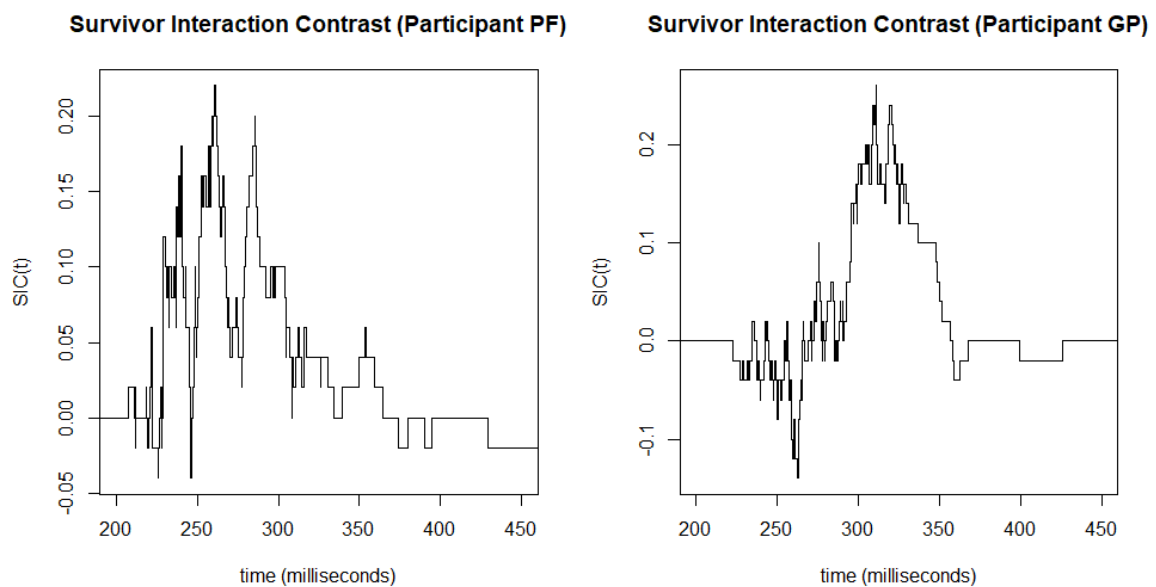


Note. Plots of the CDFs of participant PFs (*upper row*) and participant GPs (*bottom row*) performance on weak signal intensity trials (*left panels*) and strong signal intensity trials (*right panels*).

After Houpt and colleagues (2013), Figure 8 shows two plots depicting the interaction contrasts of survivor functions from the bimodal RT distributions for participant PF (left panel) and participant GP (right panel). Visual inspection of Figure 8 revealed SIC-curves that were approximately S-shaped.

Figure 8

SIC Analysis



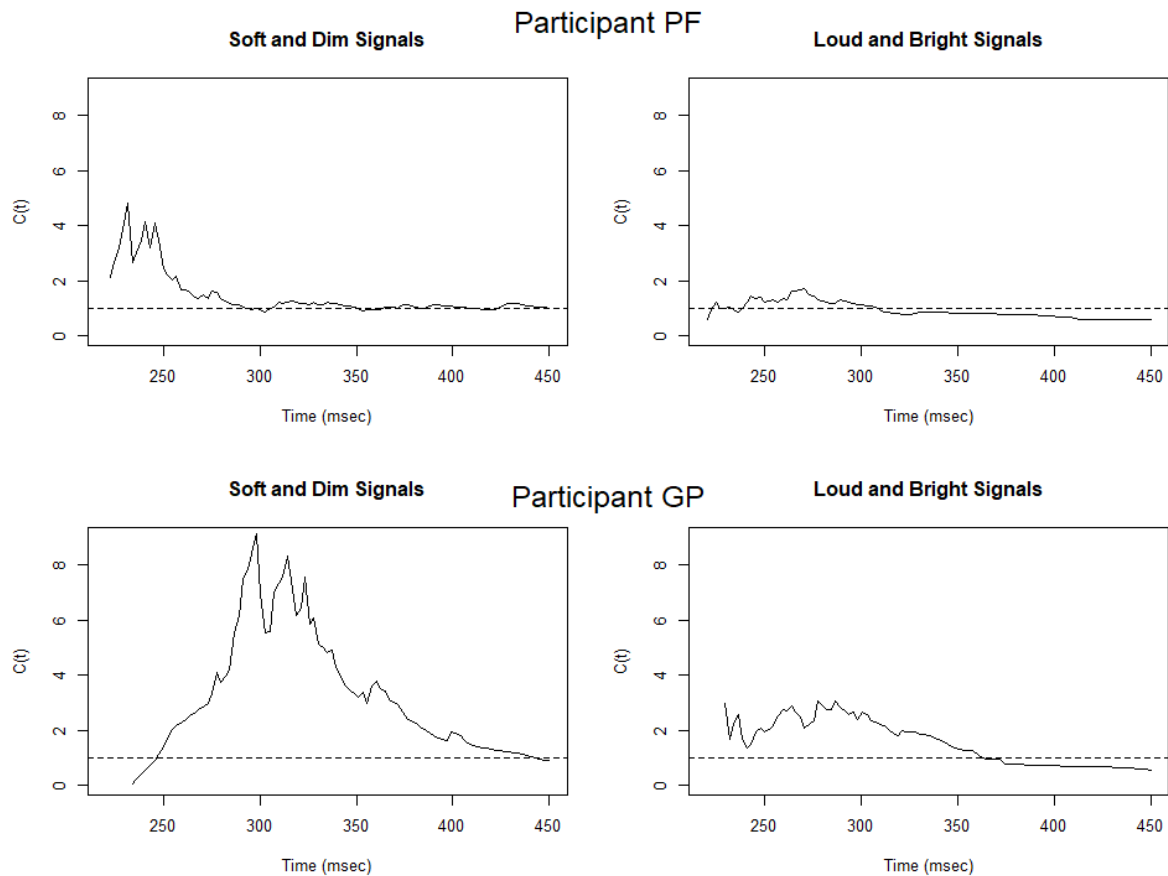
Note. SIC-curves calculated from the bimodal RT distributions for participant PF (*left panel*) and participant GP (*right panel*). Both SIC-analyses revealed approximately S-shaped curves. As discussed by Altieri and colleagues (2017) this pattern of results is indicative of latent coactive architecture

Figure 9 shows the OR-capacity coefficient $C_{OR}(t)$ obtained by dividing the sum of relevant hazards functions for the unimodal trials by the associated hazard function for the bimodal trials as promoted by Wenger and Townsend (2000). Visual inspection of the capacity analysis plots indicated that capacity was enhanced for most values of t , except for

possibly in the case of participant PF on strong signal intensity trials where capacity enhancements were less obvious.

Figure 9

Capacity Analysis



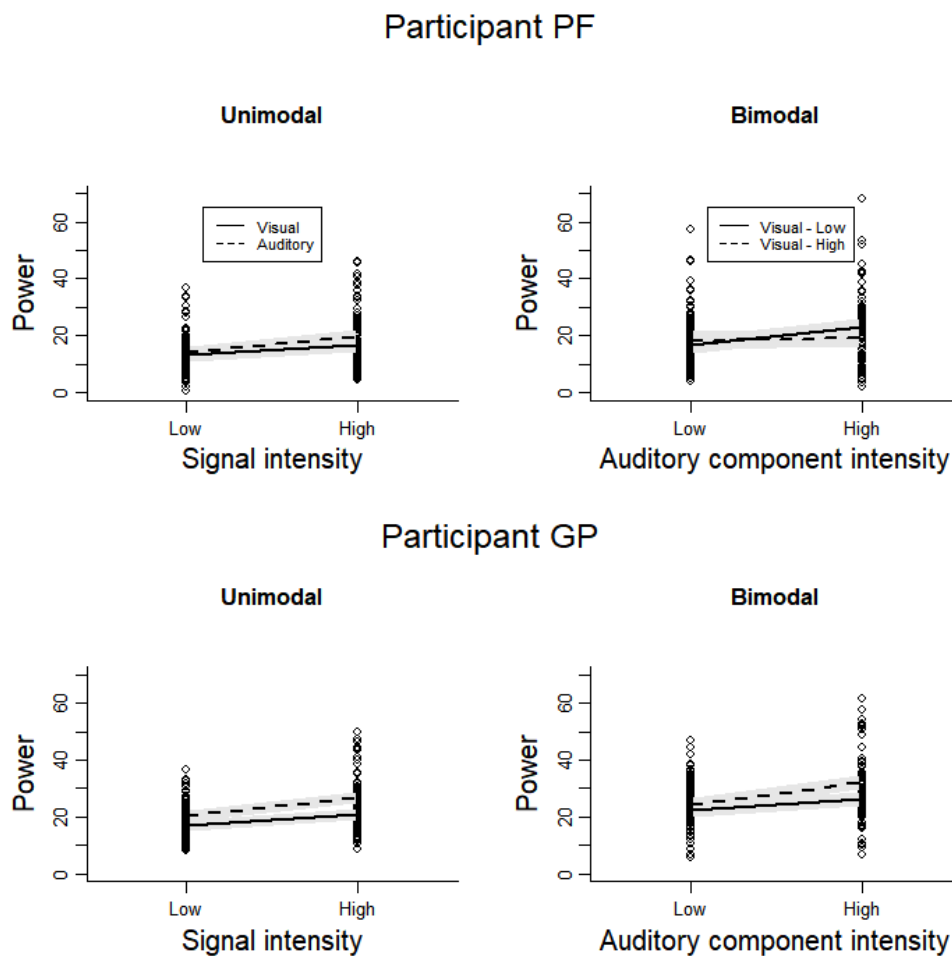
Note. Capacity analysis of participant PFs (*top row*) and GPs (*bottom row*) performance on bimodal trials incorporating weak (*left column*) and strong (*right column*) signal component intensities. The dotted lines at $C(t) = 1$ denote the performance of a system incorporating unlimited processing workload capacity.

Peak Processing Power. In the case of PF, the parameter estimates for the linear model predicting processing power based on redundancy were $b_0 = 15.85$, $b_1 = 3.52$, $\sigma = 10.09$, 95%

HDI [14.42, 17.27], [1.54, 5.50], and [9.42, 10.84], respectively. For GP, the same parameters estimates were $b_0 = 21.25$, $b_1 = 4.92$, $\sigma = 9.08$, 95% HDIs [19.98, 22.50], [3.14, 6.71], and [8.47, 9.75]. The redundancy models M_5 and M_6 outperformed the intercept models in predicting pRF in the case of PF ($BF_{50} = 36$) as well as GP ($BF_{60} > 100$), respectively.

Unimodal peak processing power predictions for PF were $b_0 = 13.27$, $b_1 = 0.78$, $b_2 = 3.19$, $b_3 = 2.40$, $\sigma = 8.75$, 95% HDIs [10.81, 15.74], [-2.69, 4.20], [-0.28, 6.65], [-2.40, 7.36], and [7.94, 9.70], respectively. For GP, $b_0 = 17.07$, $b_1 = 3.11$, $b_2 = 3.79$, $b_3 = 2.91$, $\sigma = 7.17$, 95% HDIs [15.10, 19.08], [0.29, 5.90], [0.97, 6.59], [-1.13, 6.90], and [6.50, 7.94]. For participant PF, model M_6 incorporating a main effect of stimulus intensity provided best fit to the unimodal peak processing power data ($BF_{60} = 44$). A model M_7 incorporating main effects of modality and intensity gave best fit to GPs unimodal peak processing power data ($BF_{70} > 100$).

Bimodal peak processing power predictions for PF were $b_0 = 13.27$, $b_1 = 0.78$, $b_2 = 3.19$, $b_3 = 2.40$, $\sigma = 8.75$, 95% HDIs [10.81, 15.74], [-2.69, 4.20], [-0.28, 6.65], [-2.40, 7.36], and [7.94, 9.70], respectively. For GP, $b_0 = 17.07$, $b_1 = 3.11$, $b_2 = 3.79$, $b_3 = 2.91$, $\sigma = 7.17$, 95% HDIs [15.10, 19.08], [0.29, 5.90], [0.97, 6.59], [-1.13, 6.90], and [6.50, 7.94], respectively. For participant PF, the evidence for all bimodal peak processing power models was inconclusive ($0.3 < BF_s < 3$), whereas a model M_8 incorporating main effects of both loudness and brightness gave best fit to GP's data ($BF_{80} > 100$). Figure 10 shows the results of the peak processing power analysis.

Figure 10*Peak Processing Power*

Note. Peak processing power in Newtons per second for participant PF (*top row*) and GP (*bottom row*) weak signal intensity trials (*left panels*) and strong signal intensity trials (*right panels*).

Discussion

Little to no association between pRF and RT was observed in the present experiment. This finding is perhaps counterintuitive, considering the fundamental correspondence between the forcefulness and the velocity of moving bodies at the level of physics. Possibly this observed discrepancy was due to the simplistic nature of the task, which effectively allowed participants to rest their hands on the response button, consequently leaving very

little spatial distance for their hands to traverse in order to provide a response. Experimental designs with multiple response options, all mapped accordingly to distinct response buttons, might be better fit for investigating speed-force relationships in simple perceptual and attentional tasks. Alternatively, Ulrich, Rinkenauer & Miller (1998) have suggested that the absence of a correspondence between RT and force implies that when sensory accrual reaches the response criterion, this opens a gate through which all subsequent motor activation flows until the gate closes. Because this causes response initiation and motor transmission to have differential critical time windows, the two can proceed relatively independent.

The first aim of the experiment was to replicate the RSE, i.e. the classic finding that RTs are shorter on bimodal trials as compared to unimodal trials. Despite how the experiment only comprised a single session and incorporated a fairly modest amount of trials, there was extreme evidence (following the BF interpretation heuristics of Lee & Wagenmakers, 2010) for an RSE in the case of both participants alike. Interestingly, the effect size was however diminished by a factor of $\frac{1}{2}$ for GP who was informed about the intent of the experiment. This raises the issue of whether experimental demands could have played a role in enhancing the RSE in the case of GP. In future experiments, systematic contrasts of redundancy gains in informed vs. naïve participants could provide important clues about if, and to what extent, such demand effects could potentially modulate the extent of the RSE.

The second aim of the present research was to assess latent cognitive architecture by testing the RT distributions against the race model inequality. Visual inspection of the CDFs from bimodal and combined unimodal trials revealed that the RT performance of both participants by and large violated Millers (1982) inequality. The observed RSE was therefore of a magnitude that cannot be accounted for by statistical facilitation alone. Neither can this violation be explained by interactive racing, because the experimental design contained no

beneficial interstimulus contingencies (as calculated from Equation 4 and 6 in Mordkoff & Yantis, 1991) which could theoretically have biased participants responses by allowing for crosstalk between auditory and visual processing pathways. Rather, the observed RMI violations are seemingly congruent with the coactive model of divided bimodal attention, according to which redundant auditory and visual signals are integrated somewhere in the stimulus-response chain of processing events. As an exception to the observed pattern of RMI violations, PF's RT performance on loud and bright trials did satisfy the inequality across all values of t except for the first five percent of the CDFs. Such differential redundancy gains between participants could possibly be explained by positing interindividual differences in sensory acuity, the basic idea being that PF's RT performance, but not GP's RT performance, become asymptotic on loud and bright unimodal trials. Consequently, PF's performance did not violate the RMI on trials incorporating energetic signal components, whereas GPs performance did. Unfortunately, the present research did not control for such possible interindividual differences. Future research could implement such control by starting the experiment with a short screening of sensory acuity, for instance by applying psychophysical staircase methods to estimate equivalent reference levels for all participants. These levels could later be incorporated in the experimental scripts.

Further, the methodological toolbox of SFT was applied to distinguish between alternate theoretical accounts of RMI violations. This was done to differentiate between coactivation effects proper, and other possibilities such as modality switching effects arising from temporally expensive serial monitoring of processing pathways as discussed by Patching & Quinlan (2004) and Townsend and Nozawa (1997). This revealed that the SIC-curves of both participants exhibited a sinuous shape with mean positive area underneath. As discussed by Altieri and colleagues (2017) such S-shaped SICs are characteristically produced by coactive architectures as opposed to serial and parallel architectures, independent of stopping rule.

Although not an explicit test of MSE, these results seem to conform with the interpretation that the RSEs of both PF and GP were of such magnitude as to violate the RMI due to latent coactive pooling of neural activation on bimodal trials, rather than due to modality switching costs on unimodal trials.

For PF, processing capacity enhancements on bimodal trials were somewhat attenuated for energetic as compared to weak stimuli pairs. Although PF exhibited clear evidence of bimodal super capacity for small values of t , this same effect was only partially present for strong signal trials, where performance fluctuated between limited, unlimited, and super capacity. In contrast, GP unambiguously exhibited bimodal super capacity for weak and strong signal component trials. Again, this effect could be related to interindividual differences in sensory acuity. In line with this explanation, the analysis of the unimodal RT distributions revealed extreme evidence for an intensity effect on RT performance for the unimodal trials, such that RTs decreased as an inverse function of stimulus intensity as predicted by Piéron's law. Indeed, the work of Pins and Bonnet (1996, 1997, 2000) on detection in the visual modality have shown that RT performance tends to saturate quite rapidly with intensity increases in the mesopic range, and then only incrementally for further increases in the signal-to-noise-ratio of the target. Currently, coactive models do not weigh the stimulus components according to their signal-to-noise ratios (see Chandrasekaran, 2017). But further accumulation of empirical evidence for or against this simple RT saturation principle in the integration of redundant stimuli could potentially provide useful guiding principles of experimental design in future research on divided bimodal attention.

The next aim of the presented research was to investigate perception-action links underlying performance in the bimodal divided attention paradigm. Of specific concern was the effects of intensity and redundancy manipulations on force output. The basic finding of Angel (1973) that motor output scales linearly with stimulus intensity was not replicated, as

neither PF or GP exhibited a clear-cut correspondence between pRF and the loudness or the brightness of the unimodal targets. This lack of an intensity-force relationship is contrary to the theoretical predictions of all variable output models as outlined by Ulrich, Rinckenauer and Miller (1998). The lack of a modality-specific effect of loudness on pRF is also at odds with the alternate, auditory arousal-mediated force output scaling mechanism as suggested by Jaśkowski and Włodarczyk (2006). These results instead seem to suggest that the motor component of the response proceeds in a rather invariant manner in simple RT experiments. Invariance can however not be fully ascertained by the present experiment, because certain variable output models also make the prediction that increased stimulus duration can increase pRF output. The effects of stimulus duration on motor scaling and redundancy gains in the context of bimodal divided attention remains a promising topic for future research.

The present research also failed to replicate Giray and Ulrich's (1993) main finding that coactivation leaves a trace in the motor component of the response in the form of increased pRF on bimodal trials. This finding poses a serious issue for all late stage loci models of coactivation, although it is still possible that the effects of redundancy on pRF were too small to be detected by the present experiment. Indeed, the shifts in mean pRF on bimodal trials were in the expected (increasing) direction for both participants, although the shifts were admittedly small (δ 's ~ 0.1) and the evidence supporting them anecdotal at best. This would imply an effect size inflation of a factor of four in Giray and Ulrich's original paper. Alternatively, the lack of increased pRF suggest that coactivation occurs at the early perceptual stage of stimulus detection, or possibly at a more central decision stage. The notion of a central loci is however at odds with the classic chronometric assumption that processing in signal detection tasks proceeds without a decision stage, and that simple RT is just the sum of the time needed to detect a target and respond to it by manual action (Donders, 1868/1969).

The present study also investigated the prospects for incorporating a metric of human processing power as a supplement to traditional RT and pRF analysis. *Processing power* is here taken to concern the rate at which the physical energy impinging on the sense organs is twofold transformed; first into neural activation, and then into biomechanical energy. In integral form, the power metric is simply equal to the SI-unit of the impulse $J = \int F dt$ and comes in well-defined units of Newtons per seconds. *Processing capacity*, as defined by Wenger and Townsend (2000), is in contrast a unitless metric which concerns the rate at which physical information is processed as compared to a theoretical (UCIP-OR) baseline. The observation that point estimates of peak processing power were systematically enhanced by increases in stimulus intensity on unimodal trials (and bimodal trials for GP) indicate that independent analysis of RT and pRF can be complemented by metrics that combine the speed and forcefulness of responses. For instance, contrasts of the continuous force distribution $F(t)$, akin to existing SFT contrasts of hazard and survivor functions, might hold promise as candidate dynamometric extensions of SFT.

In conclusion, the present research showed that the RSE, typically assessed through analysis conducted at the group level, could be reliably replicated at the individual case study level. SFT analysis of RT distributions further revealed that the RT distributions from both participants at least partially violated the RMI and suggested enhanced (super) capacity on bimodal trials. The SFT analysis also revealed S-shaped SIC-curves, further indicating that the observed RSE can most likely be derived from coactive pooling of neural activation from auditory and visual pathways. The absence of enhanced force output on bimodal trials further suggest that coactivation occurs in the preliminary stages of stimulus processing, as opposed to the late motor activation stage. The RSE stands in stark contrast to the common-sense notion of a focal attentional gain, according to which division of attention across multiple streams of information is detrimental to task performance. It is however in line with Lavie's

(2005) *load theory of attention*, according to which increased perceptual load can decrease interference from task-irrelevant processing. The bimodal advantage is also consistent with the many practical utilities of facilitating vigilance and reactivity with simultaneously presented auditory and visual signals. Representative illustrations include for instance the synchronous flashing and beeping of a medical heart rate monitor or an air traffic control radar system. In a more naturalistic sense, synergic interactions between multimodal cues are thought to help us to perceive, navigate and understand an ecological context that is filled with inherently multimodal physical events. Although these interactions might not be mapped to force output in a one-to-one correspondence as predicted by motor coactivation, everyday experience assures us that they most certainly do influence behavior. Future research on multisensory perception holds promise for unveiling many interesting things about exactly how the human brain integrates information from segregated attentional and sensorial processing subsystems, and how such integrative capabilities are reflected in behavioral action.

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